T.C.

SAKARYA ÜNİVERSİTESİ

BİLGİSAYAR VE BİLİŞİM BİLİMLERİ FAKÜLTESİ

BİLGİSAYAR MÜHENDİSLİĞİ BÖLÜMÜ

DERİN ÖĞRENME VE EVRİŞİMLİ SİNİR AĞLARI

2.Ödev

Hazırlayan
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Ödevde istenilen adımları sırasıyla aşağıdaki sayfalarda gösterdim ,

Ayrıca ödevi Google colab üzerinde DerinOgrenmeVeEvrisimliSinirAglari.ipynb adlı python dosyamda yaptım . Kodların bütün hepsinin açıklanmış hali bu kod dosyasında bulunmakta.

Slaytın sonuna kodları ekledim ama direk çıktıları göremediğimizden DerinOgrenmeVeEvrisimliSinirAglari.ipynb dosyamıda ödev klasörüne ayrıca ekledim

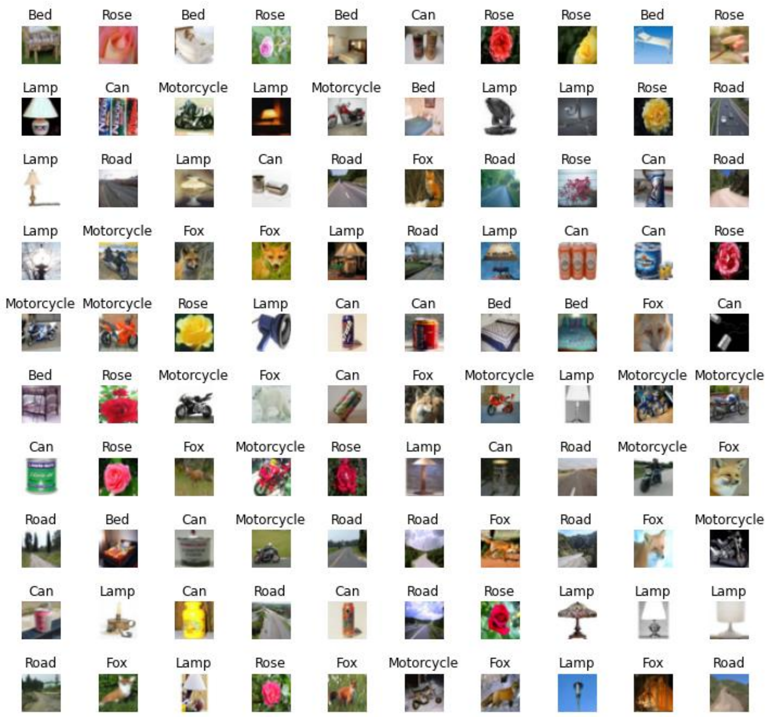
1-

```
# Burada elimizdeki dataseti içinde rastgele görüntü ve etiketi gösteriyor ve bu kod sayesinde elimizdeki bütün dataları genel şablon olarak görememizi sağlar

def showImages(num_row,num_col,X,Y):
    import matplotlib.pyplot as plt
    %matplotlib inline

    from sklearn.utils import shuffle
    (X_rand, Y_rand) = shuffle(X, Y)

    fig, axes = plt.subplots(num_row,num_col,figsize = (12,12))
    axes = axes.ravel()
    for i in range(0, num_row*num_col):
        axes[i].imshow(X_rand[i])
        axes[i].set_title("{}".format(labels[Y_rand.item(i)]))
        axes[i].axis('off')
        plt.subplots_adjust(wspace =1)

    return
```

```
labels = ['Bed', 'Can' , 'Fox'  , 'Lamp'  , 'Motorcycle', 'Road' , 'Rose']
```

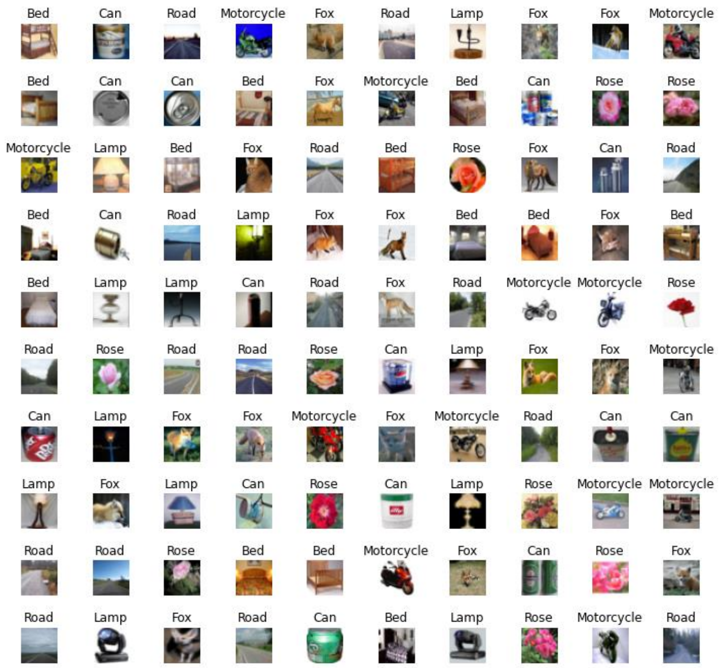
Train dataseti için

```
num_row = 10
num_col = 10
showImages(num_row,num_col,X =X_train_7Class,Y = y_train_7Class)
```



Test dataseti için

```
num_row = 10
num_col = 10
showImages(num_row,num_col,X =X_test_7Class,Y = y_test_7Class)
```

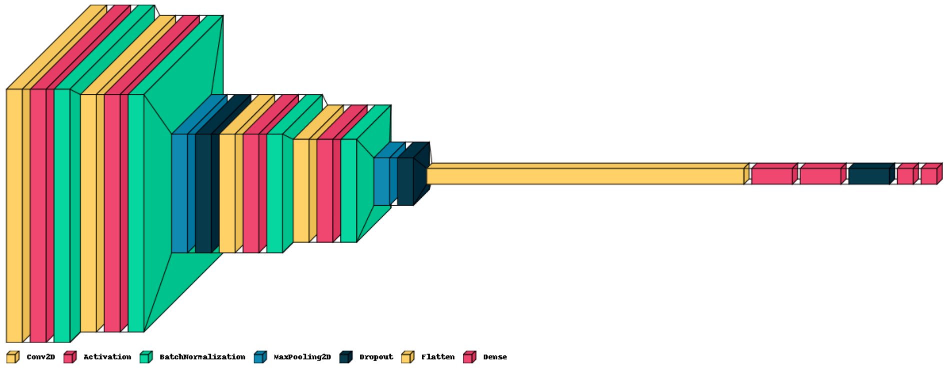


2-

Kendi Modelimizi Oluşturuyoruz

```
[35] model = Sequential()
     model.add(Conv2D(64, (3, 3), padding='same',
                      input_shape=X_train_7Class.shape[1:]))
     model.add(Activation('relu'))
     model.add(BatchNormalization())
     model.add(Conv2D(64, (3, 3)))
     model.add(Activation('relu'))
     model.add(BatchNormalization())
     model.add(MaxPooling2D(pool_size=(2, 2)))
     model.add(Dropout(0.25))

     model.add(Conv2D(128, (3, 3), padding='same'))
     model.add(Activation('relu'))
     model.add(BatchNormalization())
     model.add(Conv2D(128, (3, 3)))
     model.add(Activation('relu'))
     model.add(BatchNormalization())
     model.add(MaxPooling2D(pool_size=(2, 2)))
     model.add(Dropout(0.25))

     model.add(Flatten())
     model.add(Dense(512,kernel_regularizer=l2(0.01)))
     model.add(Activation('relu'))
     model.add(Dropout(0.5))
     model.add(Dense(num_classes))
     model.add(Activation('softmax'))
```

```
# Visualizing our model (Hidden Input)
import visualkeras
visualkeras.layered_view(model, scale_xy=10, legend=True)
```



```
print(model.summary())
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 32, 32, 64)        1792

 activation (Activation)     (None, 32, 32, 64)        0

 batch_normalization (BatchN  (None, 32, 32, 64)       256
 ormalization)

 conv2d_1 (Conv2D)           (None, 30, 30, 64)        36928

 activation_1 (Activation)   (None, 30, 30, 64)        0

 batch_normalization_1 (Batc  (None, 30, 30, 64)       256
 hNormalization)

 max_pooling2d (MaxPooling2D  (None, 15, 15, 64)       0
 )

 dropout (Dropout)           (None, 15, 15, 64)        0

 conv2d_2 (Conv2D)           (None, 15, 15, 128)       73856

 activation_2 (Activation)   (None, 15, 15, 128)       0

 batch_normalization_2 (Batc  (None, 15, 15, 128)      512
 hNormalization)

 conv2d_3 (Conv2D)           (None, 13, 13, 128)       147584

 activation_3 (Activation)   (None, 13, 13, 128)       0

 batch_normalization_3 (Batc  (None, 13, 13, 128)      512
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 6, 6, 128)        0
 2D)

 dropout_1 (Dropout)         (None, 6, 6, 128)         0

 flatten (Flatten)           (None, 4608)              0

 dense (Dense)               (None, 512)               2359808

 activation_4 (Activation)   (None, 512)               0

 dropout_2 (Dropout)         (None, 512)               0

 dense_1 (Dense)             (None, 7)                 3591

 activation_5 (Activation)   (None, 7)                 0
```

3-

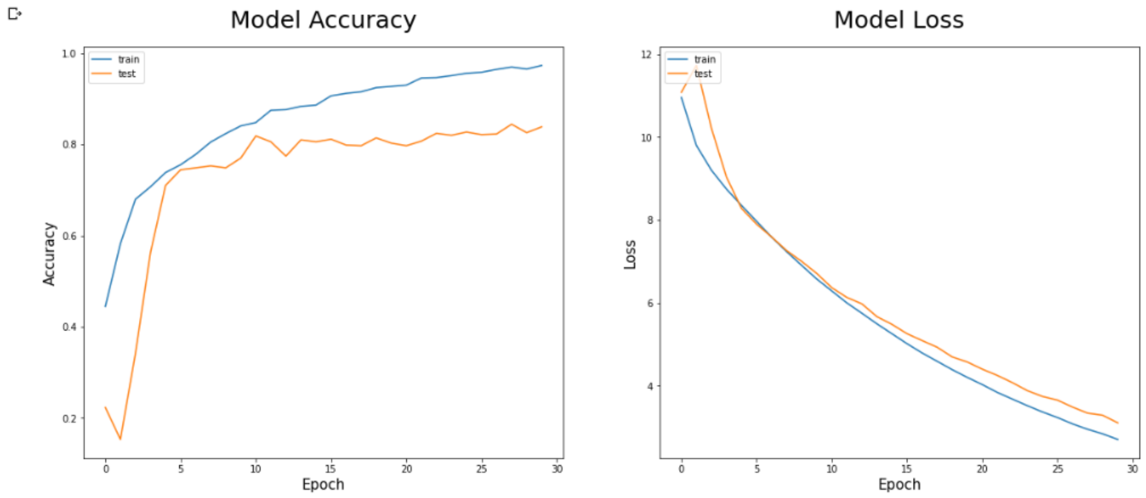
Training datasetini derliyoruz şimdi :

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

     X_train_7Class = X_train_7Class.astype('float32')
     X_test_7Class = X_test_7Class.astype('float32')

     # Normalizing the input image
     X_train_7Class /= 255
     X_test_7Class /= 255

     epochs=30

     # Training the model
     history = model.fit(X_train_7Class, y_train_7Class,
                   batch_size=batch_size,
                   epochs=epochs,
                   validation_data=(X_test_7Class, y_test_7Class),
                   shuffle=True)
```

```
Epoch 1/30
110/110 [==============================] - 59s 524ms/step - loss: 10.9579 - accuracy: 0.4446 - val_loss: 11.0826 - val_accuracy: 0.2229
Epoch 2/30
110/110 [==============================] - 56s 506ms/step - loss: 9.8004 - accuracy: 0.5823 - val_loss: 11.7293 - val_accuracy: 0.1529
Epoch 3/30
110/110 [==============================] - 55s 499ms/step - loss: 9.2021 - accuracy: 0.6797 - val_loss: 10.2148 - val_accuracy: 0.3414
Epoch 4/30
110/110 [==============================] - 53s 486ms/step - loss: 8.7461 - accuracy: 0.7071 - val_loss: 9.0366 - val_accuracy: 0.5629
Epoch 5/30
110/110 [==============================] - 53s 485ms/step - loss: 8.3515 - accuracy: 0.7383 - val_loss: 8.2797 - val_accuracy: 0.7100
Epoch 6/30
110/110 [==============================] - 53s 483ms/step - loss: 7.9706 - accuracy: 0.7554 - val_loss: 7.9003 - val_accuracy: 0.7443
Epoch 7/30
110/110 [==============================] - 54s 487ms/step - loss: 7.5882 - accuracy: 0.7780 - val_loss: 7.5919 - val_accuracy: 0.7486
Epoch 8/30
110/110 [==============================] - 53s 486ms/step - loss: 7.2365 - accuracy: 0.8051 - val_loss: 7.2619 - val_accuracy: 0.7529
```

Modelin Değerlendirilmesi

```
#  Model Accuracy & Model Loss vs Epochs Değerlerini Çizdiriyoruz
plt.figure(figsize=[20,8])

# accuracy
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy', size=25, pad=20)
plt.ylabel('Accuracy', size=15)
plt.xlabel('Epoch', size=15)
plt.legend(['train', 'test'], loc='upper left')

# loss
plt.subplot(1,2,2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss', size=25, pad=20)
plt.ylabel('Loss', size=15)
plt.xlabel('Epoch', size=15)
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```




```
[48] # Score trained model.
     scores = model.evaluate(X_test_7Class, y_test_7Class, verbose=1)
     print('Test loss:', scores[0])
     print('Test accuracy:', scores[1])
```

```
22/22 [==============================] - 5s 227ms/step - loss: 3.1076 - accuracy: 0.8386
Test loss: 3.107589006642395
Test accuracy: 0.8385714292526245
```

eğitimiz modelin test verisinde test ettiğmizde accuary ve loss değerleri

4 –

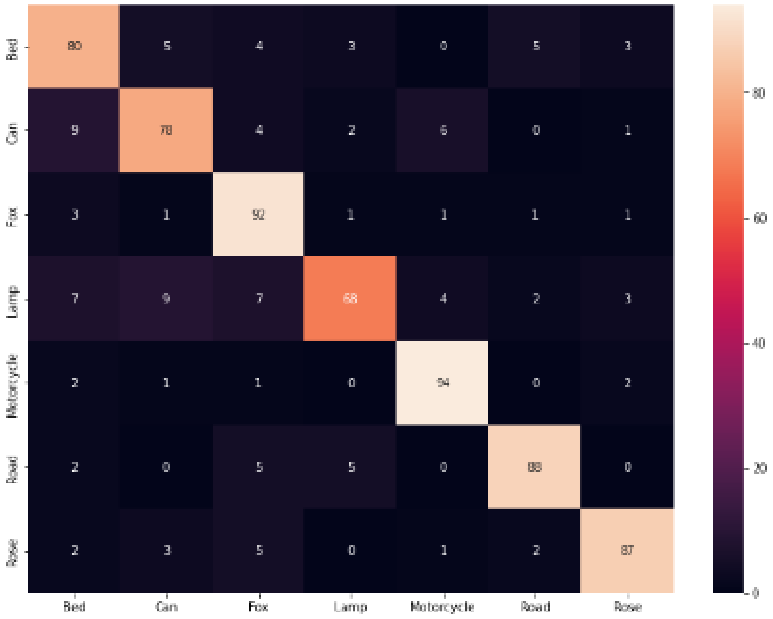
Confusion Matrix

```
import seaborn as sns
```

```
[50] # Predict the values from the validation dataset
     y_pred = model.predict(X_test_7Class)
     # Convert predictions classes to one hot vectors
     y_pred_classes = np.argmax(y_pred,axis = 1)
     # Convert validation observations to one hot vectors
     y_true = np.argmax(y_test_7Class,axis = 1)
     # compute the confusion matrix
     confusion_mtx = tf.math.confusion_matrix(y_true, y_pred_classes)
```

```
[51] plt.figure(figsize=(12, 9))
     c = sns.heatmap(confusion_mtx, annot=True, fmt='g')
     c.set(xticklabels=class_names, yticklabels=class_names)
```

```
[[Text(0, 0.5, 'Bed'),
  Text(0, 1.5, 'Can'),
  Text(0, 2.5, 'Fox'),
  Text(0, 3.5, 'Lamp'),
  Text(0, 4.5, 'Motorcycle'),
  Text(0, 5.5, 'Road'),
  Text(0, 6.5, 'Rose')],
 [Text(0.5, 0, 'Bed'),
  Text(1.5, 0, 'Can'),
  Text(2.5, 0, 'Fox'),
  Text(3.5, 0, 'Lamp'),
  Text(4.5, 0, 'Motorcycle'),
  Text(5.5, 0, 'Road'),
  Text(6.5, 0, 'Rose')]]
```

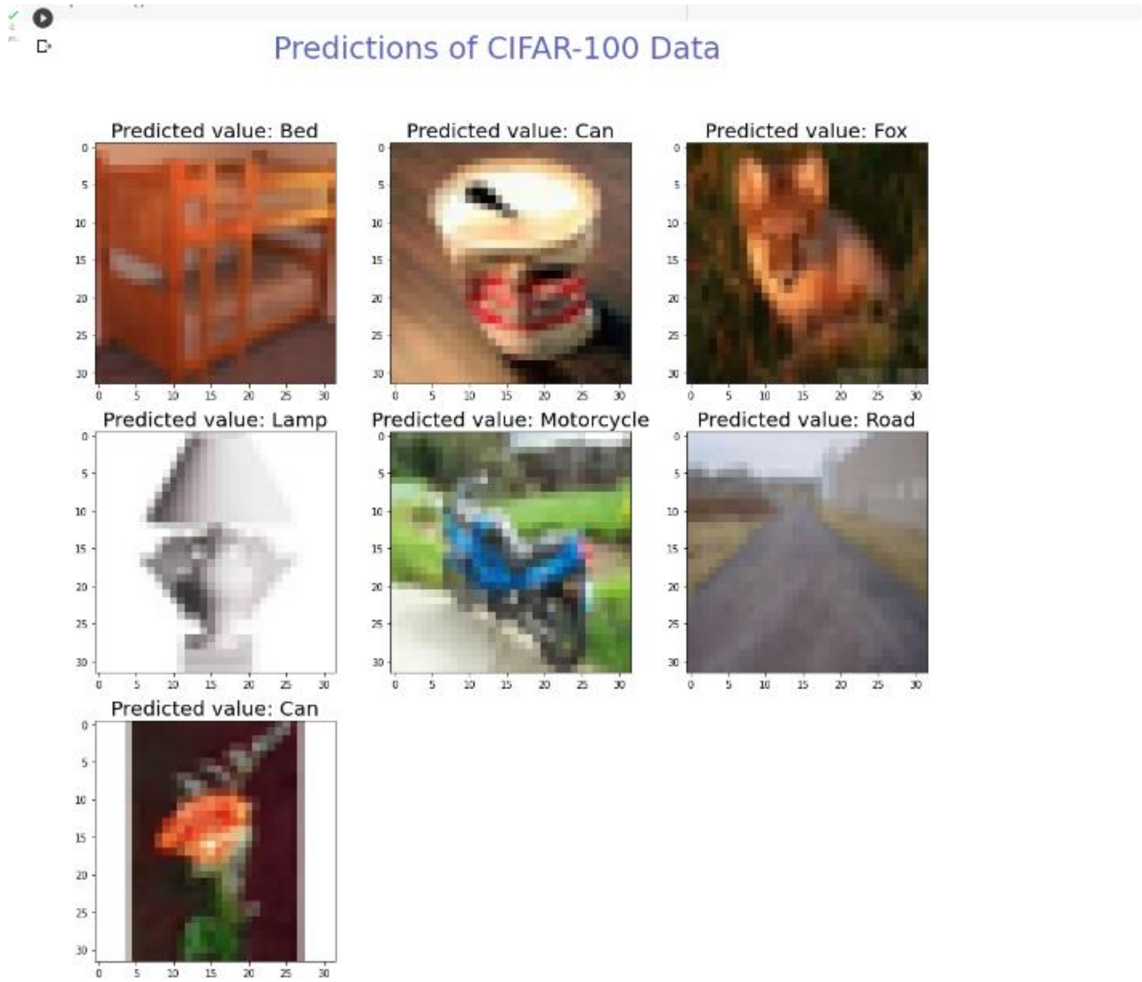


Confusion Matrix sayesinde hangi test verilerin hangi sınıflara tahmin edildiğini gösteriyor

5 –

Test datamızdaki bazı verilerin modelimize sokulduktan sonraki sonuç değerleri

```
predictions = model.predict(X_test_7Class)

plt.figure(figsize=[15,15])

class_names = ['Bed', 'Can' , 'Fox'  , 'Lamp'  , 'Motorcycle', 'Road' , 'Rose']

plt.subplot(3,3,1)
n = 55
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,2)
n = 112
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,3)
n = 234
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,4)
n = 397
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,5)
n = 415
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,6)
n = 555
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,7)
n = 689
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n], axis=0)]), size=20)
plt.grid(False)
```



7 Sınıfdan rastgele test verisini modele tahmin ettirdim sadece rose yani gülü can(teneke kutu) olarak algıladı

Kodlar

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd


from keras.datasets import cifar100
from keras.utils import np_utils
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation, Flatten
from keras.layers import BatchNormalization
from keras.layers.convolutional import Conv2D , MaxPooling2D
from keras.optimizers import sgd_experimental , adam_v2 , rmsprop_v2
import os
import tensorflow
from tensorflow import keras
from keras.regularizers import l2


# Burada elimizdeki dataseti içinde rastgele görüntü ve etiketi gösteri
yor ve bu kod sayesinde elimizdeki bütün dataları genel şablon olarak g
örememizi sağlar

def showImages(num_row,num_col,X,Y):
    import matplotlib.pyplot as plt
    %matplotlib inline

    from sklearn.utils import shuffle
    (X_rand, Y_rand) = shuffle(X, Y)

    fig, axes = plt.subplots(num_row,num_col,figsize = (12,12))
    axes = axes.ravel()
    for i in range(0, num_row*num_col):
        axes[i].imshow(X_rand[i])
        axes[i].set_title("{}".format(labels[Y_rand.item(i)]))
        axes[i].axis('off')
        plt.subplots_adjust(wspace =1)

    return


labels = ['Bed', 'Can' , 'Fox'  , 'Lamp'  , 'Motorcycle', 'Road' , 'Ros
e']


print(labels)
(X_train, y_train), (X_test, y_test) = cifar100.load_data()
```

```
#classes = {5=bed(yatak) 16=can(teneke kutu) 34=fox(tilki) 40=lamp(lamba) 48=motorcycle(motosiklet) 68=road(yol) 70=rose(gül)}
```

```
print(X_train.shape)
```

```
print(y_train.shape)
```

```
print(X_test.shape)
```

```
print(y_test.shape)
```

**şimdi cifar100 datasetinden #classes = {5=bed(yatak) 16=can(teneke kutu) 34=fox(tilki) 40=lamp(lamba) 48=motorcycle(motosiklet) 68=road(yol) 70=rose(gül)}
sadece bu classları alarak kendimize bir dataseti oluşturucağız**

cifar100 datasetinden kendimizin istediği sınıfların , bu sınıflardaki verilerin index numaralarını alıyoruz

```
index5 = np.where(y_train == 5)
index16 = np.where(y_train == 16)
index34 = np.where(y_train == 34)
index40 = np.where(y_train == 40)
index48 = np.where(y_train == 48)
index68 = np.where(y_train == 68)
index70 = np.where(y_train == 70)
```

```
#5. numaralı class daki verilerin bulunduğu X_train5  y_train5
X_train5 = X_train[index5[0]]
y_train5 = y_train[index5[0]]
print(X_train5.shape)
print(y_train5.shape)
```

yukarda gördüğümüz gibi her sınıfın train verisinde 500 adet veri bulunuyor*

```
#16 için
X_train16 = X_train[index16[0]]
y_train16 = y_train[index16[0]]

#34 için
X_train34 = X_train[index34[0]]
y_train34 = y_train[index34[0]]

#40 için
X_train40 = X_train[index40[0]]
y_train40 = y_train[index40[0]]

#48 için
X_train48 = X_train[index48[0]]
y_train48 = y_train[index48[0]]

#68 için
X_train68 = X_train[index68[0]]
y_train68 = y_train[index68[0]]

#70 için
X_train70 = X_train[index70[0]]
y_train70 = y_train[index70[0]]
```

7 adet sınıfı tek bir sınıf da topluyoruz*

```
X_train_7Class = np.append(X_train5, X_train16, axis = 0)
y_train_7Class = np.append(y_train5, y_train16, axis = 0)

X_train_7Class = np.append(X_train_7Class, X_train34, axis = 0)
y_train_7Class = np.append(y_train_7Class, y_train34, axis = 0)

X_train_7Class = np.append(X_train_7Class, X_train40, axis = 0)
y_train_7Class = np.append(y_train_7Class, y_train40, axis = 0)

X_train_7Class = np.append(X_train_7Class, X_train48, axis = 0)
y_train_7Class = np.append(y_train_7Class, y_train48, axis = 0)

X_train_7Class = np.append(X_train_7Class, X_train68, axis = 0)
y_train_7Class = np.append(y_train_7Class, y_train68, axis = 0)

X_train_7Class = np.append(X_train_7Class, X_train70, axis = 0)
y_train_7Class = np.append(y_train_7Class, y_train70, axis = 0)
```

```python
# Şimdi bunları test datası için yapıyoruz


print(X_test.shape)
print(y_test.shape)


index5_test  = np.where(y_test == 5)
index16_test = np.where(y_test == 16)
index34_test = np.where(y_test == 34)
index40_test = np.where(y_test == 40)
index48_test = np.where(y_test == 48)
index68_test = np.where(y_test == 68)
index70_test = np.where(y_test == 70)



#5 için
X_test5 = X_test[index5_test[0]]
y_test5 = y_test[index5_test[0]]

#16 için
X_test16 = X_test[index16_test[0]]
y_test16 = y_test[index16_test[0]]

#34 için
X_test34 = X_test[index34_test[0]]
y_test34 = y_test[index34_test[0]]

#40 için
X_test40 = X_test[index40_test[0]]
y_test40 = y_test[index40_test[0]]

#48 için
X_test48 = X_test[index48_test[0]]
y_test48 = y_test[index48_test[0]]

#68 için
X_test68 = X_test[index68_test[0]]
y_test68 = y_test[index68_test[0]]

#70 için
X_test70 = X_test[index70_test[0]]
y_test70 = y_test[index70_test[0]]


X_test_7Class = np.append(X_test5, X_test16, axis = 0)
```

```
y_test_7Class = np.append(y_test5, y_test16, axis = 0)

X_test_7Class = np.append(X_test_7Class, X_test34, axis = 0)
y_test_7Class = np.append(y_test_7Class, y_test34, axis = 0)

X_test_7Class = np.append(X_test_7Class, X_test40, axis = 0)
y_test_7Class = np.append(y_test_7Class, y_test40, axis = 0)

X_test_7Class = np.append(X_test_7Class, X_test48, axis = 0)
y_test_7Class = np.append(y_test_7Class, y_test48, axis = 0)

X_test_7Class = np.append(X_test_7Class, X_test68, axis = 0)
y_test_7Class = np.append(y_test_7Class, y_test68, axis = 0)

X_test_7Class = np.append(X_test_7Class, X_test70, axis = 0)
y_test_7Class = np.append(y_test_7Class, y_test70, axis = 0)
```

Şimdi y_test_7Class ve y_train_7Class değerleri olan 5 16 34 40 48 68 70 bunları sırayla karşılık gelicek şekilde 0 1 2 3 4 5 6 ile değiştiriyoruz*

```
print(y_test_7Class.shape)
```

```
print(y_test_7Class)
```

```
for x in range(0,len(y_test_7Class)):
  if x < 100:
    y_test_7Class[x][0]  = 0
  elif x < 200:
    y_test_7Class[x][0]  = 1
  elif x < 300:
    y_test_7Class[x][0]  = 2
  elif x < 400:
    y_test_7Class[x][0]  = 3
  elif x < 500:
    y_test_7Class[x][0]  = 4
  elif x < 600:
    y_test_7Class[x][0]  = 5
  elif x < 700:
    y_test_7Class[x][0]  = 6
```

```
print(y_test_7Class.shape)
```

```
print(y_test_7Class)
```

y_train_7Class için değiştiriyoruz şimdi de

```
print(y_train_7Class.shape)
```

```
print(y_train_7Class)
```

```
for x in range(0,len(y_train_7Class)):
  if x < 500:
    y_train_7Class[x][0]  = 0
  elif x < 1000:
    y_train_7Class[x][0]  = 1
  elif x < 1500:
    y_train_7Class[x][0]  = 2
  elif x < 2000:
    y_train_7Class[x][0]  = 3
  elif x < 2500:
    y_train_7Class[x][0]  = 4
  elif x < 3000:
    y_train_7Class[x][0]  = 5
  elif x < 3500:
    y_train_7Class[x][0]  = 6
```

```
print(y_train_7Class.shape)
```

```
print(y_train_7Class)
```

```
# Oluşturmuş olduğumuz datasetini görselleştiriyoruz
```

Train dataseti için

```
num_row = 10
num_col = 10
showImages(num_row,num_col,X =X_train_7Class,Y = y_train_7Class)
```

Test dataseti için

```
num_row = 10
num_col = 10
showImages(num_row,num_col,X =X_test_7Class,Y = y_test_7Class)
```

Pre-Processing The Data:

modeli eğitmeden önce bazı parametreleri tanımlıyoruz

```
batch_size = 32
num_classes = 7
epochs = 50
```

Convert class vectors to binary class matrices.

```
import tensorflow as tf
```

```
y_train_7Class = tf.keras.utils.to_categorical(y_train_7Class, num_clas
ses)
y_test_7Class = tf.keras.utils.to_categorical(y_test_7Class, num_classe
s)
```

Kendi Modelimizi Oluşturuyoruz

```
model = Sequential()
model.add(Conv2D(64, (3, 3), padding='same',
                 input_shape=X_train_7Class.shape[1:]))
model.add(Activation('relu'))
model.add(BatchNormalization())
```

```
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(128, (3, 3)))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512,kernel_regularizer=l2(0.01)))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))
```

Oluşturduğumuz Sinir Ağını 3 boyutlu model ile gösteriyoruz

```
!pip install git+https://github.com/paulgavrikov/visualkeras
```

```
# Visualizing our model (Hidden Input)
import visualkeras
visualkeras.layered_view(model, scale_xy=10, legend=True)
```

```
# Modelimiz
```

```
print(model.summary())
```

```
# Training datasetini derliyoruz şimdi :
```

```
model.compile(loss='categorical_crossentropy',
              optimizer='sgd',
```

```
              metrics=['accuracy'])

X_train_7Class = X_train_7Class.astype('float32')
X_test_7Class = X_test_7Class.astype('float32')

# Normalizing the input image
X_train_7Class /= 255
X_test_7Class /= 255

epochs=30

# Training the model
history = model.fit(X_train_7Class, y_train_7Class,
              batch_size=batch_size,
              epochs=epochs,
              validation_data=(X_test_7Class, y_test_7Class),
              shuffle=True)
```

```
## ***Modelin Değerlendirilmesi***
```

```
#  Model Accuracy & Model Loss vs Epochs Değerlerini Çizdiriyoruz
plt.figure(figsize=[20,8])

# accuracy
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy', size=25, pad=20)
plt.ylabel('Accuracy', size=15)
plt.xlabel('Epoch', size=15)
plt.legend(['train', 'test'], loc='upper left')

# loss
plt.subplot(1,2,2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss', size=25, pad=20)
plt.ylabel('Loss', size=15)
plt.xlabel('Epoch', size=15)
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

Test datamızdaki bazı verilerin modelimize sokulduktan sonraki sonuç değerleri*

```
predictions = model.predict(X_test_7Class)

plt.figure(figsize=[15,15])

class_names = ['Bed', 'Can' , 'Fox'  , 'Lamp'  , 'Motorcycle', 'Road' ,
 'Rose']

plt.subplot(3,3,1)
n = 55
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n
], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,2)
n = 112
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n
], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,3)
n = 234
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n
], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,4)
n = 397
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n
], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,5)
n = 415
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n
], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,6)
n = 555
```

```python
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n
], axis=0)]), size=20)
plt.grid(False)

plt.subplot(3,3,7)
n = 689
plt.imshow(X_test_7Class[n].reshape(32, 32, -1), cmap=plt.cm.binary)
plt.title("Predicted value: " + str(class_names[np.argmax(predictions[n
], axis=0)]), size=20)
plt.grid(False)

plt.suptitle("Predictions of CIFAR-100 Data", size=30, color="#6166B3")
```

```python
save_dir = os.path.join(os.getcwd(), 'saved_models')
model_name = 'keras_cifar100_trained_model.h5'
# modelin ağırlıklarını kayıt ediyoruz
```

```python
# Save model and weights
if not os.path.isdir(save_dir):
    os.makedirs(save_dir)
model_path = os.path.join(save_dir, model_name)
model.save(model_path)
print('Saved trained model at %s ' % model_path)
```

```python
# Score trained model.
scores = model.evaluate(X_test_7Class, y_test_7Class, verbose=1)
print('Test loss:', scores[0])
print('Test accuracy:', scores[1])
```

**eğitimiz modelin test verisinde test ettiğmizde accuary ve loss değer
leri**

```python
# Confusion Matrix

import seaborn as sns



# Predict the values from the validation dataset
y_pred = model.predict(X_test_7Class)
# Convert predictions classes to one hot vectors
y_pred_classes = np.argmax(y_pred,axis = 1)
# Convert validation observations to one hot vectors
y_true = np.argmax(y_test_7Class,axis = 1)
# compute the confusion matrix
confusion_mtx = tf.math.confusion_matrix(y_true, y_pred_classes)


plt.figure(figsize=(12, 9))
c = sns.heatmap(confusion_mtx, annot=True, fmt='g')
c.set(xticklabels=class_names, yticklabels=class_names)
```

Confusion Matrix sayesinde hangi test verilerin hangi sınıflara tahmin edildiğini gösteriyor*