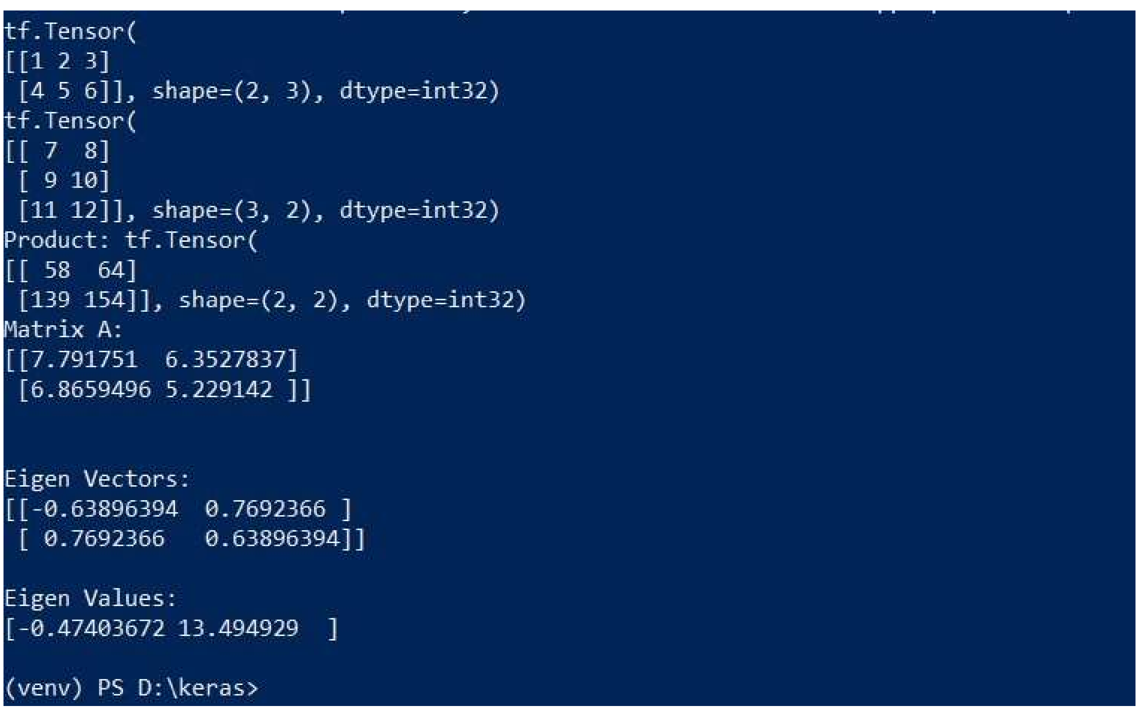
Practical No:1

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

```
import tensorflow as tf print("Matrix
Multiplication Demo")
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:



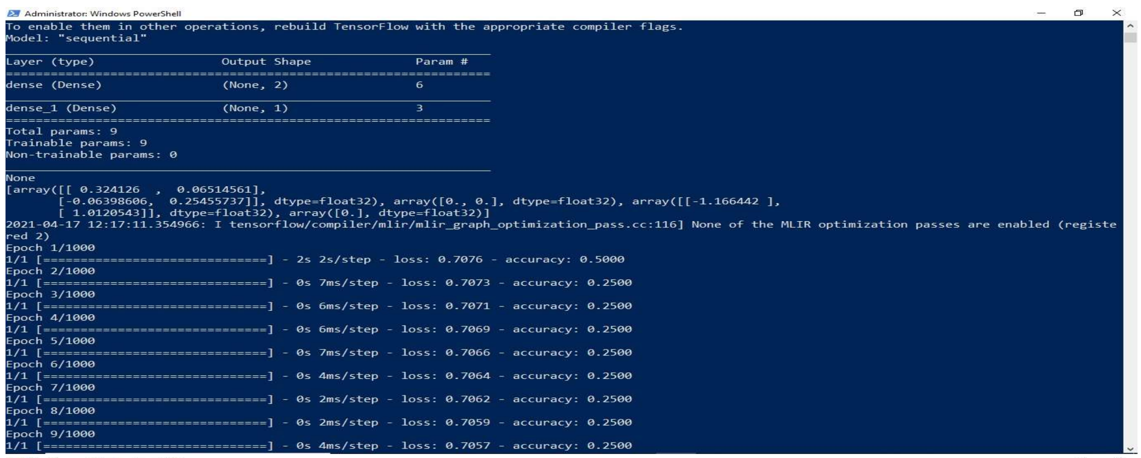
```
tf.Tensor(
[[1 2 3]
 [4 5 6]], shape=(2, 3), dtype=int32)
tf.Tensor(
[[ 7  8]
 [ 9 10]
 [11 12]], shape=(3, 2), dtype=int32)
Product: tf.Tensor(
[[ 58  64]
 [139 154]], shape=(2, 2), dtype=int32)
Matrix A:
[[7.791751  6.3527837]
 [6.8659496 5.229142 ]]


Eigen Vectors:
[[-0.63896394  0.7692366 ]
 [ 0.7692366   0.63896394]]

Eigen Values:
[-0.47403672 13.494929  ]

(venv) PS D:\keras>
```

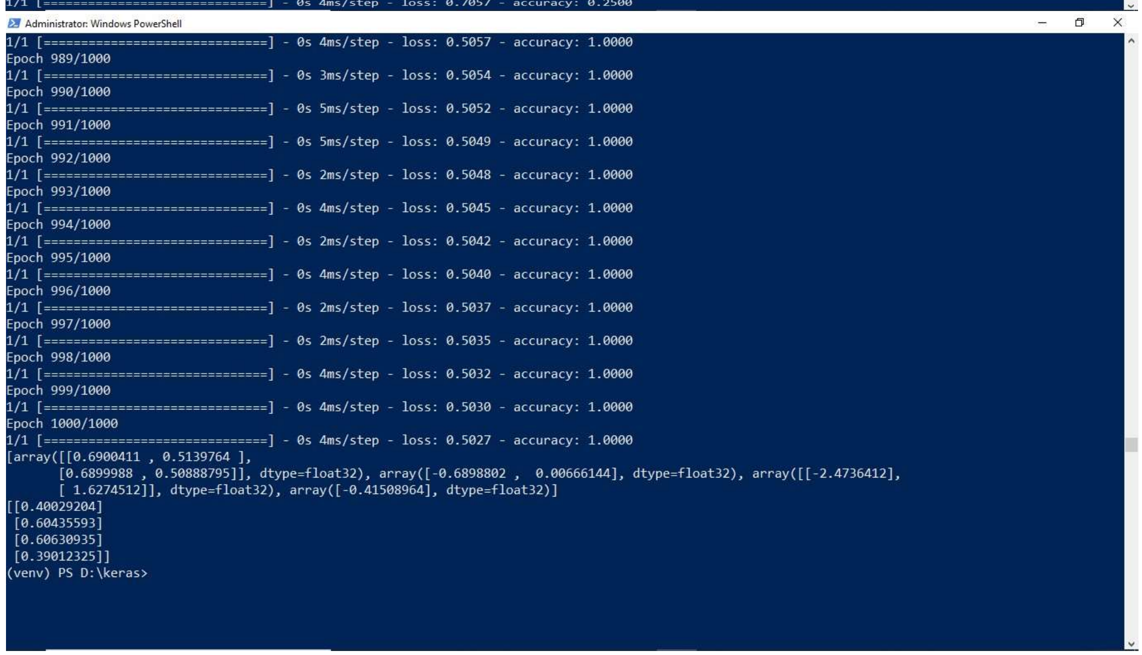
Practical No:2

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(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=1000,batch_size=4)

print(model.get_weights()) print(model.predict(X,batch_size=4))
```

OUTPUT:





Practical No:3

Aim: Implementing deep neural network for performing classification task.

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

```
>>> from numpy import loadtxt
>>> from keras.models import Sequential
>>> from keras.layers import Dense
>>>
```

```
Administrator: Windows PowerShell
>>> dataset=loadtxt('pima-indians-diabetes.csv',delimiter=',')
>>> dataset
array([[  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.   ]])
>>> X=dataset[:,0:8]
>>> Y=dataset[:,8]
>>> X
array([[  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.   ]])
>>>
>>> Y
array([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.,
```

Creating model:

```
>>> model=Sequential()
```

```
>>> model.add(Dense(12,input_dim=8,activation='relu'))
>>> model.add(Dense(8,activation='relu'))
>>> model.add(Dense(1,activation='sigmoid'))
>>>
```

Compiling and fitting model:

```
>>> model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
>>> model.fit(X,Y,epochs=150,batch_size=10)
```

```
Administrator: Windows PowerShell
>>> model.add(Dense(1,activation='sigmoid'))
>>> model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
>>> model.fit(X,Y,epochs=150,batch_size=10)
2021-04-05 17:40:32.289557: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:116] None of the MLIR optimization passes are enabled (registe
red 2)
Epoch 1/150
77/77 [==============================] - 2s 2ms/step - loss: 2.6770 - accuracy: 0.4399
Epoch 2/150
77/77 [==============================] - 0s 1ms/step - loss: 1.1332 - accuracy: 0.5064
Epoch 3/150
77/77 [==============================] - 0s 2ms/step - loss: 0.8624 - accuracy: 0.5592
Epoch 4/150
77/77 [==============================] - 0s 2ms/step - loss: 0.8135 - accuracy: 0.5700
Epoch 5/150
77/77 [==============================] - 0s 2ms/step - loss: 0.7369 - accuracy: 0.6089
Epoch 6/150
77/77 [==============================] - 0s 1ms/step - loss: 0.7405 - accuracy: 0.6269
Epoch 7/150
77/77 [==============================] - 0s 2ms/step - loss: 0.7157 - accuracy: 0.6060
Epoch 8/150
77/77 [==============================] - 0s 1ms/step - loss: 0.6852 - accuracy: 0.6354
Epoch 9/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6585 - accuracy: 0.6398
Epoch 10/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6524 - accuracy: 0.6330
Epoch 11/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6671 - accuracy: 0.6584
Epoch 12/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6216 - accuracy: 0.6857
Epoch 13/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6656 - accuracy: 0.6469
Epoch 14/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6304 - accuracy: 0.6870
Epoch 15/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6290 - accuracy: 0.6594
Epoch 16/150
77/77 [==============================] - 0s 2ms/step - loss: 0.6033 - accuracy: 0.6722
```

Evaluating the accuracy:

```
>>> _,accuracy=model.evaluate(X,Y)
24/24 [==============================] - 0s 1ms/step - loss: 0.4849 - accuracy: 0
.7591
>>> print('Accuracy of model is',(accuracy*100))
Accuracy of model is 75.91145634651184
>>>
```

Using model for prediction class:

```
>>> prediction=model.predict_classes(X)
```

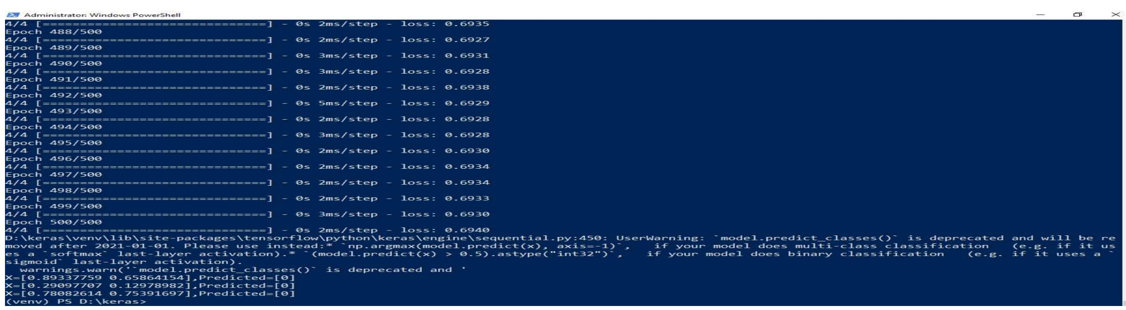
```
>>> exec("for i in range(5):print(X[i].tolist(),prediction[i],Y[i])")
[6.0, 148.0, 72.0, 35.0, 0.0, 33.6, 0.627, 50.0] [1] 1.0
[1.0, 85.0, 66.0, 29.0, 0.0, 26.6, 0.351, 31.0] [0] 0.0
[8.0, 183.0, 64.0, 0.0, 0.0, 23.3, 0.672, 32.0] [1] 1.0
[1.0, 89.0, 66.0, 23.0, 94.0, 28.1, 0.167, 21.0] [0] 0.0
[0.0, 137.0, 40.0, 35.0, 168.0, 43.1, 2.288, 33.0] [1] 1.0
>>>
```

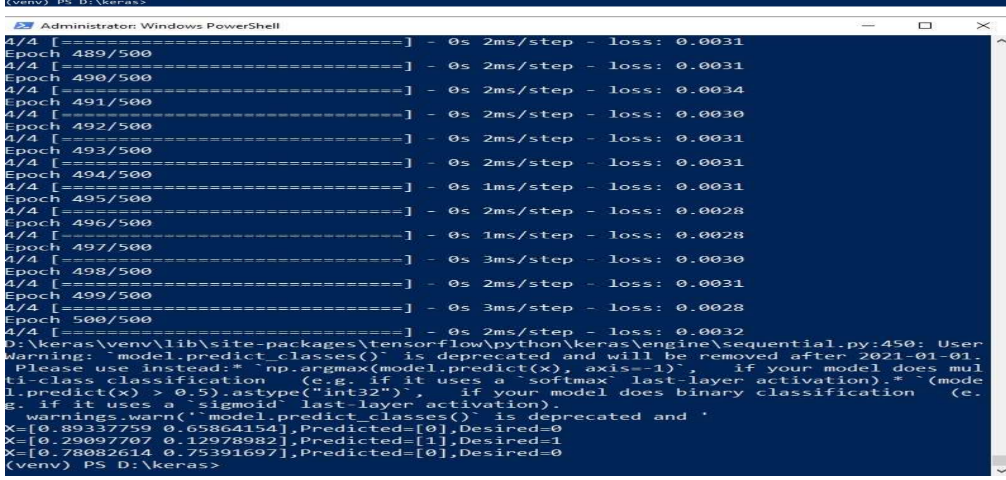
Practical No:4

a) Aim: Using deep feed forward network with two hidden layers for performing 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:

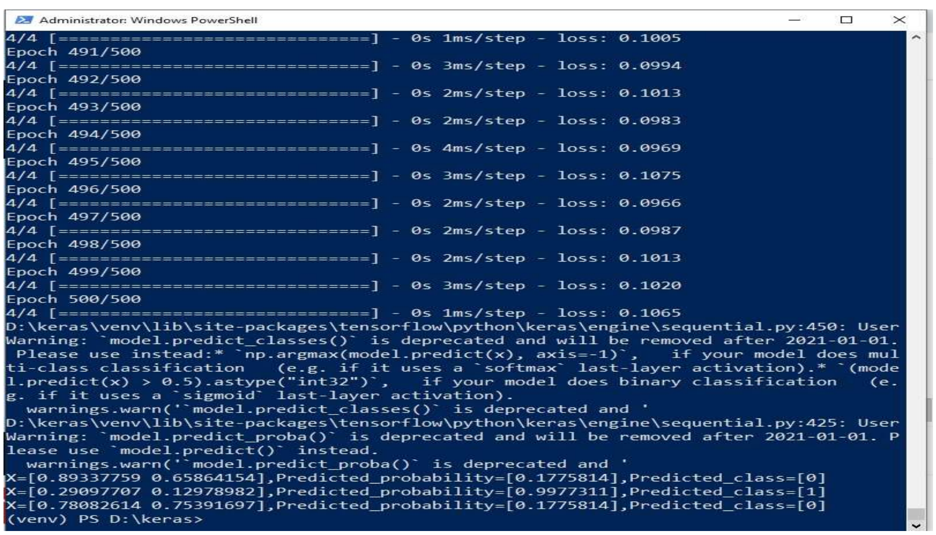




b) Aim: Using a deep field forward network with two hidden layers for performing classification and predicting the probability of class.

```
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 for performing 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'))
```

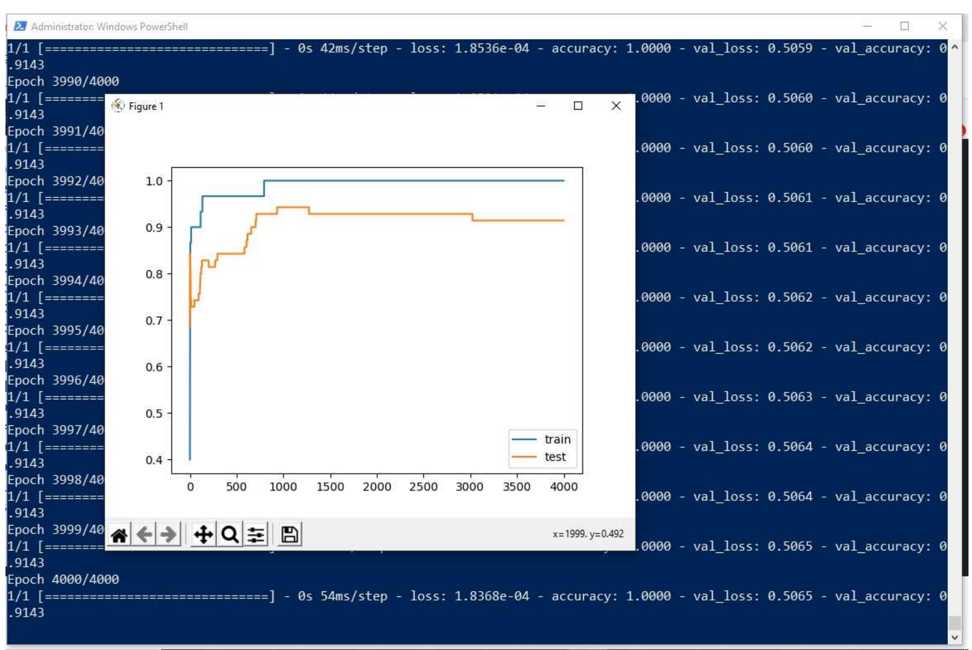
```
Wider: -22.17 (24.38) MSE
(venv) PS D:\keras>
```

Practical No :6

Aim: implementing regularization to avoid overfitting in binary classification.

```
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 less than 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 l2 regularization 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)))**

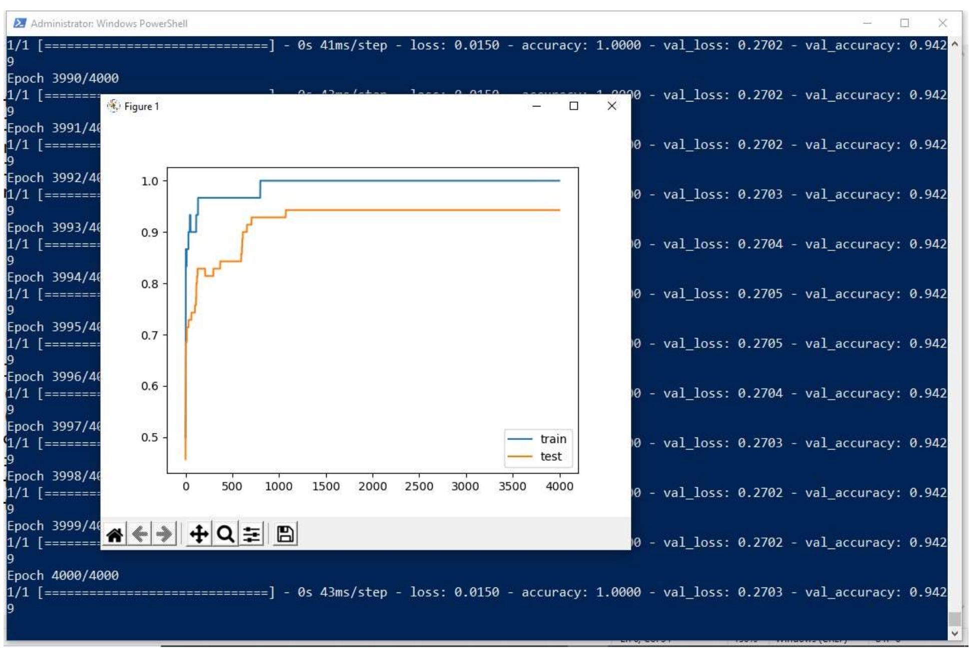
model.add(Dense(1,activation='sigmoid'))

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 the following output.

By applying l1 and l2 regularizer we can observe the following changes in accuracy of both trainig 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'])

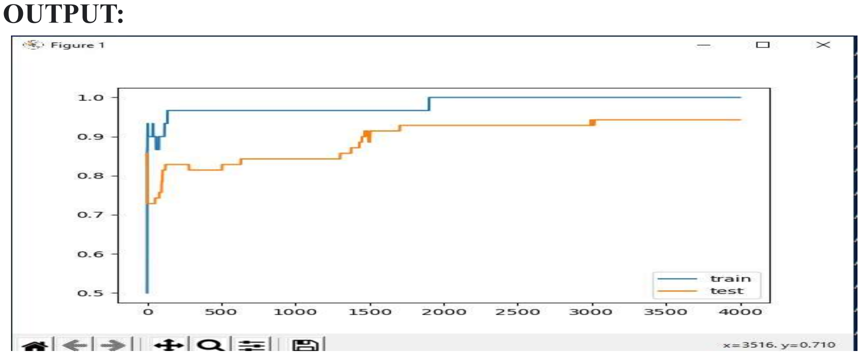
history=model.fit(trainX,trainY,validation_data=(testX,testY),epochs=4000)

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

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

pyplot.show()

OUTPUT:



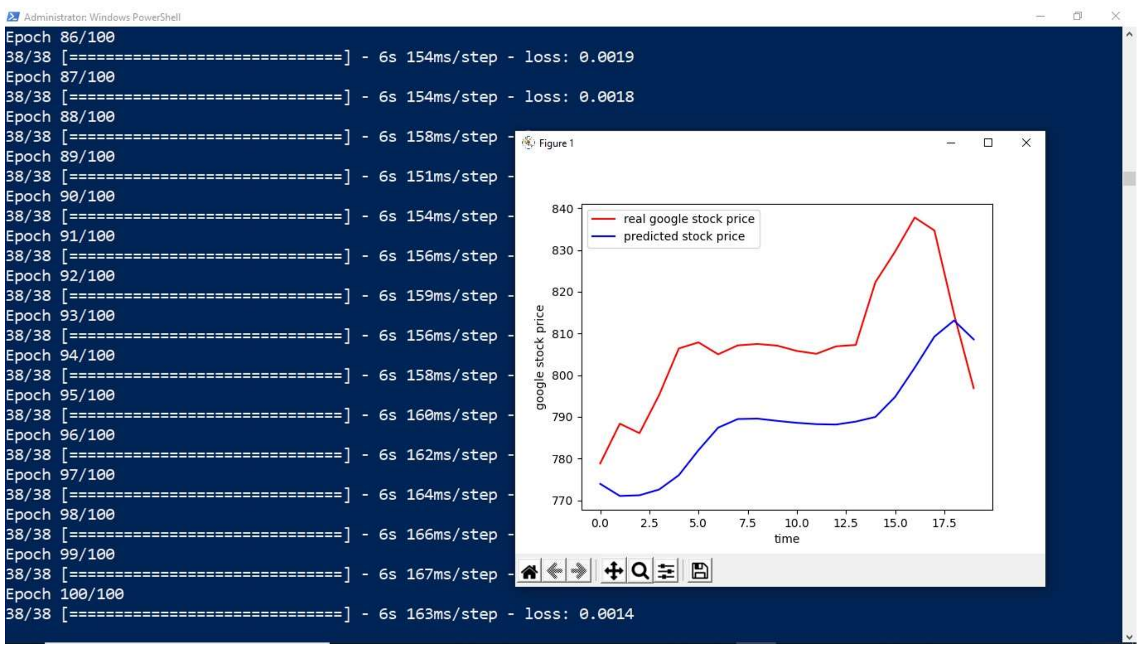
Practical No:7

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')
#print(dataset_train)
training_set=dataset_train.iloc[:,1:2].values

#print(training_set) sc=MinMaxScaler(feature_range=(0,1))
training_set_scaled=sc.fit_transform(training_set)
#print(training_set_scaled)
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:



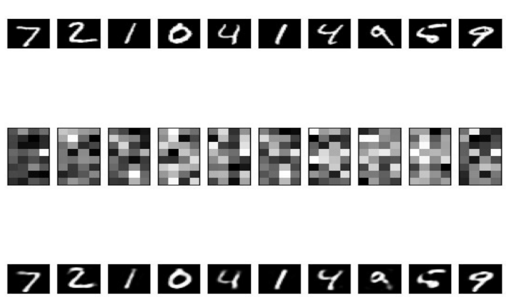
Practical No:8

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,))
#"encoded" is the encoded representation of the input
encoded=layers.Dense(encoding_dim, activation='relu')(input_img)
#"decoded" is the lossy reconstruction of the input
decoded=layers.Dense(784, activation='sigmoid')(encoded)
#creating autoencoder model
autoencoder=keras.Model(input_img,decoded)
#create the encoder model
encoder=keras.Model(input_img,encoded)
encoded_input=keras.Input(shape=(encoding_dim,)) #Retrive the
last layer of the autoencoder model
decoder_layer=autoencoder.layers[-1] #create the decoder model
decoder=keras.Model(encoded_input,decoder_layer(encoded_input))
autoencoder.compile(optimizer='adam',loss='binary_crossentropy')
#scale and make train and test dataset
(X_train,_),(X_test,_)=mnist.load_data()
X_train=X_train.astype('float32')/255.
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)
#train autoencoder with training dataset
autoencoder.fit(X_train,X_train,
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 # How
many digits we will display
```

```
plt.figure(figsize=(40, 4)) for i in range(10):
# display original     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:



Practical No:5b

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

```
#loading libraries 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

#loading dataset

df=pandas.read_csv('Flower.csv',header=None) print(df)

#splitting dataset into input and output variables

X = df.iloc[:,0:4].astype(float)    y=df.iloc[:,4]

#print(X)

#print(y)

#encoding string output into numeric output

encoder=LabelEncoder() 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():

        # create model

model = Sequential()

        model.add(Dense(8, input_dim=4, activation='relu'))

model.add(Dense(3, activation='softmax'))

        # Compile model

        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.]
 [1. 0. 0.]
 [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%)
```

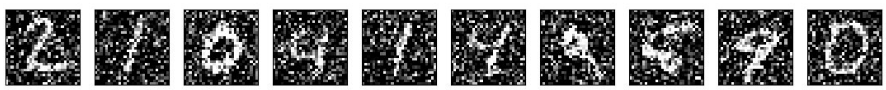
Practical No:10 Aim:

Denoising of images using autoencoder.

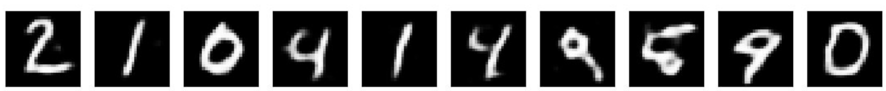
```
import keras from keras.datasets
import mnist from keras import
layers import numpy as np
from keras.callbacks import TensorBoard import
matplotlib.pyplot as plt
(X_train,_),(X_test,_)=mnist.load_data()
X_train=X_train.astype('float32')/255.
X_test=X_test.astype('float32')/255.
X_train=np.reshape(X_train,(len(X_train),28,28,1))
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:



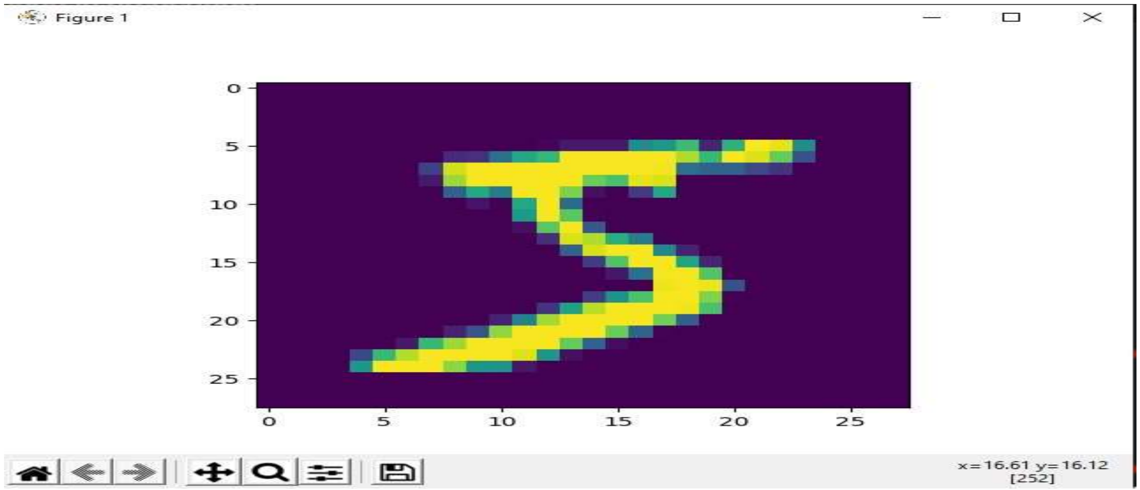
Practical No:9

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


#download mnist data and split into train and test sets

(X_train,Y_train),(X_test,Y_test)=mnist.load_data()


#plot the first image in the dataset

plt.imshow(X_train[0]) plt.show()


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]))
```

#actual results for 1st 4 images in the test set print(Y_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>
```