Assignment 3

Author: Aditya Mulik
NUID: 002127694
Email ID: mulik.a@northeastern.edu

Notes:
1. I have used Google Colab for running the jupyter files
2. The datasets are loaded in Google Colab using it's Gdrive API
3. I have linked the dataset or uploaded it in the zip file as per respective question and mentioned in its respective notes

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Question 1: Expand the basic code for building a DNN on the Pima Indian Diabetic Dataset to include:

(a) **pre-process the data by scaling/standardising the 8 columns**

Ans: Below are the currently supported pre-processing methods provided by sklearn

1. MinMaxScaler
2. StandardScaler
3. Normalizer
4. Binarizer

For testing purposes, I used the MinMaxScaler as per the below screenshot. I have added examples of other implementations as well and commented on them.

```
[7] #scale Features from 0 to 1
    transforms = MinMaxScaler(feature_range=(0,1))
    scaler_X =  transforms.fit_transform(X)
    print(scaler_X)

    [[0.35294118 0.74371859 0.59016393 ... 0.50074516 0.23441503 0.48333333]
     [0.05882353 0.42713568 0.54098361 ... 0.39642325 0.11656704 0.16666667]
     [0.47058824 0.91959799 0.52459016 ... 0.34724292 0.25362938 0.18333333]
     ...
     [0.29411765 0.6080402  0.59016393 ... 0.390462   0.07130658 0.15      ]
     [0.05882353 0.63316583 0.49180328 ... 0.4485842  0.11571307 0.43333333]
     [0.05882353 0.46733668 0.57377049 ... 0.45305514 0.10119556 0.03333333]]
```

(b) **Split the entire dataset into three parts instead of two as we currently do. One is train, two is validation, and then a test set. Build DNN model with train data, tune hyper-parameters with validation data, and finally evaluate performance on the test data**

Ans: I split the data in the train-validation-test dataset in a range of **70-15-15 ratio** by reusing the sklearn's train_test_split twice.

Later I plugged the validation set to the hyperparameters by replacing the test test and evaluated the model on the test set.

Split data into train, validation and test

```
[8] df.shape

(768, 9)
```

```
[13] X_train, X_test, Y_train, Y_test = train_test_split(scaler_X, Y, test_size=0.15, random_state=1)
     X_train, X_val, Y_train, Y_val = train_test_split(X_train, Y_train, test_size=0.15, random_state=1)
```

```
[15] print(X_train.shape,Y_train.shape,X_val.shape,Y_val.shape,X_test.shape,Y_test.shape)

(554, 8) (554, 1) (98, 8) (98, 1) (116, 8) (116, 1)
```

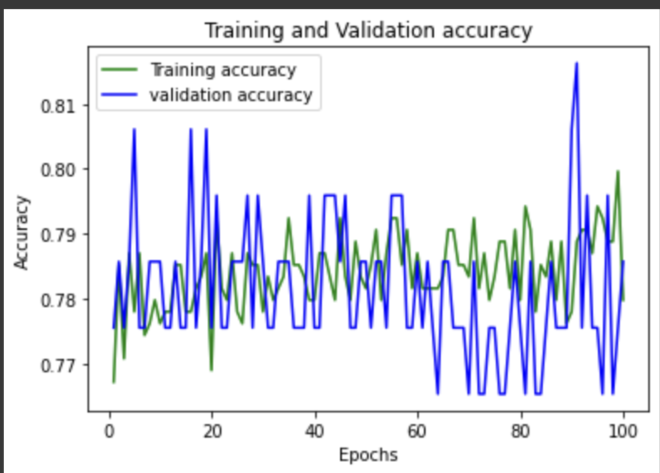
```
[20] # Fit the DNN with your train data

     model.fit(X_train, Y_train, validation_data=(X_val, Y_val), epochs=100, batch_size=5)
```

(c) **Make Epoch versus train set accuracy, and validation set accuracy**

Ans: I've plotted the graph of train/ val accuracy against the 100 epochs used.

Epoch vs Train/ Validation

```
loss_train = history.history['accuracy']
loss_val = history.history['val_accuracy']
epochs = range(1,101)
plt.plot(epochs, loss_train, 'g', label='Training accuracy')
plt.plot(epochs, loss_val, 'b', label='validation accuracy')
plt.title('Training and Validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



(d) **Report results using nice ROC curves, report AUC values. Feel free to use code from our course, or from elsewhere**

Ans: A Roc_Auc score of 84.24% received on model evaluation and the code snippet with the plot diagram is added below.

Model Evaluation

ROC vs AUC implementation using sklearn's roc_auc_score metrics

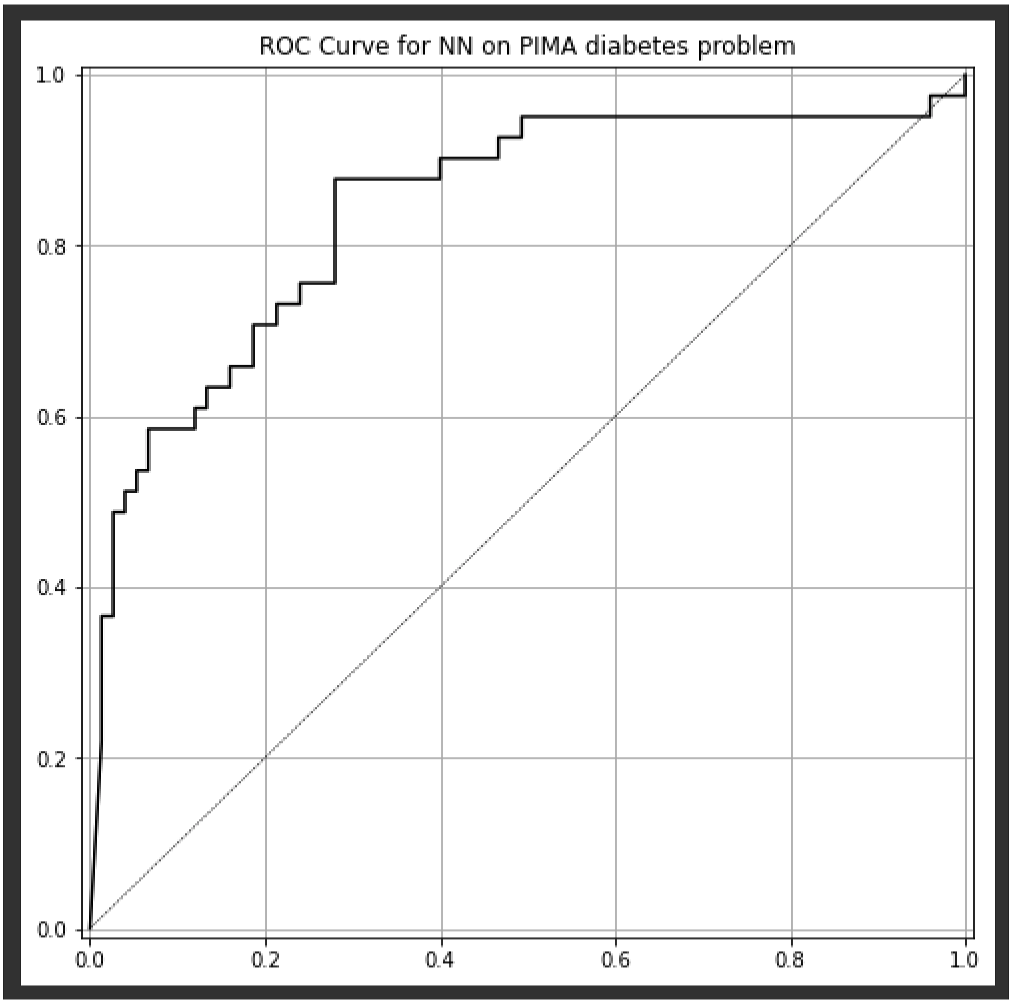
```
[45] y_pred_prob_nn_1 = model.predict(X_test)
```

```
[46] y_pred_prob_nn_1[:10]
```

```
array([[0.5604001 ],
       [0.36893898],
       [0.11501053],
       [0.05097717],
       [0.14265424],
       [0.17524552],
       [0.4865586 ],
       [0.07613519],
       [0.10438582],
       [0.07139322]], dtype=float32)
```

```
[47] print(roc_auc_score(Y_test,y_pred_prob_nn_1))
```

```
0.842439024390244
```



(e) **How would you increase dataset size? Try out at least two approaches and re-evaluate the model performance on this new and augmented dataset.**

Ans: I used the **SMOTE technique** from the imblearn library to augment the dataset for the outcome column of the pima dataset. Another method is to add **gaussian noise** to the dataset by adding dummy or random values to increase the quantity of the dataset which can be used for training the model and increasing its efficiency.

Data Augmentation

```
[ ] df3 = df.copy()
    target = 8

    print('Original class distribution:')
    print(df3[target].value_counts())

    xf = df3.columns
    X_t = df3.drop([target],axis=1)
    Y_t = df3[target]

    smote = SMOTE()
    X_t, Y_t = smote.fit_resample(X, Y)

    df3 = pd.DataFrame(X_t, columns=xf)
    df3[target] = Y_t

    print('\nClass distribution after applying SMOTE Technique:',)
    print(Y_t.value_counts())
```

```
Original class distribution:
0    500
1    268
Name: 8, dtype: int64

Class distribution after applying SMOTE Technique:
8
0    500
1    500
dtype: int64
```

```
# Example to add noice to dataset
# x is my training data
# mu is the mean
# std is the standard deviation
mu=0.0
std = 0.1
def gaussian_noise(x,mu,std):
    noise = np.random.normal(mu, std, size = x.shape)
    x_noisy = x + noise
    return x_noisy
```

Note:
All the implementation has been done in the notebook and attached as per **Question_1.ipynb** file

Dataset: https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database

Question 2: Please describe at least two ways of ensembling together DNNs and RFs. Take any dataset from Kaggle and

(1) train an RF model (2) train a DNN, and (3) a hybrid DNN and RF model. Provide detailed model and result comparison

a. **Two ways of ensembling DNNs & RFs**

Ans: The most common ways of

b. **Model and result comparison with below criteria.**
   i. **Train an RF model**
   ii. **Train an DNN model**
   iii. **Hybrid DNN and RF model**

Ans:
