```
import pickle
import pandas as pd
import numpy as np

def unpickle(file):
        with open(file, 'rb') as fo:
                dict = pickle.load(fo, encoding='bytes')
        return dict

def load_labels_name(filename):
        with open(filename, 'rb') as f:
                obj = pickle.load(f)
        return obj


from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# load data
train = unpickle('./drive/MyDrive/cifar-100-python/train')
X_train = train.get(b'data')
y_train = train.get(b'fine_labels')

name = load_labels_name('./drive/MyDrive/cifar-100-python/meta')

test = unpickle('./drive/MyDrive/cifar-100-python/test')
X_test = test.get(b'data')
y_test = test.get(b'fine_labels')
print(X_test.shape)
```

```
(10000, 3072)
```

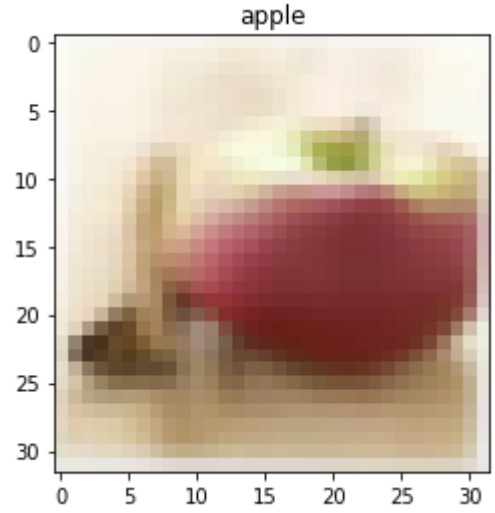
```
# vistualize sample image
# from PIL import Image
# %matplotlib inline
from matplotlib import pyplot as plt

X_train=X_train.reshape(-1,3,32,32)
X_train=np.rollaxis(X_train, 1, 4)
X_test=X_test.reshape(-1,3,32,32)
X_test=np.rollaxis(X_test, 1, 4)
X_train.shape
```

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

```
plt.figure(figsize=(4,4))
```

```
index = 2
plt.rcParams["axes.grid"] = False
plt.imshow(X_train[index])
plt.title(name['fine_label_names'][y_train[index]])
```

```
Text(0.5, 1.0, 'apple')
```




```
# from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
# print(X_train)

X_train = X_train / 255.0
X_test = X_test / 255.0
```

CNN

```
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from tensorflow.keras.losses import sparse_categorical_crossentropy
from tensorflow.keras.optimizers import Adam
# Create the model
model = Sequential()
model.add(layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(32,
model.add(layers.MaxPooling2D(pool_size=(2, 2)))
model.add(layers.Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2, 2)))
model.add(layers.Conv2D(128, kernel_size=(3, 3), activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2, 2)))
```

```
model.add(layers.Flatten())
model.add(layers.Dense(256,  activation='relu'))
model.add(layers.Dense(128,  activation='relu'))
model.add(layers.Dense(100,  activation='softmax'))


model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 30, 30, 32)        896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 15, 15, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 13, 13, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 4, 4, 128)         73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 2, 2, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 512)               0
_________________________________________________________________
dense (Dense)                (None, 256)               131328
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_2 (Dense)              (None, 100)               12900
=================================================================
Total params: 270,372
Trainable params: 270,372
Non-trainable params: 0
_________________________________________________________________
```

```
#  Model  configuration
batch_size  =  256
verbosity  =  1
epochs  =  50

X_train  =  np.array(X_train)
y_train  =  np.array(y_train)
X_test  =  np.array(X_test)
y_test  =  np.array(y_test)

#  Compile  the  model
model.compile(loss='sparse_categorical_crossentropy',  optimizer=Adam(),  metrics=['acc

#  Fit  data  to  model
history  =  model.fit(X_train,  y_train,  batch_size=batch_size,
```

```
                    epochs=epochs,
                    verbose=verbosity,validation_split=0.2)
```

```
Epoch 1/50
157/157 [==============================] - 48s 300ms/step - loss: 4.2189 - accuracy: 0.05
Epoch 2/50
157/157 [==============================] - 47s 298ms/step - loss: 3.6949 - accuracy: 0.13
Epoch 3/50
157/157 [==============================] - 47s 299ms/step - loss: 3.3707 - accuracy: 0.18
Epoch 4/50
157/157 [==============================] - 47s 298ms/step - loss: 3.1455 - accuracy: 0.22
Epoch 5/50
157/157 [==============================] - 47s 299ms/step - loss: 2.9889 - accuracy: 0.25
Epoch 6/50
157/157 [==============================] - 47s 300ms/step - loss: 2.8632 - accuracy: 0.28
Epoch 7/50
157/157 [==============================] - 47s 300ms/step - loss: 2.7629 - accuracy: 0.30
Epoch 8/50
157/157 [==============================] - 47s 300ms/step - loss: 2.6541 - accuracy: 0.32
Epoch 9/50
157/157 [==============================] - 47s 301ms/step - loss: 2.5611 - accuracy: 0.34
Epoch 10/50
157/157 [==============================] - 47s 300ms/step - loss: 2.4853 - accuracy: 0.35
Epoch 11/50
157/157 [==============================] - 47s 300ms/step - loss: 2.4058 - accuracy: 0.37
Epoch 12/50
157/157 [==============================] - 47s 299ms/step - loss: 2.3515 - accuracy: 0.38
Epoch 13/50
157/157 [==============================] - 47s 299ms/step - loss: 2.2799 - accuracy: 0.40
Epoch 14/50
157/157 [==============================] - 47s 299ms/step - loss: 2.2076 - accuracy: 0.42
Epoch 15/50
157/157 [==============================] - 47s 300ms/step - loss: 2.1496 - accuracy: 0.43
Epoch 16/50
157/157 [==============================] - 47s 301ms/step - loss: 2.0859 - accuracy: 0.44
Epoch 17/50
157/157 [==============================] - 47s 300ms/step - loss: 2.0530 - accuracy: 0.45
Epoch 18/50
157/157 [==============================] - 47s 300ms/step - loss: 1.9732 - accuracy: 0.47
Epoch 19/50
157/157 [==============================] - 47s 300ms/step - loss: 1.9300 - accuracy: 0.48
Epoch 20/50
157/157 [==============================] - 47s 300ms/step - loss: 1.8768 - accuracy: 0.49
Epoch 21/50
157/157 [==============================] - 47s 300ms/step - loss: 1.8344 - accuracy: 0.50
Epoch 22/50
157/157 [==============================] - 47s 300ms/step - loss: 1.7856 - accuracy: 0.51
Epoch 23/50
157/157 [==============================] - 47s 300ms/step - loss: 1.7436 - accuracy: 0.52
Epoch 24/50
157/157 [==============================] - 47s 300ms/step - loss: 1.6926 - accuracy: 0.53
Epoch 25/50
157/157 [==============================] - 47s 301ms/step - loss: 1.6372 - accuracy: 0.55
Epoch 26/50
157/157 [==============================] - 47s 301ms/step - loss: 1.6031 - accuracy: 0.55
Epoch 27/50
157/157 [==============================] - 47s 300ms/step - loss: 1.5539 - accuracy: 0.57
Epoch 28/50
157/157 [==============================] - 47s 300ms/step - loss: 1.5101 - accuracy: 0.57
Epoch 29/50
157/157 [==============================] - 47s 299ms/step - loss: 1.4727 - accuracy: 0.58
```

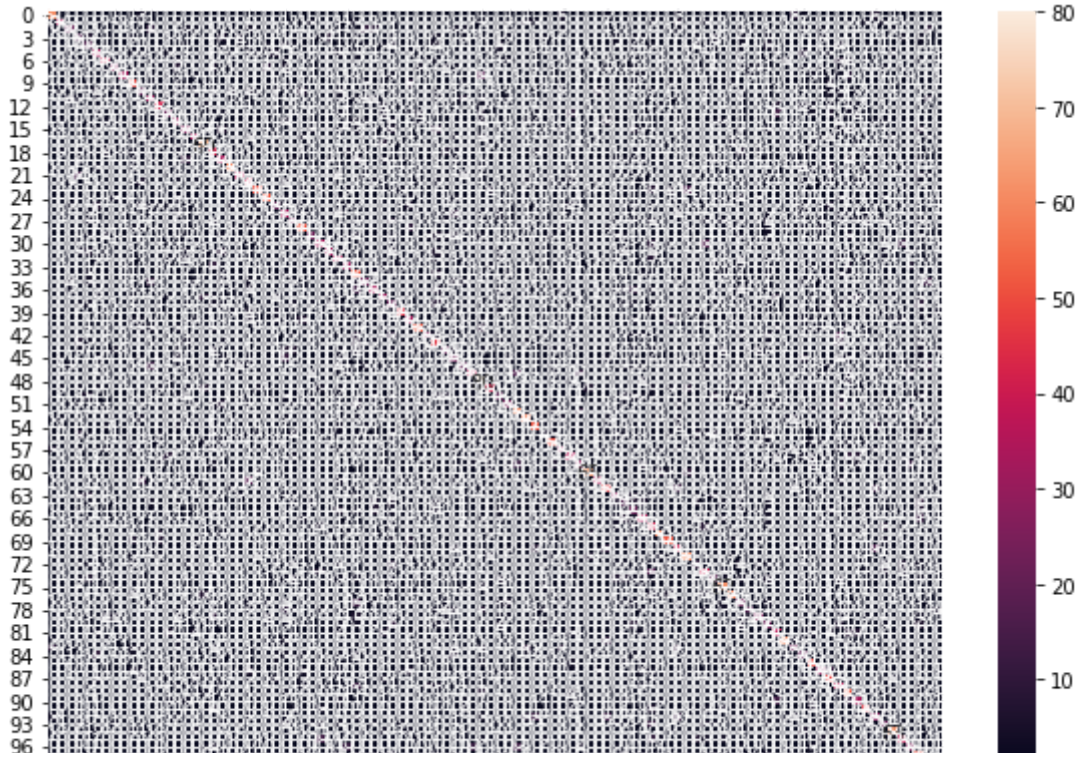
```
score = model.evaluate(X_test, y_test)
print(f'Test loss: {score[0]} / Test accuracy: {score[1]}')
```

```
313/313 [==============================] - 4s 12ms/step - loss: 3.8395 - accuracy: 0.3620
Test loss: 3.8395190238952637 / Test accuracy: 0.3619999885559082
```

```
from sklearn import metrics
import seaborn as sn
actual = y_test
y_prob = model.predict(X_test)
predicted = np.argmax(y_prob,axis=1)
print(metrics.classification_report(actual, predicted))

# show the confusion matrix
print("confusion matrix:")
m = metrics.confusion_matrix(actual, predicted)
print(m)
mplot = pd.DataFrame(m)
plt.figure(figsize=(10,7))
sn.heatmap(mplot,annot = True)
plt.show()
```

78	0.36	0.15	0.21	100
79	0.35	0.26	0.30	100
80	0.16	0.22	0.19	100
81	0.34	0.37	0.35	100
82	0.71	0.60	0.65	100
83	0.35	0.23	0.28	100
84	0.18	0.20	0.19	100
85	0.40	0.49	0.44	100
86	0.39	0.29	0.33	100
87	0.39	0.48	0.43	100
88	0.22	0.38	0.28	100
89	0.29	0.52	0.37	100
90	0.30	0.33	0.32	100
91	0.42	0.46	0.44	100
92	0.28	0.27	0.28	100
93	0.21	0.21	0.21	100
94	0.62	0.63	0.62	100
95	0.46	0.39	0.42	100
96	0.38	0.25	0.30	100
97	0.27	0.50	0.35	100
98	0.19	0.15	0.17	100
99	0.50	0.32	0.39	100
accuracy			0.36	10000
macro avg	0.38	0.36	0.36	10000
weighted avg	0.38	0.36	0.36	10000

```
confusion matrix:
[[61  0  0 ...  0  0  0]
 [ 0 36  0 ...  0  0  0]
 [ 1  0 21 ...  0  7  0]
 ...
 [ 0  0  0 ... 50  0  0]
 [ 0  0  2 ...  1 15  1]
 [ 0  0  1 ...  1  0 32]]
```



```
# Plot history: Accuracy
plt.plot(range(epochs), history.history['accuracy'], label='accuracy')
plt.plot(range(epochs), history.history['val_accuracy'], label='val_accuracy')
plt.title('accuracy history')
plt.ylabel('Accuracy value')
plt.xlabel('No. epoch')
plt.legend()
plt.grid(True)
```