

Problem Statement

- 10 Different Classes of Images from CIFAR Dataset
- 60,000 32X32 Color images
- 6000 Images of each class
- Images have low resolution of 32X32

0.airplane
1.automobile
2.bird
3.cat
4.deer
5.dog
6.frog
7.horse
8.ship
9.truck

Import Libraries

```
In [122]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import keras
```

Import Dataset

```
In [123]: from keras.datasets import cifar10
```

```
(X_train,y_train),(X_test,y_test)=cifar10.load_data()
```

Shape of Data

```
In [124]: print("X_train shape",X_train.shape)
          print("X_test shape",X_test.shape)
          print("y_train shape",y_train.shape)
          print("y_test shape",y_test.shape)
```

```
X_train shape (50000, 32, 32, 3)
X_test shape (10000, 32, 32, 3)
y_train shape (50000, 1)
y_test shape (10000, 1)
```

Visualize the Data

```
In [125]: for i in range(2):
          random=np.random.randint(1000)
          print(y_train[random])
          plt.imshow(X_train[random])
          plt.axis("off")
          plt.show()
```

```
[9]
```



[1]

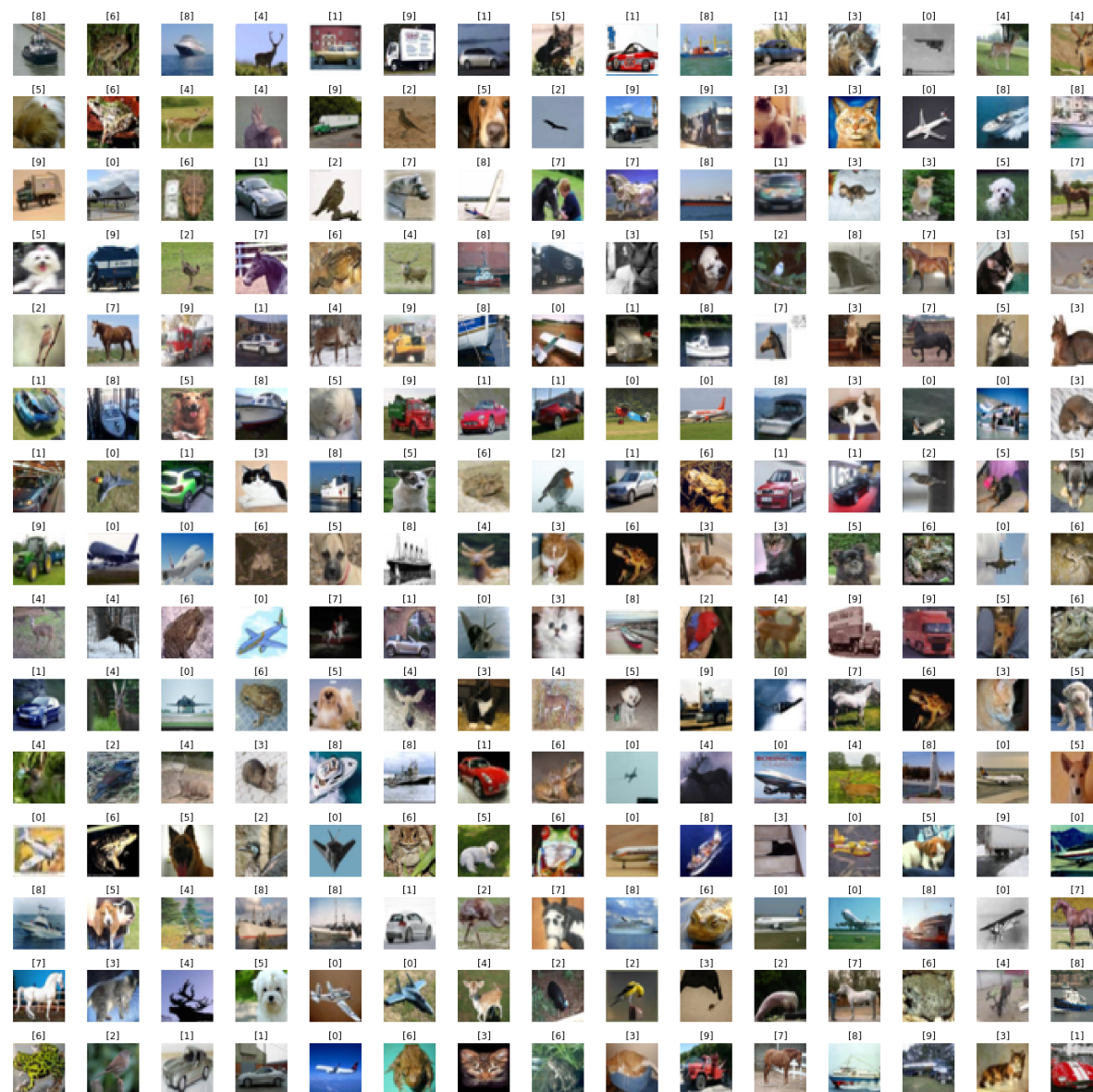


Grid Plots

```
In [126]: W_grid=15  
          L_grid=15
```

```
fig,axes=plt.subplots(L_grid,W_grid,figsize=(25,25))
# For flattening
axes=axes.ravel()
n_training=len(X_train)

for i in np.arange(0,L_grid*W_grid):
    index=np.random.randint(0,n_training)
    axes[i].imshow(X_train[index])
    axes[i].set_title(y_train[index])
    axes[i].axis("off")
plt.subplots_adjust(hspace = 0.4)
```



Data preparation

Float conversion

```
In [127]: X_train=X_train.astype("float32")
X_test=X_test.astype("float32")
```

Binary Encoding

```
In [128]: y_train=keras.utils.to_categorical(y_train,10)
y_test=keras.utils.to_categorical(y_test,10)
```

Normalizing the Data

```
In [129]: X_train=X_train/255
X_test=X_test/255
print(X_train.shape)
input_shape=X_train.shape[1:]
input_shape
```

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

```
Out[129]: (32, 32, 3)
```

Creating and Training the model

```
In [130]: from keras.models import Sequential
from keras.layers import Conv2D,MaxPooling2D, AveragePooling2D, Dense,
Flatten,Dropout
from keras.optimizers import Adam
from keras.callbacks import TensorBoard
```

```
In [10]: cnn_model=Sequential()
```

```

# First CNN Layer
cnn_model.add(Conv2D(filters=32, kernel_size=(3,3), activation='relu', input_shape=input_shape))
# Second CNN Layer
cnn_model.add(Conv2D(filters=32, kernel_size=(3,3), activation='relu'))
# MaxPooling 2D
cnn_model.add(MaxPooling2D(2,2))
# Dropout 30% of Neurons along with their weight
cnn_model.add(Dropout(0.3))

#Adding more depth with 64 filters
cnn_model.add(Conv2D(filters=64, kernel_size=(3,3), activation='relu'))
cnn_model.add(Conv2D(filters=64, kernel_size=(3,3), activation='relu'))
cnn_model.add(MaxPooling2D(2,2))
# Dropout 20% of Neurons along with their weight
cnn_model.add(Dropout(0.3))

## Flattening the data
cnn_model.add(Flatten())
## Adding Dense Layers
cnn_model.add(Dense(units=512, activation='relu'))
cnn_model.add(Dense(units=512, activation='relu'))
## Output Layer
cnn_model.add(Dense(units=10, activation='softmax'))

```

Compiling the model

```

In [11]: cnn_model.compile(loss='categorical_crossentropy', optimizer=keras.optimizers.rmsprop(lr=0.001), metrics=['accuracy'])

```

Fitting the training data with Shuffling

```

In [12]: history=cnn_model.fit(X_train,y_train,batch_size=128,epochs=10,shuffle=True)

```

```
Epoch 1/10
50000/50000 [=====] - 273s 5ms/step - loss: 1.
8270 - acc: 0.3377
Epoch 2/10
50000/50000 [=====] - 271s 5ms/step - loss: 1.
3717 - acc: 0.5109
Epoch 3/10
50000/50000 [=====] - 271s 5ms/step - loss: 1.
1602 - acc: 0.5916
Epoch 4/10
50000/50000 [=====] - 271s 5ms/step - loss: 1.
0032 - acc: 0.6485
Epoch 5/10
50000/50000 [=====] - 274s 5ms/step - loss: 0.
8847 - acc: 0.6915
Epoch 6/10
50000/50000 [=====] - 272s 5ms/step - loss: 0.
7983 - acc: 0.7208
Epoch 7/10
50000/50000 [=====] - 272s 5ms/step - loss: 0.
7255 - acc: 0.7450
Epoch 8/10
50000/50000 [=====] - 273s 5ms/step - loss: 0.
6628 - acc: 0.7673
Epoch 9/10
50000/50000 [=====] - 271s 5ms/step - loss: 0.
6122 - acc: 0.7853
Epoch 10/10
50000/50000 [=====] - 272s 5ms/step - loss: 0.
5668 - acc: 0.8010
```

Evaluate the Model

```
In [131]: print("Test accuracy",cnn_model.evaluate(X_test,y_test)[1])

## predictions
predicted_classes=cnn_model.predict(X_test)
```


10000/10000 [=====] - 20s 2ms/step
Test accuracy 0.7602

Making Predicting and True Value Matrix

```
In [132]: pred=[]
test=[]
for i in range(y_test.shape[0]):
    pred.append(np.argmax(predicted_classes[i]))
    test.append(np.argmax(y_test[i]))
predicted=np.array(pred)
true=np.array(test)
classes=np.unique(true)
```

Plotting confusion Matrix

```
In [133]: from sklearn.metrics import confusion_matrix
from sklearn.utils.multiclass import unique_labels

def plot_confusion_matrix(y_true, y_pred, classes,
                           normalize=False,
                           title=None,
                           cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    # Only use the labels that appear in the data
    classes = classes[unique_labels(y_true, y_pred)]
    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
```

```

# We want to show all ticks...
ax.set(xticks=np.arange(cm.shape[1]),
       yticks=np.arange(cm.shape[0]),
       # ... and label them with the respective list entries
       xticklabels=classes, yticklabels=classes,
       title=title,
       ylabel='True label',
       xlabel='Predicted label')

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
fmt = '.2f' if normalize else 'd'
thresh = cm.max() / 2.
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        ax.text(j, i, format(cm[i, j], fmt),
                ha="center", va="center",
                color="white" if cm[i, j] > thresh else "black")
fig.tight_layout()
return ax

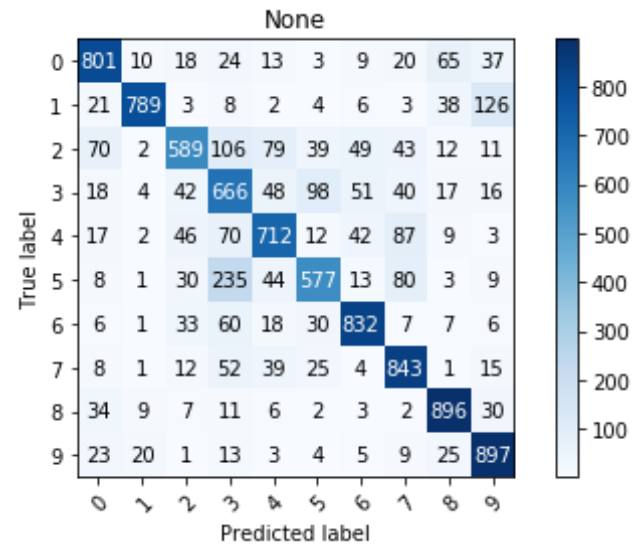
np.set_printoptions(precision=2)

```

```

In [134]: plot_confusion_matrix(true,pred,classes=classes)
plt.show()

```



Saving the Model

```
In [135]: import os
directory=os.path.join(os.getcwd(),"Saved Model")

if not os.path.isdir(directory):
    os.makedirs(directory)
model_path=os.path.join(directory,'Keras_CIFAR10_Trained_Model.h5')
cnn_model.save(model_path)
```

Improving the model with data Augmentation

Model Training using Augmented Dataset

```
In [140]: datagen=ImageDataGenerator(
            rotation_range=90,
```

```
width_shift_range=0.1,  
horizontal_flip=True,  
vertical_flip=True  
)
```

```
In [141]: datagen.fit(X_train)
```

```
In [142]: ## Steps per epoch = 50000/128 , 50000 was image data size and 128 is the batch size
```

```
In [143]: cnn_model.fit_generator(datagen.flow(X_train,y_train,batch_size=128),epochs=5,steps_per_epoch=50000/128)
```

```
Epoch 1/5  
391/390 [=====] - 282s 721ms/step - loss: 1.47  
01 - acc: 0.4760  
Epoch 2/5  
391/390 [=====] - 284s 726ms/step - loss: 1.40  
63 - acc: 0.5049  
Epoch 3/5  
391/390 [=====] - 283s 725ms/step - loss: 1.36  
72 - acc: 0.5180  
Epoch 4/5  
391/390 [=====] - 283s 723ms/step - loss: 1.34  
37 - acc: 0.5256  
Epoch 5/5  
391/390 [=====] - 283s 724ms/step - loss: 1.31  
90 - acc: 0.5352
```

```
Out[143]: <keras.callbacks.History at 0x19baf6ad1d0>
```

Saving Augmented Model

```
In [144]: import os  
directory=os.path.join(os.getcwd(),"Saved Model")
```

```
if not os.path.isdir(directory):  
    os.makedirs(directory)  
model_path=os.path.join(directory, 'Keras_CIFAR10_Augmented_Model.h5')  
cnn_model.save(model_path)
```

In []: