Predicting_Occurrence_of_Diabetes

December 17, 2022

1 Overview

This is my solution from the course project of IBM Deep Learning and Reinforcement Learning course. Since it's my first contact with Deep Learning, I chose to use the same dataset from the instructor (but with different analysis) wich is the Pima Indians Diabetes Database retrieved from Kaggle.

Here the main objective is: **build a neural network with Keras package to predict whether or not the patients in the dataset have diabetes and compare the performance with an baseline model**.

The dataset was composed by 768 pacients and 9 characteristics from them wich are: - Number of times pregnant - Plasma glucose concentration a 2 hours in an oral glucose tolerance test - Diastolic blood pressure (mm Hg) - Triceps skin fold thickness (mm) - 2-Hour serum insulin (mu U/ml) - Body mass index (weight in kg/(height in m)^2) - Diabetes pedigree function - Age (years) - Class variable (0 or 1)

2 Necessary packages

[2]:
```
#core
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import numpy as np

from sklearn.model_selection import train_test_split, cross_validate,␣
↪StratifiedKFold
from sklearn.metrics import roc_auc_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, roc_auc_score

#Auto EDA -- !pip install dataprep --
#from dataprep.eda import create_report

from keras.models  import Sequential
from keras.layers import Input, Dense, Flatten, Dropout, BatchNormalization
```

```python
from keras.optimizers import Adam, SGD, RMSprop
```

3 Glimpse on Data

[3]:
```python
PATH = "../data/"
```

[4]:
```python
#loading dataframe
df_raw = pd.read_csv(PATH+"diabetes.csv")

#create a copy to avoid edit raw data
df = df_raw.copy()
```

[5]:
```python
df.head()
```

[5]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

[ ]:
```python
df.tail()
```

[ ]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0
```

[ ]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

- There are no missing value
- All features are numerical so they don't need encode

I always like to start the analysis with an auto EDA tool to give a first look on data and and get quick insights. Here I use dataprep for this purpose.

[ ]:
```
#this code export a html file named diabetes_job.html with dataprep output␣
↪which can be opened locally by any browser
report = create_report(df, title='Diabetes Prediction')
report.save("diabetes_job.html")
```

```
Report has been saved to diabetes_job.html!
```

From the Auto EDA it's possible to note that: - Glucose, BloodPressure, SkinThickness, Insulin and BMI have 0 values wich is biologically impossible. - There is a desbalance between the classes, 65.1% from the pacients don't have diabetes meanwhile 34.9% have.

4 Fixing Inconsistences

Since the dataset has a relatively small number of observations, drop the rows with 0 value from the collumns cited is inviable. Since the features had some skewness I impute those values with the median.

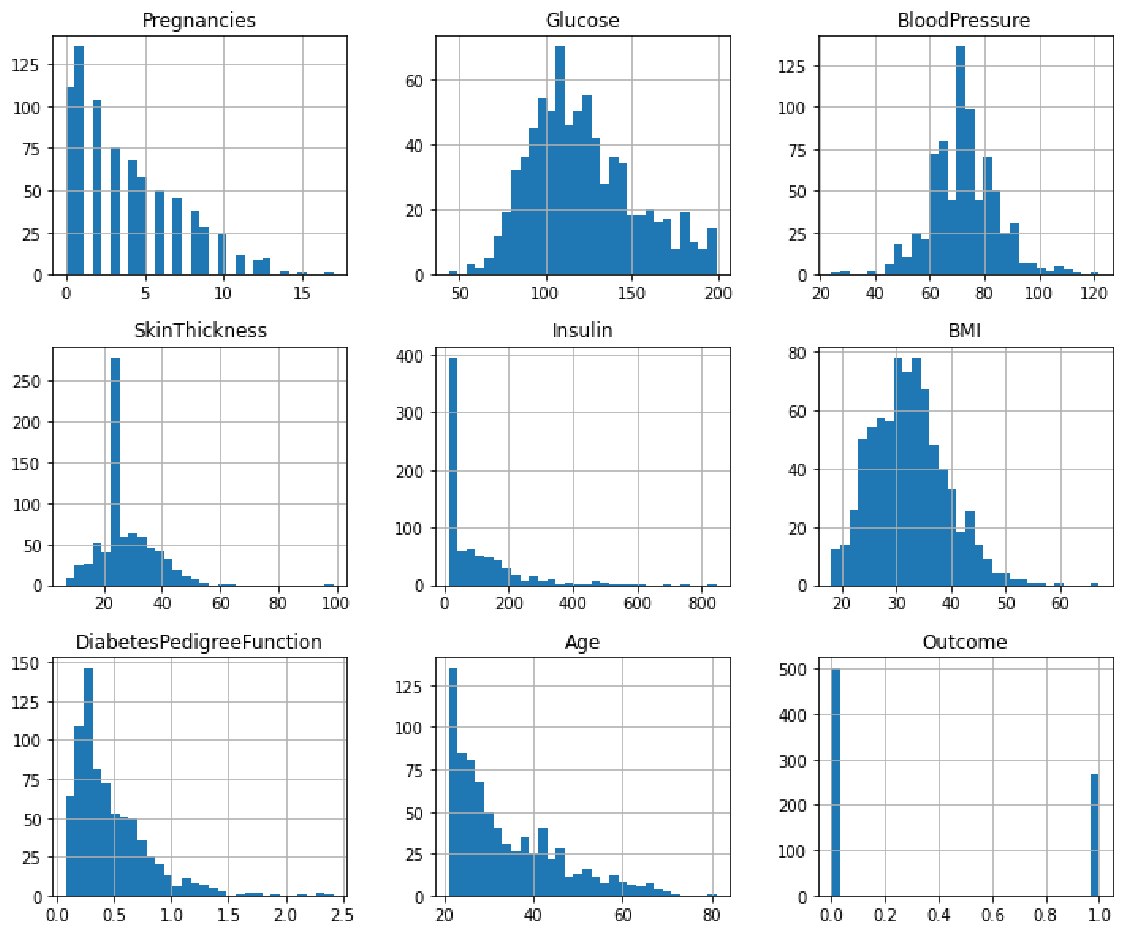
[ ]:
```
inconsistent_features = ["Glucose", "BloodPressure", "SkinThickness",␣
↪"Insulin", "BMI"]

def replace_median(feature):
  df[feature] = df[feature].replace(0, df[feature].median())

for i in inconsistent_features:
```

```
replace_median(i)
```

[ ]:
```
df.hist(figsize = (12,10), bins = 30);
```



[ ]:
```
df.Insulin.min()
```

[ ]: 14.0

5 Machine Learning

[ ]:
```
#Separating X and y features

X = df.drop("Outcome", axis = 1)
y = df["Outcome"]

X_train, X_test, y_train, y_test = train_test_split(X,y, random_state = 42,␣
↪test_size = 0.3, stratify = y)
```

6 Making a Baseline

For the baseline I will train a Random Forest. Since it's a tree method don't require any type of scale or normalization.

[ ]:
```
rf = RandomForestClassifier(n_estimators = 1000, random_state = 42, n_jobs = -1)
```

[ ]:
```
rf.fit(X_train, y_train)
```

[ ]:
```
RandomForestClassifier(n_estimators=1000, n_jobs=-1, random_state=42)
```

[ ]:
```
yhat = rf.predict(X_test)
```

[ ]:
```
#accuracy
accuracy_score(y_test, yhat)
```

[ ]:
```
0.7489177489177489
```

[ ]:
```
#roc
roc_auc_score(y_test, yhat)
```

[ ]:
```
0.7044444444444444
```

7 Build a Single Hidden Layer Neural Network

We need to scale the data to make easier the convergence of Gradient Descendent from network

[ ]:
```
scaler = StandardScaler()
X_train_scale = scaler.fit_transform(X_train)
X_test_scale = scaler.transform(X_test)
```

[ ]:
```
# The input had 8 features, so the input_shape is (8,). The model had 1 hidden␣
↪layer, 12 hidden nodes and sigmoid activation.
# Final layer has just one node with a sigmoid activation

model_1 = Sequential()
model_1.add(Dense(12,input_shape = (8,),activation = 'sigmoid'))
model_1.add(Dense(1,activation='sigmoid'))

model_1.compile(SGD(learning_rate = .003), "binary_crossentropy")
```

[ ]:
```
yhat = (model_1.predict(X_test_scale) > 0.5).astype("int32")
```

```
8/8 [==============================] - 0s 2ms/step
```

[ ]:
```
#accuracy
accuracy_score(y_test, yhat)
```

[ ]: 0.35064935064935066

[ ]:
```
#roc
roc_auc_score(y_test, yhat)
```

[ ]: 0.5

The Neural Network perform very bad related the Random Forest. This should because NN is “data hungry” and we provied few data to the model.