HW5 - ANN MODEL

December 10, 2021

Name: Ankit Pattanayak CSULB ID: 027646357‘

In this assignment, we build a simple ANN model for a dataset and we explore some methods to optimize model parameters.

0.0.1 Sequence of operations:

1) Import libaries
2) Loading data
3) Feature-engineering
4) Split data to train, validation and test data
5) Tune params using GridSearchCV
6) Apply model on validation data
7) View confusion matrix on validation data
8) If satisfied, apply model on test data
9) View confusion matrix on test data
10) Interpret the precision and recall values
11) Draw loss curves for validation and test data
12) Identify if the curves indicate overfitting problems

4- ANN project description Part 1 – Loading the required libraries and modules

[1]:
```
#Pandas
import pandas as pd

#Numpy
import numpy as np

#Mat-plot libary
import matplotlib.pyplot as plt

#SK-learn
import sklearn as sk

#Train-Test-Split
from sklearn.model_selection import train_test_split

#MLP Classifier
from sklearn.neural_network import MLPClassifier
```

```python
#Confusion Matrix
from sklearn.metrics import classification_report,confusion_matrix

#Visual effects for confusion matrix
import seaborn as sns
```

Part 2 – Reading the data and performing basic data checks 1- Use describe() method of the dataframe (e.g df.describe()) to output the data dimensions and fields basic stats.

[2]:
```python
#Reading the data
data = pd.read_csv("diabetes.csv")

#Validate loading of data
data.describe()
```

[2]:
```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

0.1 Feature-engineering

[3]:
```python
#Feature-selection based on count of zeroes in data
zeroes = {}
for c in data.columns[:-1]:
    col_data = data[c].replace(0,np.nan)
    zeroes[c] = len(data)-col_data.count()
dict(sorted(zeroes.items(), key=lambda item: item[1]))
```

[3]:
```
{'DiabetesPedigreeFunction': 0,
 'Age': 0,
```

```
 'Glucose': 5,
 'BMI': 11,
 'BloodPressure': 35,
 'Pregnancies': 111,
 'SkinThickness': 227,
 'Insulin': 374}
```

Dropping SkinThickness, Insulin and Age columns due to the presence of excess of zeroes and due to the nature of data

[4]:
```
data = data.drop(columns=["SkinThickness","Insulin","Age"])
```

Part 3 – Creating the train and test datasets

[5]:
```
#Splitting dataset into input(X) and output(Y)
X = data.drop('Outcome', axis = 1)
Y = data['Outcome']

print("Inputs\n", X.head(2))
print("-"*70, "\nOutputs")
print(Y.head(2))
```

```
Inputs
    Pregnancies  Glucose  BloodPressure   BMI  DiabetesPedigreeFunction
0            6      148             72  33.6                     0.627
1            1       85             66  26.6                     0.351
----------------------------------------------------------------------
Outputs
0    1
1    0
Name: Outcome, dtype: int64
```

1- Split your data into train, test and, validation. 2- Split your data based on the ratio of train = 0.75, validation = 0.15 and, test = 0.10 3- Print out the total number of rows and the number of rows allocated for each category above.

[6]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,test_size=0.25,␣
 ↪random_state = 0)
X_val, X_test, Y_val, Y_test = train_test_split(X_test, Y_test, test_size=0.4,␣
 ↪random_state = 0)
print(f"Total data:(100%)    {X.shape}")
print(f"Training data:(75%)  {X_train.shape}")
print(f"Testing data:(10%)   {X_test.shape}")
print(f"Validation data:(15%){X_val.shape}")
```

```
Total data:(100%)    (768, 5)
Training data:(75%)  (576, 5)
Testing data:(10%)   (77, 5)
Validation data:(15%)(115, 5)
```

Part 4 – Building your model 1- Use neural_network classifier to build your network.

[7]:
```
#Dummy classifier
clf = MLPClassifier()
clf
```

[7]:
```
MLPClassifier()
```

2- There are a few parameters needs to be adjusted in this model: a. Hidden_layer_sizes b. Activation c. Solver d. Batch_size e. Learning_rate f. Learning_rate_init

Using GridSearchCV to try params for better accuracy

[8]:
```
#Adjust Params and applying GridSearchCV to try all combinations.

from sklearn.model_selection import GridSearchCV

param_grid = [
        {
            'activation' : ['identity', 'logistic', 'tanh', 'relu'],
            'solver' : ['sgd', 'adam'],
            'hidden_layer_sizes': [
             (1,),(2,),(3,),(4,),(5,),(6,),(7,),(8,),(9,),(10,),(11,),␣
 ↪(12,),(13,),(14,),(15,),(16,),(17,),(18,),(19,),(20,),(21,)
             ],
            'learning_rate_init':[0.08],
            'learning_rate':['adaptive'],
            'max_iter':[700]
        }
       ]
clf = GridSearchCV(MLPClassifier(), param_grid, cv=5,
                           scoring='accuracy')
clf.fit(X_train, Y_train)
best_params = clf.best_params_
print(best_params)
```

```
{'activation': 'identity', 'hidden_layer_sizes': (4,), 'learning_rate':
'adaptive', 'learning_rate_init': 0.08, 'max_iter': 700, 'solver': 'adam'}
```

Creating model based on best params decided above Slightly tweaking hidden_layer_sizes to (3,) from 4 bumped up the accuracy

[9]:
```
clf = MLPClassifier(hidden_layer_sizes=(3,), activation='identity',
                    solver = 'adam',
                    learning_rate = 'adaptive',
                    learning_rate_init = 0.08,
                    random_state = 0,
                    max_iter=700)
clf.fit(X_train, Y_train)
```

```
[9]: MLPClassifier(activation='identity', hidden_layer_sizes=(3,),
                   learning_rate='adaptive', learning_rate_init=0.08, max_iter=700,
                   random_state=0)
```

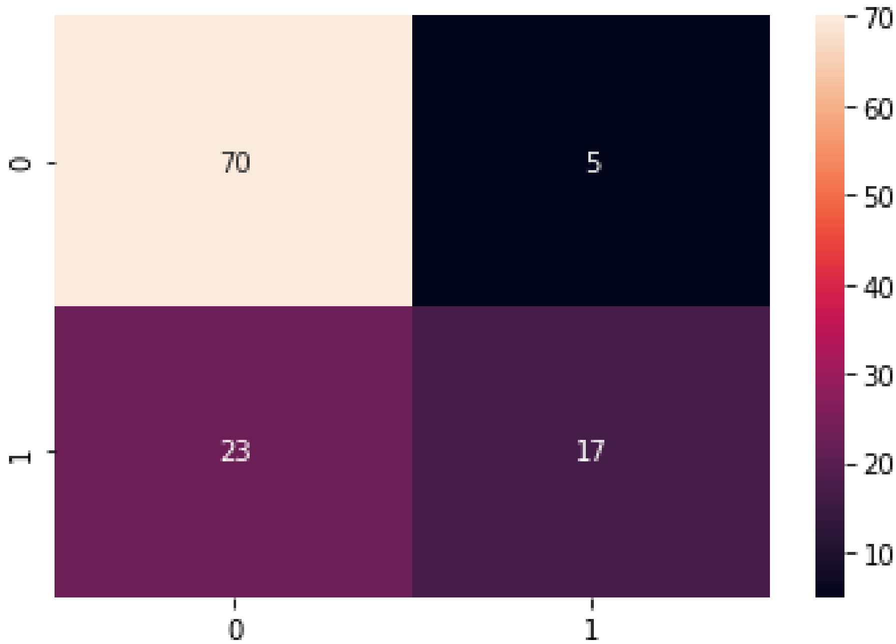
Validation: Running prediction on validation data

```
[10]: pred_val = clf.predict(X_val)
```

Part 5 – Network metric and plots 1- To evaluate your network, calculate confusion matrix. How do you interpret precision and recall?

```
[11]: print("Confusion Matrix on Validation Data")
c = confusion_matrix(Y_val,pred_val)
sns.heatmap(c, annot=True, fmt="d")
plt.show()
print(classification_report(Y_val, pred_val))
```

```
Confusion Matrix on Validation Data
```




```
              precision    recall  f1-score   support

           0       0.75      0.93      0.83        75
           1       0.77      0.42      0.55        40

    accuracy                           0.76       115
   macro avg       0.76      0.68      0.69       115
```

```
weighted avg       0.76      0.76      0.73       115
```

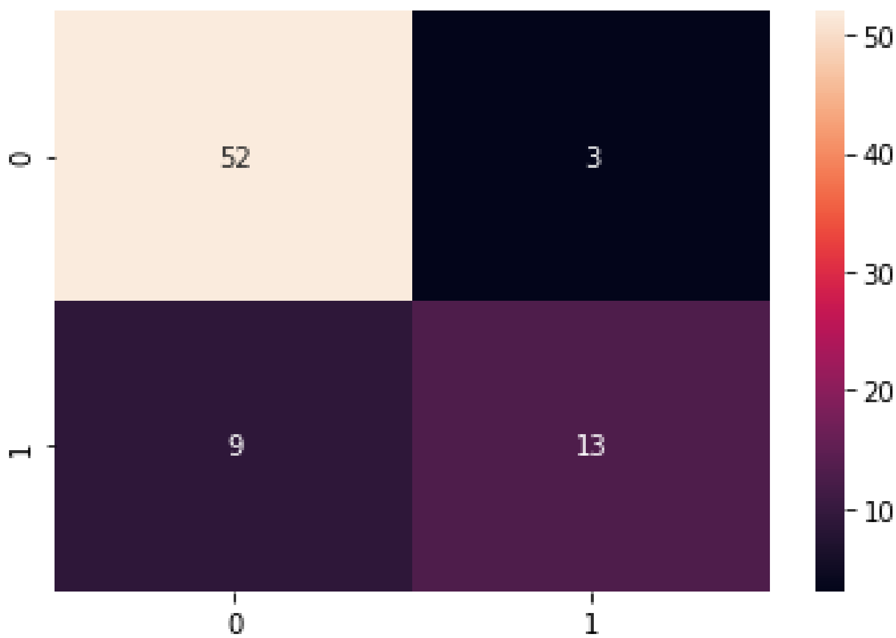
Observation: Considering accuracy and f1-score on validation data, this model's parameters seem fit. Going ahead by applying model for test-data

[12]:
```python
pred_test = clf.predict(X_test)
```

Drawing confusion matrix for test-data

[13]:
```python
print("Confusion Matrix on Test Data")
c = confusion_matrix(Y_test,pred_test)
sns.heatmap(c, annot=True, fmt="d")
plt.show()
print(classification_report(Y_test, pred_test))
```

```
Confusion Matrix on Test Data
```




```
              precision    recall  f1-score   support

           0       0.85      0.95      0.90        55
           1       0.81      0.59      0.68        22

    accuracy                           0.84        77
   macro avg       0.83      0.77      0.79        77
weighted avg       0.84      0.84      0.84        77
```

Extracting parameters from confusion matrix of test-data

[14]:
```
#Getting True Negatives, False Positives, False Negatives and True Postiives
TN, FP, FN, TP = c.ravel()
```

Accuracy: (TP + TN) / (TN + FP + FN + TP) – 84.42%

[15]:
```
accuracy = ((TP + TN) / (TN + FP + FN + TP))*100.0
print(f"Accuracy is {accuracy:.2f}%")
```

```
Accuracy is 84.42%
```

Precision: (true positives / predicted positives) = TP / TP + FP. - 81.25%

[16]:
```
precision = (TP/(TP + FP))*100.0
print(f"Precision is {precision:.2f}%")
```

```
Precision is 81.25%
```

Recall: TP/(TP + FN) –> 59.09%

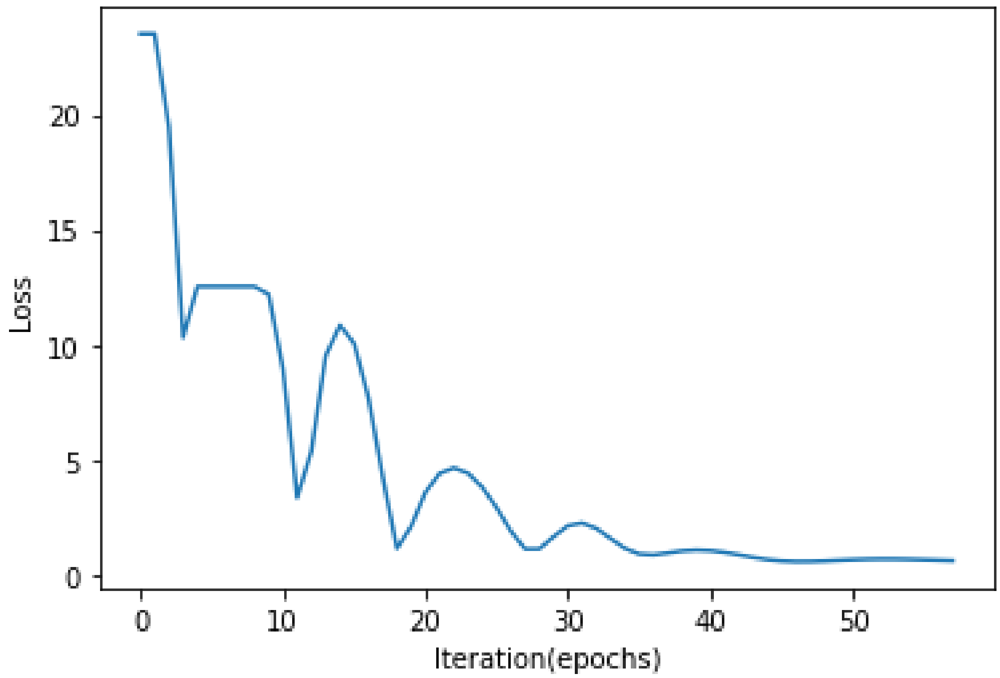
[17]:
```
recall = (TP/(TP + FN))*100.0
print(f"Recall is {recall:.2f}%")
```

```
Recall is 59.09%
```

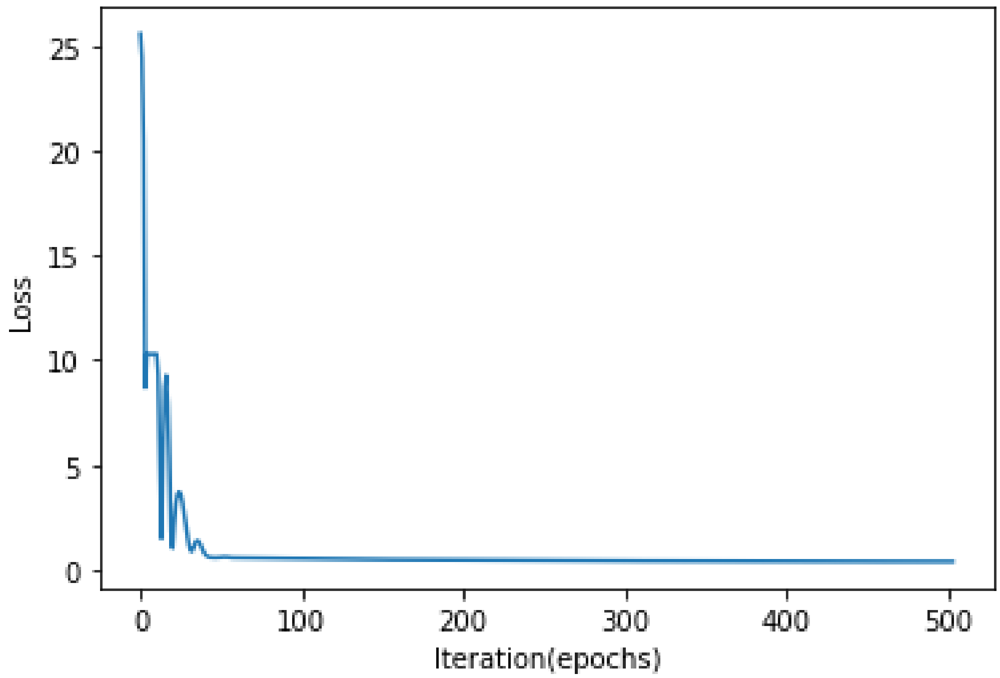
Interpretation: 1. Precision of 81.25% indicates that this model correctly predicted 81 diabetic outcomes out of 100. We can safely trust its positive prediction most of the times. 2. Recall of 59.09% indicates that this model is capable to predict 60 diabetic outcomes out of 100 actual diabetic outcomes. This is fairly accurate as well.

2- Plot error plot for each iteration (epoch) for both validate and train. Based on your parameter setting you may see an overfitting problem. Try to spot it if that's happened. 3- Once you finish your parameter tunning, run your model on your test data set and create a plot for your test the same as previous step

[18]:
```
#For validation data
clf.fit(X_val, Y_val)
plt.xlabel("Iteration(epochs)")
plt.ylabel("Loss")
plt.plot(clf.loss_curve_)
plt.show()
```



[19]:
```
#For test data
clf.fit(X_test, Y_test)
plt.xlabel("Iteration(epochs)")
plt.ylabel("Loss")
plt.plot(clf.loss_curve_)
plt.show()
```



Observation showing overfitting problem: 1) This model has a high validation loss at the beginning but gradually decreases upon adding training data 2) This model's training and validation loss are a lot different from each other.