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EXPERIMENT #2

DATE: 01-09-2020

TITLE: ML II ASSIGNMENT 2

AIM

Perform Digit Recognizer using MNIST dataset.

OBJECTIVE

1. Implement DNN for Digit Recogniton using MNIST dataset.

DRIVE LINK - https://drive.google.com/drive/u/0/folders/1VFRRP-lpjH_iq-Beojnorny4Rm53uT6E

*Notebook, code, pdf, output snapshots have been stored on the above given drive link.

- MNIST

```
from tensorflow.keras.datasets import mnist

from matplotlib import pyplot as plt

from tensorflow import keras

import tensorflow as tf

import numpy as np

from sklearn.model_selection import train_test_split

from tensorflow.keras.utils import to_categorical as tcg

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense, Flatten
```

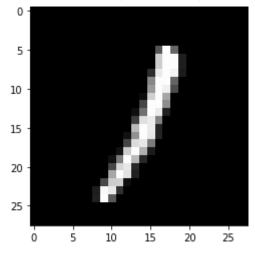
(xtr,ytr),(xte,yte)=mnist.load_data()

xtr.shape

[→ (60000, 28, 28)

+ Code — + Text -

plt.imshow(xtr[99], cmap='gray')



ytr[99]

xte=xte.reshape(xte.shape[0],xte.shape[1],xte.shape[2],1).astype('float32')/255
xtr=xtr.reshape(xtr.shape[0],xtr.shape[1],xtr.shape[2],1).astype('float32')/255

xtr.shape

```
ytr=tcg(ytr)
yte=tcg(yte)
model = Sequential([
 Flatten(input_shape=(28, 28, 1)),
 Dense(784, activation='relu'),
 Dense(512, activation='relu'),
 Dense(392, activation='relu'),
 Dense(256, activation='relu'),
 Dense(128, activation='relu'),
 Dense(64, activation='relu'),
 Dense(32, activation='relu'),
 Dense(16, activation='relu'),
 Dense(10, activation='softmax'),
])
model.compile(loss='categorical_crossentropy',optimizer='adam', metrics=['accuracy'])
x_train,x_valid = xtr[5000:],xtr[:5000]
y_train,y_valid = ytr[5000:],ytr[:5000]
from keras.callbacks import ModelCheckpoint
checkpoint = ModelCheckpoint(filepath = 'best_model.h5',save_best_only = True,verbose=1)
history = model.fit(x_train,y_train,batch_size=256, epochs = 8,
          validation_data=(x_valid,y_valid),
          callbacks=[checkpoint],
          verbose=2, shuffle=True)
 F→ Epoch 1/8
     Epoch 00001: val_loss improved from inf to 0.16810, saving model to best_model.h5
     215/215 - 8s - loss: 0.4184 - accuracy: 0.8697 - val_loss: 0.1681 - val_accuracy: 0.9510
    Epoch 2/8
    Epoch 00002: val_loss improved from 0.16810 to 0.09107, saving model to best_model.h5
     215/215 - 8s - loss: 0.1131 - accuracy: 0.9670 - val_loss: 0.0911 - val_accuracy: 0.9752
    Epoch 3/8
    Epoch 00003: val_loss did not improve from 0.09107
     215/215 - 8s - loss: 0.0734 - accuracy: 0.9777 - val_loss: 0.1067 - val_accuracy: 0.9706
    Epoch 4/8
    Epoch 00004: val_loss improved from 0.09107 to 0.08936, saving model to best_model.h5
     215/215 - 8s - loss: 0.0577 - accuracy: 0.9820 - val_loss: 0.0894 - val_accuracy: 0.9752
    Epoch 5/8
    Epoch 00005: val loss improved from 0.08936 to 0.08676, saving model to best model.h5
     215/215 - 8s - loss: 0.0399 - accuracy: 0.9878 - val_loss: 0.0868 - val_accuracy: 0.9772
    Epoch 6/8
    Epoch 00006: val_loss improved from 0.08676 to 0.07425, saving model to best_model.h5
     215/215 - 8s - loss: 0.0356 - accuracy: 0.9891 - val_loss: 0.0743 - val_accuracy: 0.9802
    Epoch 7/8
    Epoch 00007: val_loss did not improve from 0.07425
     215/215 - 8s - loss: 0.0269 - accuracy: 0.9916 - val_loss: 0.0865 - val_accuracy: 0.9784
    Epoch 00008: val_loss did not improve from 0.07425
     215/215 - 8s - loss: 0.0233 - accuracy: 0.9923 - val_loss: 0.0866 - val_accuracy: 0.9808
np.save('my_history.npy',history.history)
history=np.load('my_history.npy',allow_pickle='TRUE').item()
plt.plot(history['accuracy'])
plt.plot(history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

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```
model accuracy

0.99

0.99

0.99

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0.99

0.90

model.evaluate(xtr,ytr)

[0.016175806522369385, 0.9951500296592712]

Frain

test

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```

score = model.evaluate(xte,yte)

print('Test loss:', score[0])
print('Test accuracy:', score[1])

Test loss: 0.07490140944719315
 Test accuracy: 0.9797999858856201