GURU NANAK COLLEGE OF ARTS, SCIENCE & COMMERCE

G.T.B NAGAR, MUMBAI-400037

DEPARTMENT OF INFORMATION TECHNOLOGY

MSc(IT) PART I SEMESTER II

Practical Journal IN

DEEP LEARNING

Submitted by
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GURU NANAK COLLEGE OF ARTS, SCIENCE & COMMERCE
G.T.B NAGAR, MUMBAI-400037

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CERTIFICATE

This is to certify that Mr. / Miss. ______________Aniket HInukale___________________ of MSc(IT) Part-I Semester II Seat No. 2510261 has successfully completed the practical's in the subject of **DEEP LEARNING** as per the requirement of University Of Mumbai in part fulfillment for the completion of Degree of Master of Science (INFORMATION TECHNOLOGY). It is also to certify that this is the original work of the candidate done during the academic year 2021-2022.

Subject In-Charge **In-Charge,MSc(IT)**

Date **College Seal** **Examiner**

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Practical No:1

Aim: Performing matrix multiplication and finding eigen vectors and eigen values using TensorFlow.

```
import tensorflow as tf
print("Matrix Multiplication Demo done by Ankit kumar")
x=tf.constant([1,2,3,4,5,6],shape=[2,3])
print(x)
y=tf.constant([7,8,9,10,11,12],shape=[3,2])
print(y)
z=tf.matmul(x,y)
print("Product:",z)
e_matrix_A=tf.random.uniform([2,2],minval=3,maxval=10,dtype=tf.float32,name="matrixA")
print("Matrix A:\n{}\n\n".format(e_matrix_A))
eigen_values_A,eigen_vectors_A=tf.linalg.eigh(e_matrix_A)
print("Eigen Vectors:\n{}\n\nEigen Values:\n{}\n".format(eigen_vectors_A,eigen_values_A))
```

OUTPUT:

```
Matrix Multiplication Demo by Ankit Kumar
tf.Tensor(
[[1 2 3]
 [4 5 6]], shape=(2, 3), dtype=int32)
tf.Tensor(
[[ 7  8]
 [ 9 10]
 [11 12]], shape=(3, 2), dtype=int32)
Product: tf.Tensor(
[[ 58  64]
 [139 154]], shape=(2, 2), dtype=int32)
Matrix A:
[[7.8445125 7.8003845]
 [4.211911  9.099544 ]]


Eigen Vectors:
[[-0.7574165 -0.6529321]
 [ 0.6529321 -0.7574165]]

Eigen Values:
[ 4.2136283 12.730429 ]
```

Practical No:2

Aim: Solving XOR problem using deep feed forward network.

```
import numpy as np
from keras.layers import Dense
from keras.models import Sequential
model=Sequential()
model.add(Dense(units=2,activation='relu',input_dim=2))
model.add(Dense(units=1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy']
)
print("Practical 2 by Ankit Kumar")
print(model.summary())
print(model.get_weights())
X=np.array([[0.,0.],[0.,1.],[1.,0.],[1.,1.]])
Y=np.array([0.,1.,1.,0.])
model.fit(X,Y,epochs=3,batch_size=4)
print(model.get_weights())
print(model.predict(X,batch_size=4))
```

OUTPUT:

```
Practical2
Practical 2 by Ankit Kumar, Roll No. 01
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 2)                 6

 dense_1 (Dense)             (None, 1)                 3

=================================================================
Total params: 9
Trainable params: 9
Non-trainable params: 0

_________________________________________________________________
None
[array([[-0.46206504, -0.9918246 ],
       [-1.0191078 ,  0.23025429]], dtype=float32), array([0., 0.], dtype=float32), array([[ 0.04946017],
       [-1.0253624 ]], dtype=float32), array([0.], dtype=float32)]
Epoch 1/2000
1/1 [==============================] - 0s 328ms/step - loss: 0.7244 - accuracy: 0.5000
Epoch 2/2000
1/1 [==============================] - 0s 0s/step - loss: 0.7241 - accuracy: 0.2500
Epoch 1999/2000
1/1 [==============================] - 0s 0s/step - loss: 0.5388 - accuracy: 0.7500
Epoch 2000/2000
1/1 [==============================] - 0s 0s/step - loss: 0.5387 - accuracy: 0.7500
[array([[ 0.93819654,  0.5128767 ],
       [ 0.9379006 , -0.9174774 ]], dtype=float32), array([-0.9381738, -0.5276242], dtype=float32), array([[-1.9472638],
       [-0.4995001]], dtype=float32), array([0.38711813], dtype=float32)]
[[0.59558874]
 [0.59558874]
 [0.5955781 ]
 [0.19165897]]

Process finished with exit code 0
```

Practical No:3

Aim: Implementing deep neural network for performing classification task.

Problem statement: the given dataset comprises of health information about diabetic womenpatient. we need to create deep feed forward network that will classify women suffering fromdiabetes mellitus as 1.

```
from numpy import loadtxt
from keras.layers import Dense
from keras.models import Sequential
dataset=loadtxt('pima-indians-diabetes.csv',delimiter=',')
print("Practical 3 by Ankit Kumar, Roll No. 01")
print(dataset)
x = dataset[:,0:8]
y = dataset[:,8]
print(x)
print(y)
model=Sequential()
model.add(Dense(12,input_dim=8,activation='relu'))
model.add(Dense(8,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy']
)
model.fit(x,y,epochs=150,batch_size=10)
accuracy=model.evaluate(x,y)
print('Accuracy of model is',(accuracy*100))
prediction = model.predict_step(x)
exec("for i in range(5):print(x[i].tolist(),prediction[i],y[i])")
```

OUTPUT:

```
Practical3
Practical 3 by Ankit Kumar, Roll No. 01
[[  6.     148.      72.     ...   0.627  50.       1.    ]
 [  1.      85.      66.     ...   0.351  31.       0.    ]
 [  8.     183.      64.     ...   0.672  32.       1.    ]
 ...
 [  5.     121.      72.     ...   0.245  30.       0.    ]
 [  1.     126.      60.     ...   0.349  47.       1.    ]
 [  1.      93.      70.     ...   0.315  23.       0.    ]]
[[  6.     148.      72.     ...  33.6      0.627  50.    ]
 [  1.      85.      66.     ...  26.6      0.351  31.    ]
 [  8.     183.      64.     ...  23.3      0.672  32.    ]
 ...
 [  5.     121.      72.     ...  26.2      0.245  30.    ]
 [  1.     126.      60.     ...  30.1      0.349  47.    ]
 [  1.      93.      70.     ...  30.4      0.315  23.    ]]
[1. 0. 1. 0. 1. 0. 1. 0. 1. 1. 0. 1. 0. 1. 1. 1. 1. 1. 0. 1. 0. 0. 1. 1.
 1. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 1. 0. 1. 0. 0.
 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0.
 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0.
 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0.
 1. 0. 0. 0. 1. 1. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.
 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 0. 0.
 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 1. 1. 0. 0.
 1. 1. 0. 1. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 1. 1. 1.
 1. 0. 1. 1. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 1. 1. 1. 0.
```

```
Epoch 1/150
77/77 [==============================] - 1s 973us/step - loss: 11.3283 - accuracy: 0.4219
Epoch 2/150
77/77 [==============================] - 0s 986us/step - loss: 1.8362 - accuracy: 0.6484
Epoch 3/150
77/77 [==============================] - 0s 986us/step - loss: 1.1811 - accuracy: 0.6576
Epoch 4/150
77/77 [==============================] - 0s 960us/step - loss: 0.9848 - accuracy: 0.6380

Epoch 149/150
77/77 [==============================] - 0s 740us/step - loss: 0.4716 - accuracy: 0.7773
Epoch 150/150
77/77 [==============================] - 0s 822us/step - loss: 0.4768 - accuracy: 0.7695
24/24 [==============================] - 0s 1ms/step - loss: 0.4693 - accuracy: 0.7721
Accuracy of model is [0.4693426191806793, 0.7721354365348816, 0.4693426191806793, 0.7721354365348816, 0.4693426191806793, 0.7721354365348816, 0.46934261918
[6.0, 148.0, 72.0, 35.0, 0.0, 33.6, 0.627, 50.0] tf.Tensor([0.6152066], shape=(1,), dtype=float32) 1.0
[1.0, 85.0, 66.0, 29.0, 0.0, 26.6, 0.351, 31.0] tf.Tensor([0.06132615], shape=(1,), dtype=float32) 0.0
[8.0, 183.0, 64.0, 0.0, 0.0, 23.3, 0.672, 32.0] tf.Tensor([0.72365546], shape=(1,), dtype=float32) 1.0
[1.0, 89.0, 66.0, 23.0, 94.0, 28.1, 0.167, 21.0] tf.Tensor([0.04896328], shape=(1,), dtype=float32) 0.0
[0.0, 137.0, 40.0, 35.0, 168.0, 43.1, 2.288, 33.0] tf.Tensor([0.5023409], shape=(1,), dtype=float32) 1.0

Process finished with exit code 0
```

Practical No:4

a) Aim: Using deep feed forward network with two hidden layers forperforming classification and predicting the class.

```
from keras.models import Sequential
from keras.layers import Dense
from sklearn.datasets import make_blobs
from sklearn.preprocessing import MinMaxScaler

X,Y=make_blobs(n_samples=100,centers=2,n_features=2,random_state=1) scalar=MinMaxScaler()
scalar.fit(X) X=scalar.transform(X)

model=Sequential() model.add(Dense(4,input_dim=2,activation='relu'))
model.add(Dense(4,activation='relu')) model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam') model.fit(X,Y,epochs=500)

Xnew,Yreal=make_blobs(n_samples=3,centers=2,n_features=2,random_state=1)
Xnew=scalar.transform(Xnew)

Ynew=model.predict_classes(Xnew)for i in range(len(Xnew)):
print("X=%s,Predicted=%s,Desired=%s"%(Xnew[i],Ynew[i],Yreal[i]))
```

OUTPUT:

Administrator: Windows PowerShell

```
4/4 [============================] - 0s 2ms/step - loss: 0.6935
Epoch 488/500
4/4 [============================] - 0s 2ms/step - loss: 0.6927
Epoch 489/500
4/4 [============================] - 0s 3ms/step - loss: 0.6931
Epoch 490/500
4/4 [============================] - 0s 3ms/step - loss: 0.6928
Epoch 491/500
4/4 [============================] - 0s 2ms/step - loss: 0.6938
Epoch 492/500
4/4 [============================] - 0s 5ms/step - loss: 0.6929
Epoch 493/500
4/4 [============================] - 0s 2ms/step - loss: 0.6928
Epoch 494/500
4/4 [============================] - 0s 3ms/step - loss: 0.6928
Epoch 495/500
4/4 [============================] - 0s 2ms/step - loss: 0.6930
Epoch 496/500
4/4 [============================] - 0s 2ms/step - loss: 0.6934
Epoch 497/500
4/4 [============================] - 0s 2ms/step - loss: 0.6934
Epoch 498/500
4/4 [============================] - 0s 2ms/step - loss: 0.6933
Epoch 499/500
4/4 [============================] - 0s 3ms/step - loss: 0.6930
Epoch 500/500
4/4 [============================] - 0s 2ms/step - loss: 0.6940
D:\keras\venv\lib\site-packages\tensorflow\python\keras\engine\sequential.py:450: UserWarning: `model.predict_classes()` is deprecated and will be re
moved after 2021-01-01. Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi-class classification   (e.g. if it us
es a `softmax` last-layer activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it uses a `
sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
X=[0.89337759 0.65864154],Predicted=[0]
X=[0.29097707 0.12978982],Predicted=[0]
X=[0.78082614 0.75391697],Predicted=[0]
(venv) PS D:\keras>
```

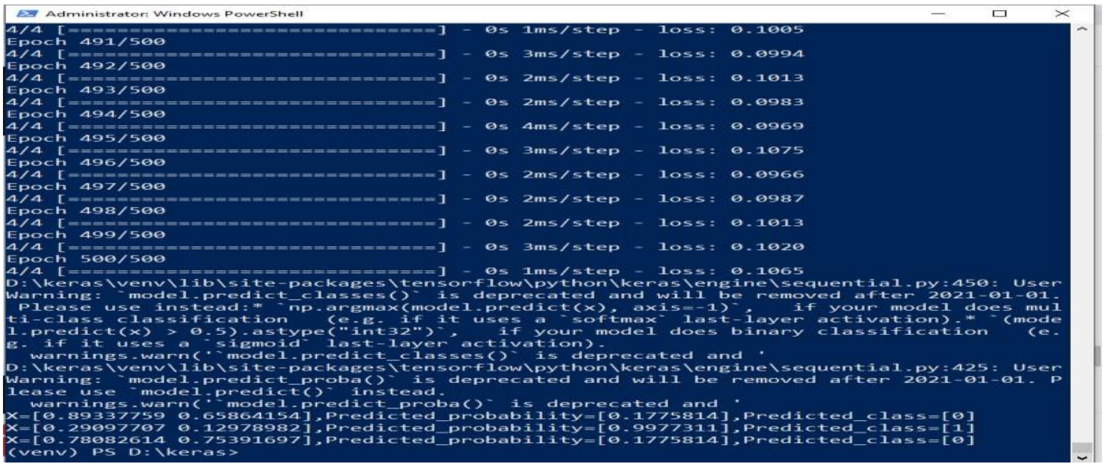
Administrator: Windows PowerShell

```
4/4 [============================] - 0s 2ms/step - loss: 0.0031
Epoch 489/500
4/4 [============================] - 0s 2ms/step - loss: 0.0031
Epoch 490/500
4/4 [============================] - 0s 2ms/step - loss: 0.0034
Epoch 491/500
4/4 [============================] - 0s 2ms/step - loss: 0.0030
Epoch 492/500
4/4 [============================] - 0s 2ms/step - loss: 0.0031
Epoch 493/500
4/4 [============================] - 0s 2ms/step - loss: 0.0031
Epoch 494/500
4/4 [============================] - 0s 1ms/step - loss: 0.0031
Epoch 495/500
4/4 [============================] - 0s 2ms/step - loss: 0.0028
Epoch 496/500
4/4 [============================] - 0s 1ms/step - loss: 0.0028
Epoch 497/500
4/4 [============================] - 0s 3ms/step - loss: 0.0030
Epoch 498/500
4/4 [============================] - 0s 2ms/step - loss: 0.0031
Epoch 499/500
4/4 [============================] - 0s 3ms/step - loss: 0.0028
Epoch 500/500
4/4 [============================] - 0s 2ms/step - loss: 0.0032
D:\keras\venv\lib\site-packages\tensorflow\python\keras\engine\sequential.py:450: User
Warning: `model.predict_classes()` is deprecated and will be removed after 2021-01-01.
 Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does mul
ti-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(mode
l.predict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.
g. if it uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
X=[0.89337759 0.65864154],Predicted=[0],Desired=0
X=[0.29097707 0.12978982],Predicted=[1],Desired=1
X=[0.78082614 0.75391697],Predicted=[0],Desired=0
(venv) PS D:\keras>
```

b) Aim: Using a deep field forward network with two hidden layers forperforming classification and predicting the probability of class.

```
from keras.models import Sequential
from keras.layers import Dense
from sklearn.datasets import make_blobs
from sklearn.preprocessing import MinMaxScaler
X,Y=make_blobs(n_samples=100,centers=2,n_features=2,random_state=1)
scalar=MinMaxScaler()
scalar.fit(X)
X=scalar.transform(X)
model=Sequential()
model.add(Dense(4,input_dim=2,activation='relu'))
model.add(Dense(4,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam')
model.fit(X,Y,epochs=500)
Xnew,Yreal=make_blobs(n_samples=3,centers=2,n_features=2,random_state=1)
Xnew=scalar.transform(Xnew)
Yclass=model.predict_classes(Xnew)
Ynew=model.predict_proba(Xnew)
for i in range(len(Xnew)):
print("X=%s,Predicted_probability=%s,Predicted_class=%s"%(Xnew[i],Ynew[i],Yclass[i]))
```

OUTPUT:



```
Administrator: Windows PowerShell
4/4 [==============================] - 0s 1ms/step - loss: 0.1005
Epoch 491/500
4/4 [==============================] - 0s 3ms/step - loss: 0.0994
Epoch 492/500
4/4 [==============================] - 0s 2ms/step - loss: 0.1013
Epoch 493/500
4/4 [==============================] - 0s 2ms/step - loss: 0.0983
Epoch 494/500
4/4 [==============================] - 0s 4ms/step - loss: 0.0969
Epoch 495/500
4/4 [==============================] - 0s 3ms/step - loss: 0.1075
Epoch 496/500
4/4 [==============================] - 0s 2ms/step - loss: 0.0966
Epoch 497/500
4/4 [==============================] - 0s 2ms/step - loss: 0.0987
Epoch 498/500
4/4 [==============================] - 0s 2ms/step - loss: 0.1013
Epoch 499/500
4/4 [==============================] - 0s 3ms/step - loss: 0.1020
Epoch 500/500
4/4 [==============================] - 0s 1ms/step - loss: 0.1065
D:\keras\venv\lib\site-packages\tensorflow\python\keras\engine\sequential.py:450: User
Warning: `model.predict_classes()` is deprecated and will be removed after 2021-01-01.
 Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does mul
ti-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(mode
l.predict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.
g. if it uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
D:\keras\venv\lib\site-packages\tensorflow\python\keras\engine\sequential.py:425: User
Warning: `model.predict_proba()` is deprecated and will be removed after 2021-01-01. P
lease use `model.predict()` instead.
  warnings.warn('`model.predict_proba()` is deprecated and '
X=[0.89337759 0.65864154],Predicted_probability=[0.1775814],Predicted_class=[0]
X=[0.29097707 0.12978982],Predicted_probability=[0.9977311],Predicted_class=[1]
X=[0.78082614 0.75391697],Predicted_probability=[0.1775814],Predicted_class=[0]
(venv) PS D:\keras>
```

c) Aim: Using a deep field forward network with two hidden layers forperforming linear regression and predicting values.

```
from keras.models import Sequential
from keras.layers import Dense
from sklearn.datasets import make_regression
from sklearn.preprocessing import MinMaxScaler
X,Y=make_regression(n_samples=100,n_features=2,noise=0.1,random_state=1)
scalarX,scalarY=MinMaxScaler(),MinMaxScaler()
scalarX.fit(X)
scalarY.fit(Y.reshape(100,1))
X=scalarX.transform(X)
Y=scalarY.transform(Y.reshape(100,1))
model=Sequential()
model.add(Dense(4,input_dim=2,activation='relu'))
model.add(Dense(4,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='mse',optimizer='adam')
model.fit(X,Y,epochs=1000,verbose=0)
Xnew,a=make_regression(n_samples=3,n_features=2,noise=0.1,random_state=1)
Xnew=scalarX.transform(Xnew)
Ynew=model.predict(Xnew)
for i in range(len(Xnew)): print("X=%s,Predicted=%s"%(Xnew[i],Ynew[i]))
```

OUTPUT:

```
X=[0.29466096 0.30317302],Predicted=[0.18255734]
X=[0.39445118 0.79390858],Predicted=[0.7581165]
X=[0.02884127 0.6208843 ],Predicted=[0.3932857]
(venv) PS D:\keras>
```

Practical No:5(a)

Aim: Evaluating feed forward deep network for regression using KFold cross validation.

```
import pandas as pd
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
dataframe=pd.read_csv("housing.csv",delim_whitespace=True,header=None)
dataset=dataframe.values
X=dataset[:,0:13]
Y=dataset[:,13]
def wider_model():
model=Sequential()
model.add(Dense(15,input_dim=13,kernel_initializer='normal',activation='relu'))
model.add(Dense(13,kernel_initializer='normal',activation='relu'))
model.add(Dense(1,kernel_initializer='normal'))
model.compile(loss='mean_squared_error',optimizer='adam')
return model estimators=[]
estimators.append(('standardize',StandardScaler()))
estimators.append(('mlp',KerasRegressor(build_fn=wider_model,epochs=100,batch_size=5)))
pipeline=Pipeline(estimators)
kfold=KFold(n_splits=10)
results=cross_val_score(pipeline,X,Y,cv=kfold)
print("Wider: %.2f (%.2f) MSE" % (results.mean(), results.std()))
```

OUTPUT:

```
Wider: -20.88 (24.29) MSE
(venv) PS D:\keras>
```

(After changing neuron)

```
model.add(Dense(20, input_dim=13,kernel_initializer='normal',activation='relu'))
```

```
Wider: -22.17 (24.38) MSE
(venv) PS D:\keras>
```

Practical No:5b

Aim: Evaluating feed forward deep network for multiclass Classification using KFold cross-validation.

```
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier
from keras.utils import np_utils
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.preprocessing import LabelEncoder
y = df.iloc[:, 4]  # print(X) #print(y)
encoder.fit(y)
encoded_y = encoder.transform(y)
print(encoded_y)
dummy_Y = np_utils.to_categorical(encoded_y)
print(dummy_Y)
def baseline_model():
model.add(Dense(8, input_dim=4, activation='relu'))
model.add(Dense(3, activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
return model
estimator = baseline_model()
estimator.fit(X, dummy_Y, epochs=100, shuffle=True)
action = estimator.predict(X)
for i in range(25): print(dummy_Y[i])
print('^^^^^^^^^^^^^^^^^^^^^^')
for i in range(25):
    print(action[i])
```

OUTPUT:

```
       0    1    2    3               4
0    5.1  3.5  1.4  0.2     Iris-setosa
1    4.9  3.0  1.4  0.2     Iris-setosa
2    4.7  3.2  1.3  0.2     Iris-setosa
3    4.6  3.1  1.5  0.2     Iris-setosa
4    5.0  3.6  1.4  0.2     Iris-setosa
..   ...  ...  ...  ...             ...
145  6.7  3.0  5.2  2.3  Iris-virginica
146  6.3  2.5  5.0  1.9  Iris-virginica
147  6.5  3.0  5.2  2.0  Iris-virginica
148  6.2  3.4  5.4  2.3  Iris-virginica
149  5.9  3.0  5.1  1.8  Iris-virginica

[150 rows x 5 columns]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
[[1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
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 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
```

```
Epoch 98/100
5/5 [==============================] - 0s 0s/step - loss: 0.3899 - accuracy: 0.9313
Epoch 99/100
5/5 [==============================] - 0s 0s/step - loss: 0.3896 - accuracy: 0.9230
Epoch 100/100
5/5 [==============================] - 0s 0s/step - loss: 0.3682 - accuracy: 0.9361
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
```

```
^^^^^^^^^^^^^^^^^^^^^^
[0.9145307  0.08423453 0.00123477]
[0.88751584 0.1100563  0.00242792]
[0.8999843  0.09803853 0.00197715]
[0.858188   0.13759544 0.00421653]
[0.9138275  0.08489472 0.00127787]
[0.8994011  0.09916449 0.0014343 ]
[0.8872866  0.11023647 0.00247695]
[0.89339536 0.10458492 0.00201967]
[0.8545533  0.14064151 0.00480518]
[0.87742513 0.11963753 0.00293737]
[0.9203753  0.07866727 0.00095734]
[0.8665611  0.1300417  0.00339716]
[0.88403696 0.11323617 0.0027269 ]
[0.9008803  0.09682965 0.00229002]
[9.5539063e-01 4.4350266e-02 2.5906262e-04]
[9.4327897e-01 5.6333560e-02 3.8754733e-04]
[9.3672138e-01 6.2714875e-02 5.6370755e-04]
[0.91191673 0.08680107 0.00128225]
[0.9100969  0.08882014 0.00108295]
[0.91078293 0.08794734 0.00126965]
[0.8827079  0.11510085 0.00219123]
[0.9060573  0.09255142 0.00139134]
[9.3434143e-01 6.4821333e-02 8.3730859e-04]
[0.85551745 0.14102885 0.00345369]
[0.80272377 0.1895675  0.00770868]
```

Code 2:

```
import pandas
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier
from keras.utils import np_utils
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.preprocessing import LabelEncoder
dataset = pandas.read_csv("Flower.csv", header=None)
dataset1 = dataset.values
X = dataset1[:, 0:4].astype(float)
Y = dataset1[:, 4]
print(Y)
encoder = LabelEncoder()
encoder.fit(Y)
encoder_Y = encoder.transform(Y)
print(encoder_Y)
dummy_Y = np_utils.to_categorical(encoder_Y)
print(dummy_Y)
def baseline_model():
    model = Sequential()
    model.add(Dense(8, input_dim=4, activation='relu'))
    model.add(Dense(3, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
return model
estimator = KerasClassifier(build_fn=baseline_model, epochs=100, batch_size=5)
kfold = KFold(n_splits=10, shuffle=True)
results = cross_val_score(estimator, X, dummy_Y, cv=kfold)
print("Baseline: %.2f%% (%.2f%%)" % (results.mean() * 100, results.std() * 100))
```

```
3/3 [==============================] - 0s 2ms/step - loss: 0.2491 - accuracy: 0.9333
Baseline: 96.00% (4.42%)
```

(Changing neuron)

```
model.add(Dense(10,input_dim=4,activation='relu'))
```

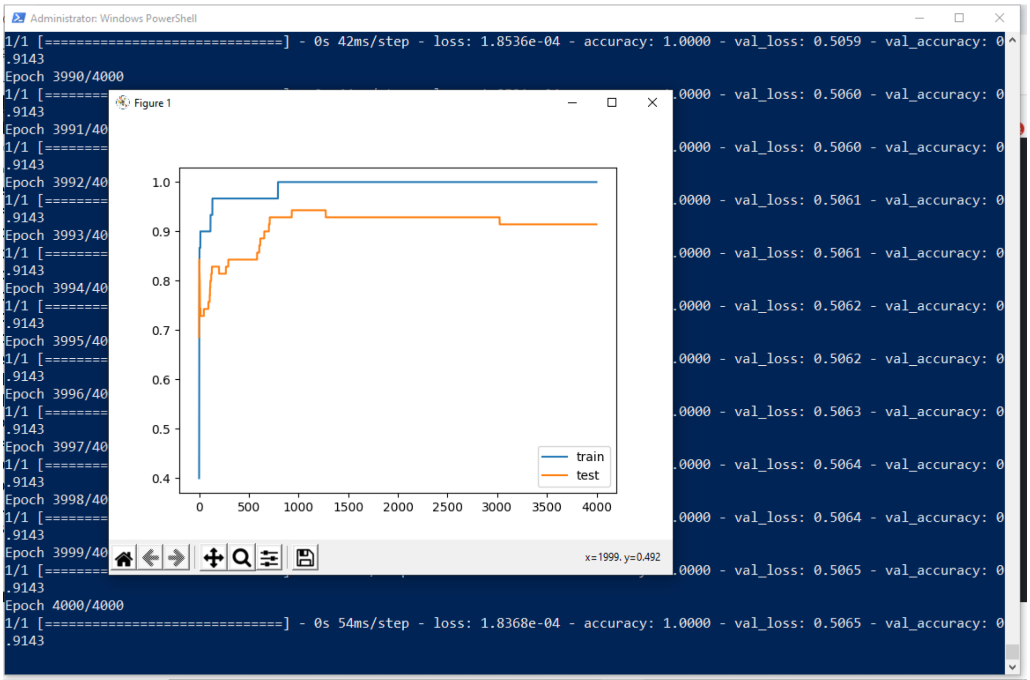
```
3/3 [==============================] - 0s 999us/step - loss: 0.1436 - accuracy: 1.0000
Baseline: 98.67% (2.67%)
```

Practical No :6

Aim: implementing regularization to avoid overfitting in binaryclassification.

```
from matplotlib import pyplot
from sklearn.datasets import make_moons
from keras.models import  Sequential
from keras.layers import Dense
X,Y=make_moons(n_samples=100,noise=0.2,random_state=1)
n_train=30
trainX,testX=X[:n_train,:],X[n_train:]
trainY,testY=Y[:n_train],Y[n_train:] #print(trainX)
#print(trainY) #print(testX) #print(testY) model=Sequential()
model.add(Dense(500,input_dim=2,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
history=model.fit(trainX,trainY,validation_data=(testX,testY),epochs=4000)
pyplot.plot(history.history['accuracy'],label='train')
pyplot.plot(history.history['val_accuracy'],label='test')
pyplot.legend()
pyplot.show()
```

OUTPUT:



The above code and resultant graph demonstrate overfitting with accuracy of testing data lessthan accuracy of training data also the accuracy of testing data increases once and then start decreases gradually.to solve this problem we can use regularization

Hence, we will add two lines in the above code as highlighted below to implement l2regularization with alpha=0.001

from matplotlib import pyplot

from sklearn.datasets import make_moons

from keras.models import Sequential

from keras.layers import Dense

from keras.regularizers import l2

X,Y=make_moons(n_samples=100,noise=0.2,random_state=1)

n_train=30

trainX,testX=X[:n_train,:],X[n_train:]

trainY,testY=Y[:n_train],Y[n_train:] #print(trainX)

#print(trainY) #print(testX) #print(testY) model=Sequential()

model.add(Dense(500,input_dim=2,activation='relu',**kernel_regularizer=l2(0.001)**))

model.add(Dense(1,activation='sigmoid'))

model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])

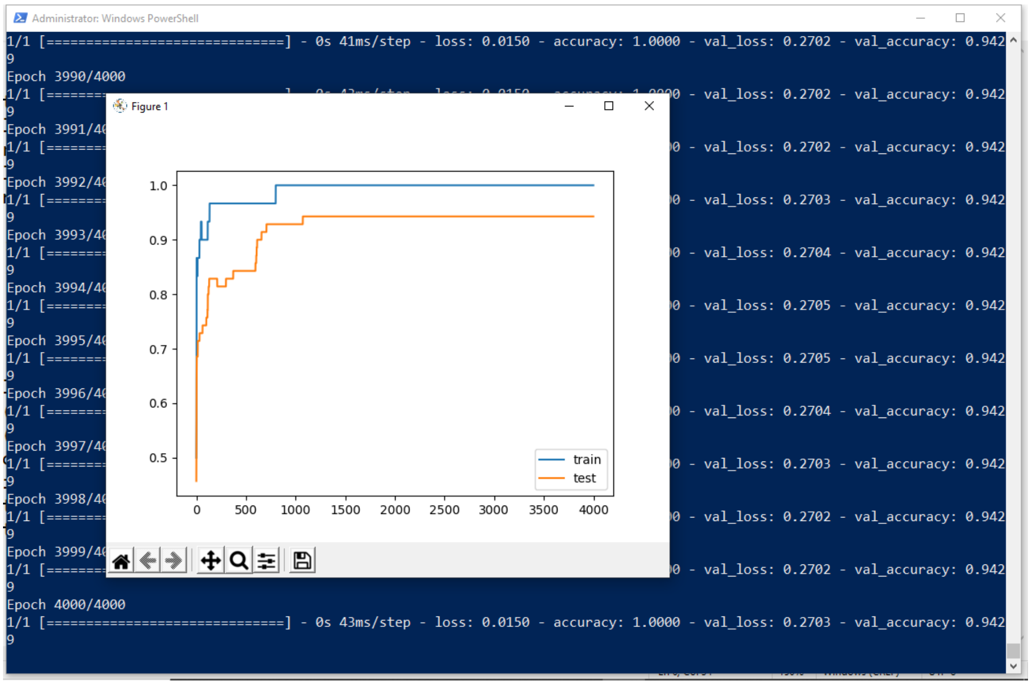
history=model.fit(trainX,trainY,validation_data=(testX,testY),epochs=4000)

pyplot.plot(history.history['accuracy'],label='train')

pyplot.plot(history.history['val_accuracy'],label='test')

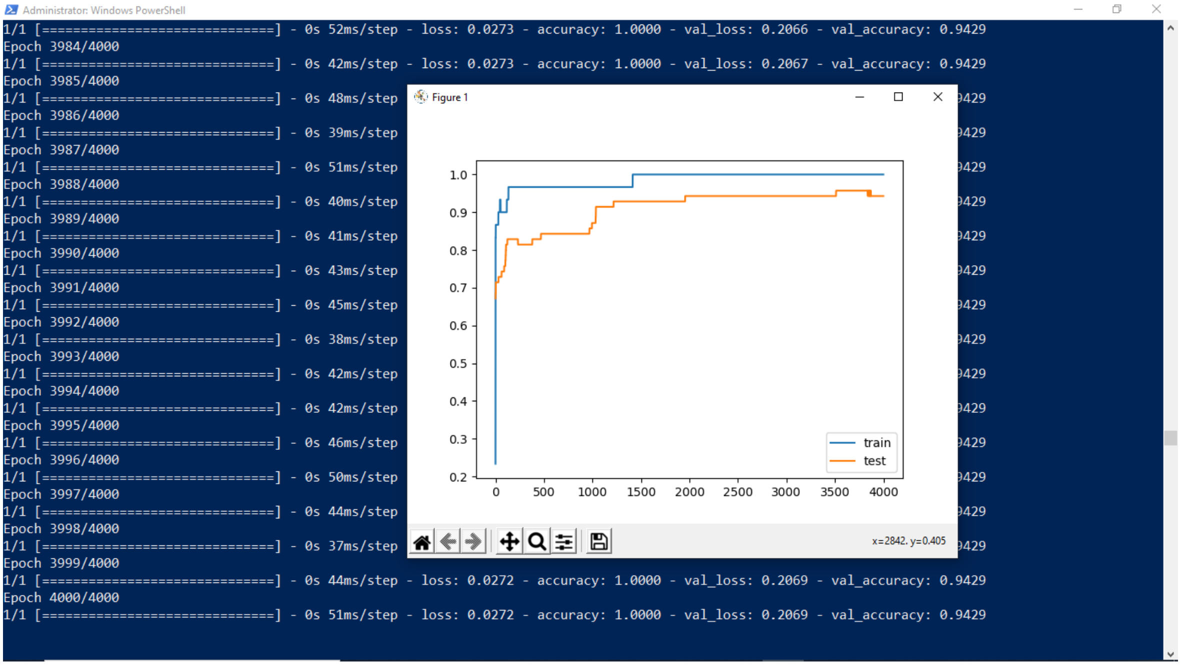
pyplot.legend()

pyplot.show()



By replacing l2 regularizer with l1 regularizer at the same learning rate 0.001 we get thefollowing output.

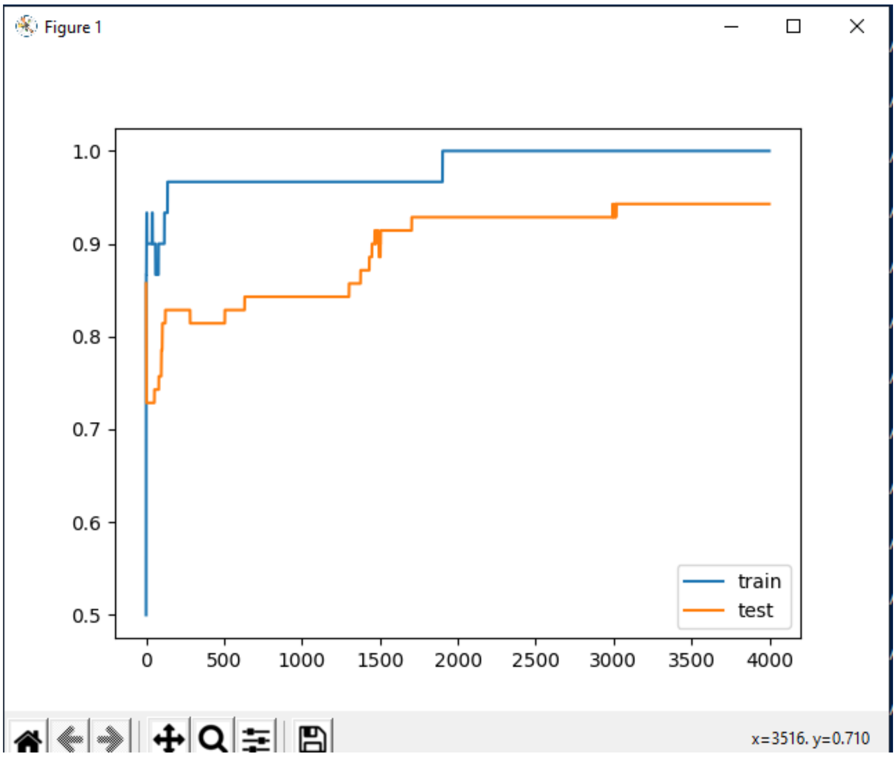
DEEP LEARNING



By applying l1 and l2 regularizer we can observe the following changes in accuracy of bothtrainig and testing data. The changes in code are also highlighted.

```
from matplotlib import pyplot
from sklearn.datasets import make_moons
from keras.models  import Sequential
from keras.layers import Dense
from keras.regularizers import l1_l2
X,Y=make_moons(n_samples=100,noise=0.2,random_state=1)
n_train=30
trainX,testX=X[:n_train,:],X[n_train:]
trainY,testY=Y[:n_train],Y[n_train:] #print(trainX)
#print(trainY) #print(testX) #print(testY) model=Sequential()
model.add(Dense(500,input_dim=2,activation='relu',kernel_regularizer=l1_l2(l1=0.001,l2=0.001)))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
history=model.fit(trainX,trainY,validation_data=(testX,testY),epochs=4000)
pyplot.plot(history.history['accuracy'],label='train')
pyplot.plot(history.history['val_accuracy'],label='test')
pyplot.legend()
pyplot.show()
```

OUTPUT:



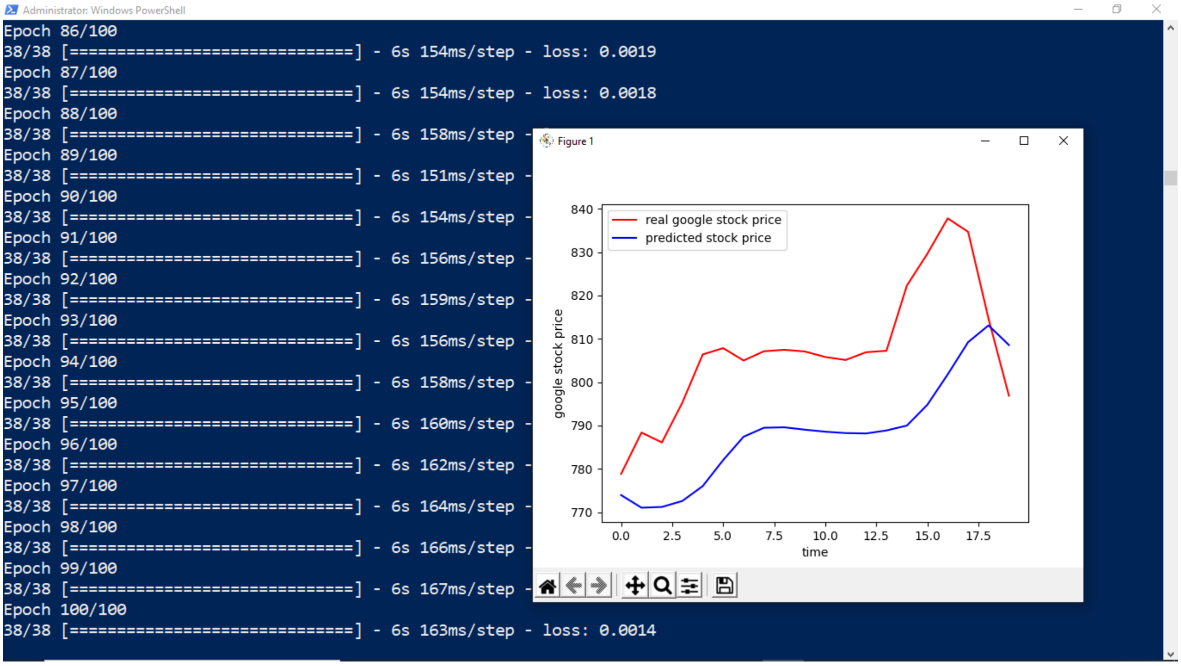
Practical No:7

Aim: Demonstrate recurrent neural network that learns to perform sequence analysis for stock price.

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
from sklearn.preprocessing import MinMaxScaler
dataset_train = pd.read_csv(
    'Google_Stock_price_train.csv')
X_train = []
Y_train = []
for i in range(60, 1258): X_train.append(training_set_scaled[i - 60:i, 0])
Y_train.append(training_set_scaled[i, 0])
X_train, Y_train = np.array(X_train), np.array(Y_train)
print(X_train)
print('*********************************************')
print(Y_train)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
print('**********************************************')
print(X_train)
regressor = Sequential()
regressor.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50))
regressor.add(Dropout(0.2))
regressor.add(Dense(units=1))
regressor.compile(optimizer='adam', loss='mean_squared_error')
regressor.fit(X_train, Y_train, epochs=100, batch_size=32)
dataset_test = pd.read_csv('Google_Stock_price_Test.csv')
real_stock_price = dataset_test.iloc[:, 1:2].values
dataset_total = pd.concat((dataset_train['Open'], dataset_test['Open']), axis=0)
inputs = dataset_total[len(dataset_total) - len(dataset_test) - 60:].values
inputs = inputs.reshape(-1, 1)
inputs = sc.transform(inputs)
X_test = []
for i in range(60, 80):
X_test.append(inputs[i - 60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

```
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
plt.plot(real_stock_price, color='red', label='real google stock price')
plt.plot(predicted_stock_price, color='blue', label='predicted stock price')
plt.xlabel('time')
plt.ylabel('google stock price')
plt.legend()
plt.show()
```

OUTPUT:



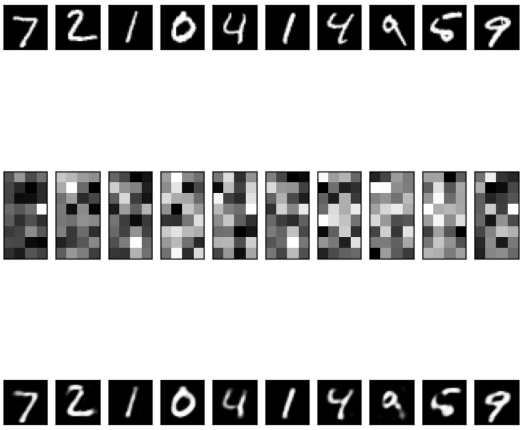
Practical No:8

Aim: Performing encoding and decoding of images using deep autoencoder.

```
import keras
from keras import layers
from keras.datasets import mnist
import numpy as np
encoding_dim = 32  # this is our input image
input_img = keras.Input(shape=(784,))
X_test = X_test.astype('float32') / 255.
X_train = X_train.reshape((len(X_train), np.prod(X_train.shape[1:])))
X_test = X_test.reshape((len(X_test), np.prod(X_test.shape[1:])))
print(X_train.shape)
print(X_test.shape)
epochs = 50, batch_size = 256, shuffle = True,
validation_data = (X_test, X_test)) encoded_imgs = encoder.predict(X_test)
decoded_imgs = decoder.predict(encoded_imgs)
import matplotlib.pyplot as plt
n = 10
for i in range(10):
    ax = plt.subplot(3, 20, i + 1)
plt.imshow(X_test[i].reshape(28, 28))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
# display encoded image
ax = plt.subplot(3, 20, i + 1 + 20)
plt.imshow(encoded_imgs[i].reshape(8, 4))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)  # display reconstruction
ax = plt.subplot(3, 20, 2 * 20 + i + 1)
plt.imshow(decoded_imgs[i].reshape(28, 28))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
plt.show()
```

OUTPUT:


Administrator: Windows PowerShell
235/235 [==============================] - 3s 13ms/step - loss: 0.0929 - val_loss: 0.0918
Epoch 34/50
235/235 [==============================] - 3s 13ms/step - loss: 0.0926 - val_loss: 0.0917
Epoch 35/50
235/235 [==============================] - 3s 13ms/step - loss: 0.0928 - val_loss: 0.0917
Epoch 36/50
Epoch 37/50
Epoch 38/50
Epoch 39/50
Epoch 40/50
Epoch 41/50
Epoch 42/50
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Figure 1
Epoch 48/50
235/235 [==============================] - 3s 14ms/step - loss: 0.0927 - val_loss: 0.0915
Epoch 49/50
235/235 [==============================] - 3s 13ms/step - loss: 0.0927 - val_loss: 0.0915
Epoch 50/50
235/235 [==============================] - 3s 15ms/step - loss: 0.0926 - val_loss: 0.0914

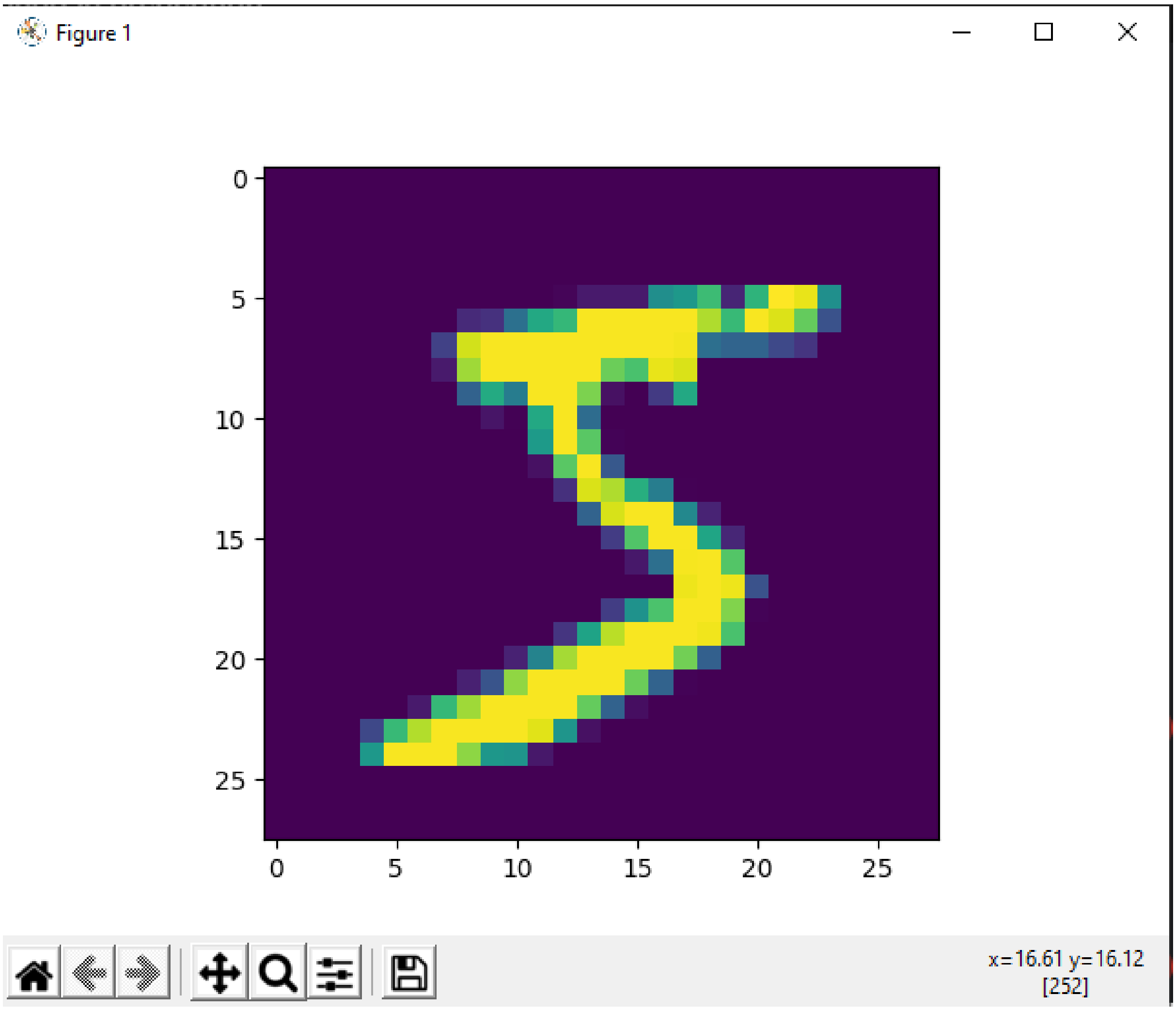


Practical No:9

Aim: Implementation of convolutional neural network to predict numbers from number images

```
from keras.datasets import mnist
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten
import matplotlib.pyplot as plt
print(X_train[0].shape)
X_train = X_train.reshape(60000, 28, 28, 1)
X_test = X_test.reshape(10000, 28, 28, 1)
Y_train = to_categorical(Y_train)
Y_test = to_categorical(Y_test)
Y_train[0]
print(Y_train[0])
model = Sequential() # add model layers #learn image features
model.add(Conv2D(64, kernel_size=3, activation='relu', input_shape=(28, 28, 1)))
model.add(Conv2D(32, kernel_size=3, activation='relu'))
model.add(Flatten())
model.add(Dense(10, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])  #
train
model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=3)
print(model.predict(X_test[:4]))
```

OUTPUT:



(28, 28)

[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]

```
(venv) PS D:\keras> python pract6.py
(28, 28)
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

```
Epoch 1/3
1875/1875 [==============================] - 235s 124ms/step - loss: 0.9714 - accuracy: 0.9111
- val_loss: 0.1084 - val_accuracy: 0.9661
Epoch 2/3
1875/1875 [==============================] - 242s 129ms/step - loss: 0.0663 - accuracy: 0.9789
- val_loss: 0.0787 - val_accuracy: 0.9758
Epoch 3/3
1875/1875 [==============================] - 241s 128ms/step - loss: 0.0458 - accuracy: 0.9854
- val_loss: 0.0904 - val_accuracy: 0.9751
[[8.5066381e-09 1.9058415e-15 1.5103029e-09 6.2544638e-07 4.8599115e-14
  3.8009873e-13 8.0967405e-13 9.9999940e-01 2.3813423e-10 1.8504194e-09]
 [4.6695381e-10 4.9075446e-09 1.0000000e+00 1.4425230e-12 5.5351397e-15
  1.4244286e-16 4.9031729e-10 2.1196991e-15 8.1773255e-13 2.7225001e-19]
 [1.4877173e-06 9.9855584e-01 1.0760028e-04 1.4199993e-07 1.0726219e-03
  6.1853432e-05 5.0982948e-05 6.4035441e-05 8.5100648e-05 3.5164564e-07]
 [9.9999988e-01 7.7231385e-13 9.2269055e-08 2.9055267e-10 1.8901826e-10
  2.9204628e-09 8.1175129e-09 4.1387605e-12 6.0085120e-10 1.4425010e-08]]
[[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
(venv) PS D:\keras>
```

Practical No:10

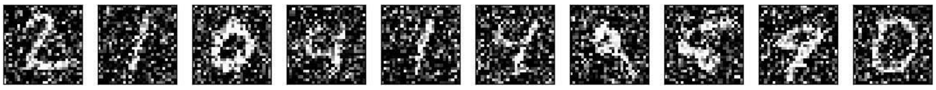
Aim: Denoising of images using autoencoder.

```
import keras
from keras.datasets import mnist
from keras import layers
import numpy as np
from keras.callbacks import TensorBoard
import matplotlib.pyplot as plt
(X_train, _), (X_test, _) = mnist.load_data()
X_train = X_train.astype('float32') / 255.
X_test = X_test.astype('float32') / 255.
X_train = np.reshape(X_train, (len(X_train), 28, 28, 1))
X_test = np.reshape(X_test, (len(X_test), 28, 28, 1))
noise_factor = 0.5
X_train_noisy = X_train + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=X_train.shape)
X_test_noisy = X_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=X_test.shape)
X_train_noisy = np.clip(X_train_noisy, 0., 1.)
X_test_noisy = np.clip(X_test_noisy, 0., 1.)
n = 10
plt.figure(figsize=(20, 2))
for i in range(1, n + 1):
    ax = plt.subplot(1, n, i)
    plt.imshow(X_test_noisy[i].reshape(28, 28))
    plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
plt.show()
input_img = keras.Input(shape=(28, 28, 1))
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
x = layers.MaxPooling2D((2, 2), padding='same')(x)
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(x)
encoded = layers.MaxPooling2D((2, 2), padding='same')(x)
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(encoded)

x = layers.UpSampling2D((2, 2))(x)
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(x)
x = layers.UpSampling2D((2, 2))(x)
decoded = layers.Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)
autoencoder = keras.Model(input_img, decoded)
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
autoencoder.fit(X_train_noisy, X_train,
            epochs=3, batch_size=128, shuffle=True,
            validation_data=(X_test_noisy, X_test),
            callbacks=[TensorBoard(log_dir='/tmo/tb', histogram_freq=0, write_graph=False)])
```

```
predictions = autoencoder.predict(X_test_noisy)
m = 10
plt.figure(figsize=(20, 2))
for i in range(1, m + 1):
    ax = plt.subplot(1, m, i)
    plt.imshow(predictions[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```

OUTPUT:



After 3 epochs: