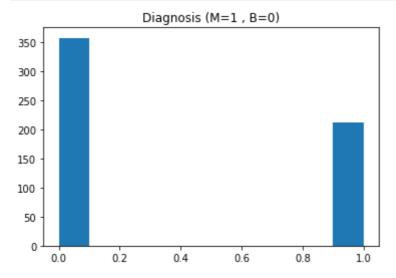
```
#Importing the Libraries
 In [1]:
           import pandas as pd
           import numpy as np
           import seaborn as sns
           import matplotlib.pyplot as plt
            %matplotlib inline
           df=pd.read csv('data.csv')
 In [2]:
 In [3]:
           df.head(5)
 Out[3]:
                       diagnosis
                                 radius_mean texture_mean perimeter_mean area_mean smoothne
               842302
           0
                                        17.99
                                                     10.38
                                                                    122.80
                                                                               1001.0
                              M
               842517
           1
                                        20.57
                                                     17.77
                                                                    132.90
                                                                               1326.0
                              M
           2 84300903
                                                     21.25
                                                                    130.00
                                                                               1203.0
                              M
                                        19.69
             84348301
                              M
                                        11.42
                                                     20.38
                                                                     77.58
                                                                                386.1
             84358402
                              M
                                        20.29
                                                     14.34
                                                                    135.10
                                                                               1297.0
          5 rows × 33 columns
 In [4]:
           df.drop('id',axis=1,inplace=True)
           df.drop('Unnamed: 32',axis=1,inplace=True)
           df.shape
 In [6]:
           (569, 31)
 Out[6]:
 In [7]:
           df.diagnosis.unique()
          array(['M', 'B'], dtype=object)
 Out[7]:
           df['diagnosis'] = df['diagnosis'].map({'M':1,'B':0})
 In [8]:
           df.head()
 Out[8]:
             diagnosis
                        radius_mean texture_mean perimeter_mean area_mean smoothness_mean
           0
                     1
                              17.99
                                           10.38
                                                          122.80
                                                                     1001.0
                                                                                      0.11840
                              20.57
                                                          132.90
                                                                                      0.08474
           1
                     1
                                            17.77
                                                                     1326.0
           2
                     1
                              19.69
                                           21.25
                                                          130.00
                                                                     1203.0
                                                                                      0.10960
           3
                              11.42
                                            20.38
                                                           77.58
                                                                      386.1
                                                                                      0.14250
                                                                                      0.10030
           4
                     1
                              20.29
                                           14.34
                                                          135.10
                                                                     1297.0
          5 rows × 31 columns
In [10]:
           #Checking out statistics (mean, median standard deviation)
           df.describe()
Out[10]:
                  diagnosis radius_mean texture_mean perimeter_mean
                                                                       area_mean smoothness_n
```

count	569.000000	569.000000	569.000000	569.000000	569.000000	569.00
mean	0.372583	14.127292	19.289649	91.969033	654.889104	0.09
std	0.483918	3.524049	4.301036	24.298981	351.914129	0.01
min	0.000000	6.981000	9.710000	43.790000	143.500000	0.05
25%	0.000000	11.700000	16.170000	75.170000	420.300000	0.08
50%	0.000000	13.370000	18.840000	86.240000	551.100000	0.09
75%	1.000000	15.780000	21.800000	104.100000	782.700000	0.10
max	1.000000	28.110000	39.280000	188.500000	2501.000000	0.16

## 8 rows × 31 columns

```
In [11]: df.describe()
  plt.hist(df['diagnosis'])
  plt.title('Diagnosis (M=1 , B=0)')
  plt.show()
```



```
In [12]: features_mean=list(df.columns[1:11])

# split dataframe into two based on diagnosis
dfM=df[df['diagnosis'] ==1]
dfB=df[df['diagnosis'] ==0]
```

```
In [15]: from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import MinMaxScaler

def getNormalizedData(X):
    # fit scaler on training data
    norm = MinMaxScaler().fit(X)

# transform training data
X_train_norm = norm.transform(X)
X_train_norm = pd.DataFrame(X_train_norm, columns=X.columns.values)

return X_train_norm
```

```
In [17]: #'Diagnosis' is the target variable, change as applicable
    y = df.diagnosis
    X = df.drop('diagnosis',1)
```

```
X = getNormalizedData(X)
In [18]: train_X, val_X, train_y, val_y = train_test split(X, y, random state=42,
In [19]:
       def get nn simplemodel(n inputs=22, n outputs=1, optimizerinput='adam'):
           # create model
           model = Sequential()
           model.add(layers.Dense(n inputs, input dim=n inputs, kernel initiali
           model.add(layers.Dense(2000, activation='relu'))
           model.add(layers.Dense(1))
           model.compile(loss='mean squared error', optimizer=optimizerinput)
           return model
In [20]:
       from keras.wrappers.scikit learn import KerasRegressor
        from keras.models import Sequential
        from tensorflow.keras import layers
        #Hyperparameter Tuning to Tune Batch Size and Number of Epochs
        from sklearn.model selection import GridSearchCV
        #https://scikit-learn.org/stable/modules/generated/sklearn.model selecti
        # create model
        model = KerasRegressor(build fn=get nn simplemodel, n inputs=len(X.colum
        #model = KerasClassifier(build fn=create model, verbose=0)
        # define the grid search parameters
        batch size = [5, 10, 20, 30, 40]
        epochs = [10, 50, 100]
        param_grid = dict(batch size=batch size, epochs=epochs)
        grid = GridSearchCV(estimator=model, param grid=param grid, n jobs=-1, c
        grid result = grid.fit(X, y)
        # summarize results
       print(grid result)
        print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_p
        means = grid_result.cv_results_['mean_test_score']
        stds = grid result.cv results ['std test score']
        params = grid_result.cv_results_['params']
        for mean, stdev, param in zip(means, stds, params):
           print("%f (%f) with: %r" % (mean, stdev, param))
       Epoch 1/50
       114/114 [============= ] - 0s 1ms/step - loss: 0.1086
       Epoch 2/50
       Epoch 3/50
       Epoch 4/50
       Epoch 5/50
       Epoch 6/50
       Epoch 7/50
       Epoch 8/50
```

```
Epoch 9/50
Epoch 10/50
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
Epoch 17/50
Epoch 18/50
Epoch 19/50
Epoch 20/50
114/114 [============= ] - 0s 1ms/step - loss: 0.0191
Epoch 21/50
114/114 [============ ] - 0s 1ms/step - loss: 0.0189
Epoch 22/50
114/114 [============ ] - 0s 2ms/step - loss: 0.0166
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
Epoch 27/50
Epoch 28/50
Epoch 29/50
Epoch 30/50
114/114 [=============] - 0s 1ms/step - loss: 0.0150
Epoch 31/50
Epoch 32/50
114/114 [============= ] - 0s 1ms/step - loss: 0.0160
Epoch 33/50
Epoch 34/50
Epoch 35/50
Epoch 36/50
114/114 [============ ] - 0s 1ms/step - loss: 0.0187
Epoch 37/50
114/114 [============ ] - Os 1ms/step - loss: 0.0135
Epoch 38/50
114/114 [============ ] - 0s 1ms/step - loss: 0.0142
Epoch 39/50
114/114 [============ ] - 0s 1ms/step - loss: 0.0247
Epoch 40/50
114/114 [============ ] - 0s 1ms/step - loss: 0.0152
Epoch 41/50
114/114 [============ ] - 0s 1ms/step - loss: 0.0146
Epoch 42/50
```

```
Epoch 43/50
       Epoch 44/50
      Epoch 45/50
      Epoch 46/50
      Epoch 47/50
      Epoch 48/50
      Epoch 49/50
      Epoch 50/50
      GridSearchCV(cv=3,
                estimator=<tensorflow.python.keras.wrappers.scikit learn.Ker
       asRegressor object at 0x0000016D0D05BA60>,
                n jobs=-1,
                param_grid={'batch size': [5, 10, 20, 30, 40],
                         'epochs': [10, 50, 100]})
       Best: -0.023331 using {'batch size': 5, 'epochs': 50}
       -0.037746 (0.011950) with: {'batch size': 5, 'epochs': 10}
       -0.023331 (0.012707) with: {'batch_size': 5, 'epochs': 50}
       -0.025792 (0.014083) with: {'batch size': 5, 'epochs': 100}
       -0.050562 (0.017155) with: {'batch size': 10, 'epochs': 10}
       -0.025862 (0.003204) with: {'batch size': 10, 'epochs': 50}
       -0.029090 (0.005693) with: {'batch size': 10, 'epochs': 100}
       -0.050995 (0.005893) with: {'batch_size': 20, 'epochs': 10}
       -0.026017 (0.006634) with: {'batch size': 20, 'epochs': 50}
       -0.024380 (0.010593) with: {'batch size': 20, 'epochs': 100}
       -0.062723 (0.020652) with: {'batch_size': 30, 'epochs': 10}
       -0.026098 (0.012060) with: {'batch size': 30, 'epochs': 50}
       -0.023892 (0.010491) with: {'batch_size': 30, 'epochs': 100}
       -0.072307 (0.019946) with: {'batch_size': 40, 'epochs': 10}
       -0.029889 (0.005592) with: {'batch_size': 40, 'epochs': 50}
       -0.026316 (0.003739) with: {'batch_size': 40, 'epochs': 100}
      #Hyperparameter Tuning to Tune Optimization Algorithm
In [21]:
       from sklearn.model selection import GridSearchCV
       # create model
       model = KerasRegressor(build fn=get nn simplemodel, n inputs=len(X.colum
       # define the grid search parameters
       optimizer = ['RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', 'Nadam'
       param grid = dict(optimizerinput=optimizer)
       grid = GridSearchCV(estimator=model, param grid=param grid, n jobs=-1, c
       grid result = grid.fit(X, y)
       # summarize results
       print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_p
       means = grid_result.cv_results_['mean_test_score']
       stds = grid result.cv results ['std test score']
       params = grid result.cv results ['params']
       for mean, stdev, param in zip(means, stds, params):
          print("%f (%f) with: %r" % (mean, stdev, param))
       Epoch 1/200
       Epoch 2/200
       114/114 [============ ] - 0s 851us/step - loss: 0.0699
```

Epoch 3/200

```
Epoch 4/200
Epoch 5/200
Epoch 6/200
Epoch 7/200
Epoch 8/200
Epoch 9/200
Epoch 10/200
Epoch 11/200
Epoch 12/200
Epoch 13/200
Epoch 14/200
114/114 [============ ] - 0s 852us/step - loss: 0.0309
Epoch 15/200
114/114 [============ ] - 0s 908us/step - loss: 0.0284
Epoch 16/200
114/114 [============ ] - 0s 793us/step - loss: 0.0268
Epoch 17/200
114/114 [============ ] - 0s 866us/step - loss: 0.0261
Epoch 18/200
Epoch 19/200
Epoch 20/200
Epoch 21/200
Epoch 22/200
Epoch 23/200
Epoch 24/200
Epoch 25/200
Epoch 26/200
114/114 [============== ] - 0s 903us/step - loss: 0.0180
Epoch 27/200
Epoch 28/200
Epoch 29/200
Epoch 30/200
Epoch 31/200
114/114 [============ ] - 0s 930us/step - loss: 0.0174
Epoch 32/200
114/114 [============ ] - 0s 1ms/step - loss: 0.0166
Epoch 33/200
114/114 [============ ] - 0s 853us/step - loss: 0.0164
Epoch 34/200
114/114 [============= ] - 0s 839us/step - loss: 0.0156
Epoch 35/200
114/114 [============= ] - 0s 849us/step - loss: 0.0159
Epoch 36/200
114/114 [============= ] - 0s 827us/step - loss: 0.0145
Epoch 37/200
```

```
Epoch 38/200
Epoch 39/200
Epoch 40/200
Epoch 41/200
Epoch 42/200
Epoch 43/200
Epoch 44/200
Epoch 45/200
Epoch 46/200
Epoch 47/200
Epoch 48/200
114/114 [============= ] - 0s 823us/step - loss: 0.0132
Epoch 49/200
114/114 [============ ] - 0s 834us/step - loss: 0.0134
Epoch 50/200
114/114 [============= ] - 0s 849us/step - loss: 0.0125
Epoch 51/200
Epoch 52/200
Epoch 53/200
Epoch 54/200
Epoch 55/200
Epoch 56/200
Epoch 57/200
Epoch 58/200
114/114 [============= ] - 0s 817us/step - loss: 0.0109
Epoch 59/200
114/114 [============== ] - 0s 838us/step - loss: 0.0130
Epoch 60/200
Epoch 61/200
Epoch 62/200
Epoch 63/200
Epoch 64/200
Epoch 65/200
114/114 [============= ] - 0s 851us/step - loss: 0.0118
Epoch 66/200
114/114 [============= ] - 0s 840us/step - loss: 0.0113
Epoch 67/200
114/114 [============= ] - 0s 926us/step - loss: 0.0115
Epoch 68/200
114/114 [============ ] - 0s 793us/step - loss: 0.0105
Epoch 69/200
114/114 [============ ] - 0s 799us/step - loss: 0.0124
Epoch 70/200
114/114 [============ ] - 0s 880us/step - loss: 0.0104
Epoch 71/200
```

```
Epoch 72/200
Epoch 73/200
Epoch 74/200
Epoch 75/200
Epoch 76/200
Epoch 77/200
Epoch 78/200
Epoch 79/200
Epoch 80/200
Epoch 81/200
Epoch 82/200
114/114 [============= ] - 0s 801us/step - loss: 0.0101
Epoch 83/200
114/114 [============ ] - 0s 911us/step - loss: 0.0088
Epoch 84/200
114/114 [============ ] - 0s 800us/step - loss: 0.0108
Epoch 85/200
114/114 [============ ] - 0s 978us/step - loss: 0.0098
Epoch 86/200
Epoch 87/200
Epoch 88/200
Epoch 89/200
Epoch 90/200
Epoch 91/200
Epoch 92/200
114/114 [============] - 0s 794us/step - loss: 0.0093
Epoch 93/200
Epoch 94/200
114/114 [============== ] - 0s 839us/step - loss: 0.0096
Epoch 95/200
Epoch 96/200
Epoch 97/200
Epoch 98/200
Epoch 99/200
114/114 [============= ] - 0s 830us/step - loss: 0.0091
Epoch 100/200
114/114 [============ ] - Os 825us/step - loss: 0.0075
Epoch 101/200
114/114 [============ ] - 0s 815us/step - loss: 0.0099
Epoch 102/200
114/114 [============ ] - 0s 827us/step - loss: 0.0090
Epoch 103/200
114/114 [============ ] - 0s 799us/step - loss: 0.0077
Epoch 104/200
114/114 [============ ] - 0s 830us/step - loss: 0.0076
Epoch 105/200
```

```
Epoch 106/200
Epoch 107/200
Epoch 108/200
Epoch 109/200
Epoch 110/200
Epoch 111/200
Epoch 112/200
Epoch 113/200
Epoch 114/200
Epoch 115/200
Epoch 116/200
114/114 [============ ] - 0s 817us/step - loss: 0.0069
Epoch 117/200
114/114 [============ ] - 0s 835us/step - loss: 0.0093
Epoch 118/200
114/114 [============ ] - 0s 998us/step - loss: 0.0086
Epoch 119/200
114/114 [============= ] - 0s 785us/step - loss: 0.0072
Epoch 120/200
Epoch 121/200
Epoch 122/200
Epoch 123/200
Epoch 124/200
Epoch 125/200
Epoch 126/200
Epoch 127/200
Epoch 128/200
Epoch 129/200
Epoch 130/200
Epoch 131/200
Epoch 132/200
Epoch 133/200
114/114 [============ ] - 0s 797us/step - loss: 0.0060
Epoch 134/200
114/114 [============ ] - 0s 807us/step - loss: 0.0065
Epoch 135/200
114/114 [============ ] - 0s 793us/step - loss: 0.0064
Epoch 136/200
114/114 [============= ] - 0s 798us/step - loss: 0.0071
Epoch 137/200
114/114 [============= ] - 0s 827us/step - loss: 0.0059
Epoch 138/200
114/114 [============= ] - 0s 785us/step - loss: 0.0070
Epoch 139/200
```

```
Epoch 140/200
Epoch 141/200
Epoch 142/200
Epoch 143/200
Epoch 144/200
Epoch 145/200
Epoch 146/200
Epoch 147/200
Epoch 148/200
Epoch 149/200
Epoch 150/200
114/114 [============= ] - 0s 846us/step - loss: 0.0061
Epoch 151/200
114/114 [============= ] - 0s 960us/step - loss: 0.0062
Epoch 152/200
114/114 [============ ] - 0s 855us/step - loss: 0.0049
Epoch 153/200
114/114 [============ ] - 0s 917us/step - loss: 0.0055
Epoch 154/200
Epoch 155/200
Epoch 156/200
Epoch 157/200
Epoch 158/200
Epoch 159/200
Epoch 160/200
114/114 [=============] - 0s 804us/step - loss: 0.0047
Epoch 161/200
Epoch 162/200
Epoch 163/200
Epoch 164/200
Epoch 165/200
Epoch 166/200
Epoch 167/200
114/114 [============ ] - 0s 883us/step - loss: 0.0049
Epoch 168/200
114/114 [============ ] - 0s 796us/step - loss: 0.0050
Epoch 169/200
114/114 [============= ] - 0s 866us/step - loss: 0.0050
Epoch 170/200
114/114 [============ ] - 0s 1ms/step - loss: 0.0054
Epoch 171/200
114/114 [============ ] - 0s 817us/step - loss: 0.0047
Epoch 172/200
114/114 [============ ] - 0s 1ms/step - loss: 0.0042
Epoch 173/200
```

```
Epoch 174/200
Epoch 175/200
Epoch 176/200
Epoch 177/200
Epoch 178/200
114/114 [=============== ] - Os 829us/step - loss: 0.0045
Epoch 179/200
Epoch 180/200
Epoch 181/200
Epoch 182/200
Epoch 183/200
Epoch 184/200
114/114 [============= ] - 0s 853us/step - loss: 0.0052
Epoch 185/200
114/114 [============= ] - 0s 816us/step - loss: 0.0042
Epoch 186/200
114/114 [============= ] - 0s 789us/step - loss: 0.0056
Epoch 187/200
114/114 [============ ] - 0s 813us/step - loss: 0.0041
Epoch 188/200
Epoch 189/200
Epoch 190/200
Epoch 191/200
Epoch 192/200
Epoch 193/200
Epoch 194/200
Epoch 195/200
114/114 [============ ] - 0s 947us/step - loss: 0.0034
Epoch 196/200
Epoch 197/200
Epoch 198/200
Epoch 199/200
Epoch 200/200
Best: -0.023221 using {'optimizerinput': 'Adamax'}
-0.034766 (0.008045) with: {'optimizerinput': 'RMSprop'}
-0.062387 (0.018451) with: {'optimizerinput': 'Adagrad'}
-0.130494 (0.025806) with: {'optimizerinput': 'Adadelta'}
-0.029354 (0.012870) with: {'optimizerinput': 'Adam'}
-0.023221 (0.009218) with: {'optimizerinput': 'Adamax'}
-0.047123 (0.015469) with: {'optimizerinput': 'Nadam'}
from sklearn.model selection import cross val score
```

In [22]:

from sklearn.model\_selection import cross\_val\_score
from sklearn.model\_selection import KFold

```
# evaluate model
     estimator = KerasRegressor(build fn=get nn simplemodel, n inputs=len(X.c
     kfold = KFold(n splits=5)
     results = cross val score(estimator, X, y, cv=kfold)
     print("Baseline: %.2f (%.2f) MSE" % (results.mean(), results.std()))
     Baseline: -0.03 (0.01) MSE
In [23]:
     model=get nn simplemodel(len(X.columns),1, optimizerinput = 'Adam');
     history = model.fit(train X, train y, verbose=1, epochs=100, batch size=
     Epoch 1/100
     46/46 [============= ] - Os 4ms/step - loss: 0.1442 - val
     loss: 0.0814
     Epoch 2/100
     46/46 [=========== ] - Os 2ms/step - loss: 0.0737 - val
     loss: 0.0637
     Epoch 3/100
     loss: 0.0541
     Epoch 4/100
     loss: 0.0614
     Epoch 5/100
     loss: 0.0461
     Epoch 6/100
     loss: 0.0422
     Epoch 7/100
     loss: 0.0405
     Epoch 8/100
     loss: 0.0430
     Epoch 9/100
     loss: 0.0441
     Epoch 10/100
     loss: 0.0304
     Epoch 11/100
     loss: 0.0319
     Epoch 12/100
     loss: 0.0238
     Epoch 13/100
     46/46 [============ ] - Os 2ms/step - loss: 0.0214 - val
     loss: 0.0270
     Epoch 14/100
     46/46 [============= ] - Os 2ms/step - loss: 0.0216 - val
     loss: 0.0229
     Epoch 15/100
     loss: 0.0260
     Epoch 16/100
     loss: 0.0341
     Epoch 17/100
     loss: 0.0240
     Epoch 18/100
     46/46 [============= ] - Os 2ms/step - loss: 0.0178 - val
     loss: 0.0201
     Epoch 19/100
```

```
loss: 0.0246
Epoch 20/100
loss: 0.0250
Epoch 21/100
loss: 0.0298
Epoch 22/100
loss: 0.0253
Epoch 23/100
loss: 0.0230
Epoch 24/100
loss: 0.0290
Epoch 25/100
loss: 0.0240
Epoch 26/100
46/46 [============ ] - Os 2ms/step - loss: 0.0231 - val
loss: 0.0338
Epoch 27/100
46/46 [=========== ] - Os 3ms/step - loss: 0.0173 - val
loss: 0.0230
Epoch 28/100
46/46 [============ ] - Os 2ms/step - loss: 0.0139 - val
loss: 0.0251
Epoch 29/100
loss: 0.0210
Epoch 30/100
loss: 0.0288
Epoch 31/100
loss: 0.0308
Epoch 32/100
loss: 0.0243
Epoch 33/100
loss: 0.0351
Epoch 34/100
loss: 0.0377
Epoch 35/100
loss: 0.0265
Epoch 36/100
loss: 0.0284
Epoch 37/100
loss: 0.0264
Epoch 38/100
46/46 [============= ] - Os 2ms/step - loss: 0.0122 - val
loss: 0.0277
Epoch 39/100
46/46 [============= ] - Os 1ms/step - loss: 0.0139 - val
loss: 0.0302
Epoch 40/100
loss: 0.0263
Epoch 41/100
loss: 0.0251
```

```
Epoch 42/100
loss: 0.0248
Epoch 43/100
loss: 0.0258
Epoch 44/100
loss: 0.0367
Epoch 45/100
loss: 0.0242
Epoch 46/100
loss: 0.0317
Epoch 47/100
loss: 0.0258
Epoch 48/100
loss: 0.0282
Epoch 49/100
46/46 [============ ] - Os 2ms/step - loss: 0.0152 - val
loss: 0.0304
Epoch 50/100
46/46 [============ ] - Os 1ms/step - loss: 0.0143 - val
loss: 0.0272
Epoch 51/100
46/46 [============ ] - Os 2ms/step - loss: 0.0184 - val
loss: 0.0407
Epoch 52/100
loss: 0.0256
Epoch 53/100
loss: 0.0237
Epoch 54/100
loss: 0.0318
Epoch 55/100
loss: 0.0285
Epoch 56/100
loss: 0.0276
Epoch 57/100
loss: 0.0238
Epoch 58/100
loss: 0.0272
Epoch 59/100
loss: 0.0256
Epoch 60/100
loss: 0.0268
Epoch 61/100
46/46 [============= ] - 0s 1ms/step - loss: 0.0086 - val
loss: 0.0281
Epoch 62/100
46/46 [============= ] - Os 1ms/step - loss: 0.0095 - val
loss: 0.0460
Epoch 63/100
loss: 0.0299
Epoch 64/100
```

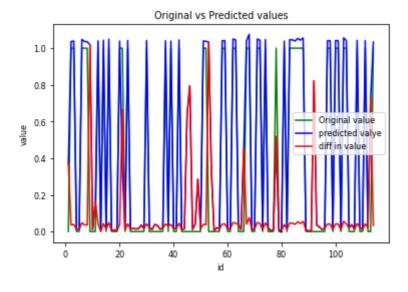
```
loss: 0.0315
Epoch 65/100
loss: 0.0315
Epoch 66/100
loss: 0.0340
Epoch 67/100
loss: 0.0295
Epoch 68/100
loss: 0.0313
Epoch 69/100
loss: 0.0317
Epoch 70/100
loss: 0.0291
Epoch 71/100
loss: 0.0271
Epoch 72/100
46/46 [============ ] - Os 2ms/step - loss: 0.0058 - val
loss: 0.0414
Epoch 73/100
46/46 [============ ] - Os 2ms/step - loss: 0.0077 - val
loss: 0.0290
Epoch 74/100
loss: 0.0320
Epoch 75/100
loss: 0.0332
Epoch 76/100
loss: 0.0352
Epoch 77/100
loss: 0.0345
Epoch 78/100
loss: 0.0321
Epoch 79/100
loss: 0.0279
Epoch 80/100
loss: 0.0280
Epoch 81/100
loss: 0.0294
Epoch 82/100
loss: 0.0391
Epoch 83/100
46/46 [============= ] - Os 2ms/step - loss: 0.0076 - val
loss: 0.0310
Epoch 84/100
46/46 [============= ] - 0s 2ms/step - loss: 0.0058 - val
loss: 0.0394
Epoch 85/100
loss: 0.0350
Epoch 86/100
loss: 0.0347
Epoch 87/100
```

```
loss: 0.0298
     Epoch 88/100
     loss: 0.0265
     Epoch 89/100
     loss: 0.0390
     Epoch 90/100
     loss: 0.0287
     Epoch 91/100
     loss: 0.0303
     Epoch 92/100
     loss: 0.0345
     Epoch 93/100
     loss: 0.0360
     Epoch 94/100
     46/46 [============ ] - Os 2ms/step - loss: 0.0047 - val
     loss: 0.0340
     Epoch 95/100
     46/46 [============ ] - Os 1ms/step - loss: 0.0046 - val
     loss: 0.0386
     Epoch 96/100
     46/46 [============ ] - Os 2ms/step - loss: 0.0072 - val
     loss: 0.0306
     Epoch 97/100
     loss: 0.0445
     Epoch 98/100
     loss: 0.0296
     Epoch 99/100
     loss: 0.0282
     Epoch 100/100
     loss: 0.0501
     from datetime import datetime
In [24]:
      # Code to create graph for train vs validation error for different epoch
      loss train = history.history['loss']
      loss val = history.history['val loss']
      diff in loss=abs(np.subtract(loss val, loss train));
      df = pd.DataFrame({'loss train':loss train, 'loss val':loss val, 'diff i
     print(df.head(10))
      epochs = range(1,len(loss train)+1)
      plt.plot(epochs, loss train, 'g', label='Training loss')
      plt.plot(epochs, loss val, 'b', label='validation loss')
     plt.plot(epochs, diff in loss, 'r', label='diff in loss')
     plt.title('Training and Validation loss')
     plt.xlabel('Epochs')
     plt.ylabel('Loss')
     plt.legend()
      timeStr=datetime.now().strftime("%Y%m%d-%H%M%S");
```

```
fileName = 'train vs Validation loss '+timeStr
           plt.savefig(fileName+'.png', format='png', dpi=2000)
           df.to excel("neural network train vs val loss"+timeStr+".xlsx", sheet na
           plt.show()
             loss train loss val diff in loss
               0.\overline{144155} 0.08\overline{1368}
                                      0.062787
          0
               0.073730 0.063680
          1
                                         0.010050
               0.063003 0.054149
                                         0.008854
               0.056380 0.061395
                                         0.005015
               0.058851 0.046058
                                         0.012793
               0.044713 0.042212
          5
                                         0.002500
               0.042888 0.040501
          6
                                          0.002387
               0.035001 0.042954
          7
                                          0.007954
          8
               0.035377
                          0.044071
                                          0.008694
               0.034865 0.030361
                                          0.004504
                              Training and Validation loss

    Training loss

            0.14
                                                     validation loss
                                                     diff in loss
            0.12
            0.10
            0.08
            0.06
            0.04
            0.02
            0.00
                         20
                                  40
                                          60
                                                   80
                                                           100
                                     Epochs
         #code to print actual, predicted, diff in values
In [25]:
           predicted=model.predict(val X);
           actual=val y;
          y flat=actual.values.flatten();
In [26]:
           predicted flat=predicted.flatten()
           residue=abs(np.subtract(y flat,predicted flat))
          #Plot
In [27]:
           xasix = range(1, len(y flat) + 1)
           plt.plot(xasix, y_flat, 'g', label='Original value')
           plt.plot(xasix, predicted_flat, 'b', label='predicted valye')
           plt.plot(xasix, residue, 'r', label='diff in value')
           plt.title('Original vs Predicted values')
           plt.xlabel('id')
           plt.ylabel('value')
           plt.legend()
           timeStr=datetime.now().strftime("%Y%m%d-%H%M%S");
           fileName = 'Original vs Predicted y'+timeStr
```



In [ ]: