

# **Digital Egypt Youth**

Internet of things (IoT) and artificial Intelligent (AI)



# Coronary Heart Disease (CHD) Diagnosis and predict Using Traditional machine learning and MLP

**Presented By** 

Fikrya Ahmed Seddik Ahmed
Ahmed Mohie AbdElazeem Younis
Abdelrhman Mohamed Fawzy Ibrahim
Ibrahim Abd-elghany Ibrahim Salem

**Presented To** 

Dr. Mohamed Elzorkany

## **Abstract**

The report will describe a feasibility study to assess the use of neural networks and traditional machine learning algorithms to solve coronary heart disease (CHD) - Diagnosis and also predict a brief description of some algorithms of traditional machine learning we used.

## Introduction

Traditional machine learning is a set of mathematical, statistical and computational methods for developing algorithms that can solve a problem not in a direct way but based on finding patterns in a variety of input data. The solution is calculated not according to a formula, but according to the established dependence of the results on a specific set of features and their values. The neural network concept is to simulate a human's neural system. Its ability to learn using previous experience and thus make fewer errors next time. This is the main feature of neural networks.

#### **Datasets 1**

## We used two data sets one for diagnosis and other for prediction

#### First data set

## It contains of 9 feature and 1 output



#### **Features**

(sbp)---systolic blood pressure

(Tobacco)---yearly tobacco use (in kg)

(Idl)---low density lipoprotein adiposity

(Family history)--- (0 or 1)

(typea)---type A personality score

(Obesity)---(body mass index)

(alcohol use)

(Age)

## **Output**

The diagnosis of CHD (0 or 1).

## Models' analysis using Neural Network

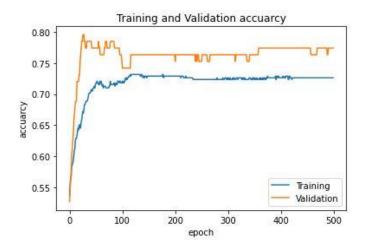
```
#import Libraries
import keras
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.model selection import train test split
import matplotlib.pyplot as plt
#import data
chd_data=pd.read_csv('/content/CHDdata diagnosis.csv')
chd data
#check for null value
chd data.isnull().sum()
#check for duplicated
chd data.duplicated().sum()
#check data types
chd data.dtypes
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(chd data.iloc[:,4])
list(le.classes )
chd data.iloc[:,4]=le.transform(chd data.iloc[:,4])
chd data
#spliting data
x=chd data.iloc[:,:-1]
y=chd data.iloc[:,-1]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
random state=54)
x train.iloc[0:4,:]
mms = StandardScaler()
x train= mms.fit transform(x train)
x test= mms.transform(x test)
x test[0:4,:]
model = keras.Sequential()
model.add(keras.layers.Dense(1, input shape= (9,),activation = 'sigmoid'))
model.compile(optimizer='sgd', loss='binary crossentropy', metrics=['binar
y accuracy'])
```

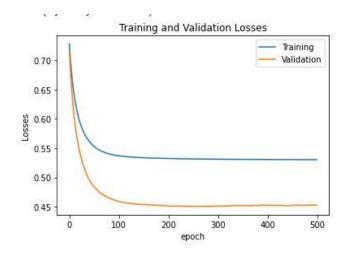
```
results = model.fit(x = x \text{ train}, y = y \text{ train}, \text{shuffle=True}, \text{ epochs} = 500,
    batch size =32, validation data = (x \text{ test, } y \text{ test)})
eval = model.evaluate(x = x test, y = y test)
import matplotlib.pyplot as plt
plt.plot(results.history['loss'])
plt.plot(results.history['val loss'])
plt.legend(['Training', 'Validation'])
plt.title('Training and Validation Losses')
plt.xlabel('epoch')
plt.ylabel('Losses')
plt.plot(results.history['binary accuracy'])
plt.plot(results.history['val binary accuracy'])
plt.legend(['Training', 'Validation'])
plt.title('Training and Validation accuarcy')
plt.xlabel('epoch')
plt.ylabel('accuarcy')
```

#### The results: -

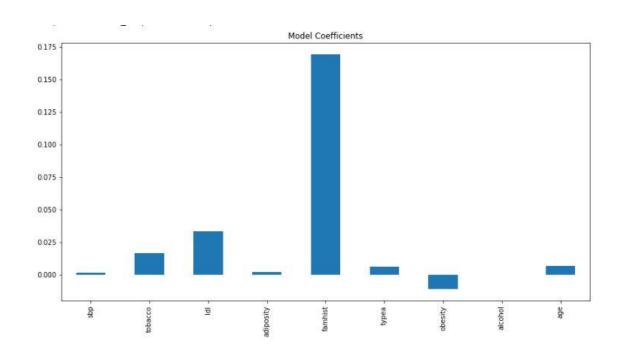
```
12/12 [============= 0.5364 - binary_accuracy: 0.7263 - val_loss: 0.4528 - val_binary_accuracy: 0.7742
   Epoch 495/500
   12/12 [=====
                 ==========] - 0s 5ms/step - loss: 0.5304 - binary_accuracy: 0.7263 - val_loss: 0.4529 - val_binary_accuracy: 0.7742
   Epoch 496/500
                12/12 [======
   Epoch 497/500
   12/12 [=====
                      =========] - 0s 5ms/step - loss: 0.5304 - binary_accuracy: 0.7263 - val_loss: 0.4528 - val_binary_accuracy: 0.7742
   Epoch 498/500
                       :========] - 0s 5ms/step - loss: 0.5304 - binary_accuracy: 0.7263 - val_loss: 0.4528 - val_binary_accuracy: 0.7742
   12/12 [======
   Epoch 499/500
                      ========] - 0s 5ms/step - loss: 0.5304 - binary_accuracy: 0.7263 - val_loss: 0.4529 - val_binary_accuracy: 0.7742
   12/12 [======
   Epoch 500/500
   12/12 [=============] - 0s Sms/step - loss: 0.5304 - binary_accuracy: 0.7263 - val_loss: 0.4528 - val_binary_accuracy: 0.7742
[ ] eval = model.evaluate(x = x_test, y = y_test)
```

3/3 [===========] - 0s 6ms/step - loss: 0.4528 - binary\_accuracy: 0.7742





## By using lasso-regression to do automatic feature selection

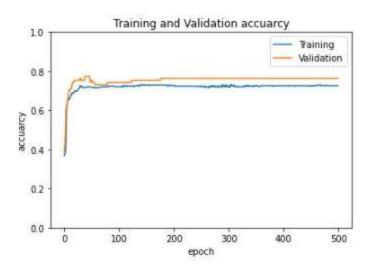


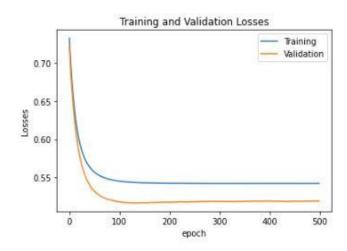
#### By dropping 6 low features: (binary\_accuracy: 0.7634)

```
x.drop(['sbp','adiposity', 'obesity','ldl','typea', 'alcohol'],inplace=Tru
e,axis=1)

model = keras.Sequential()
model.add(keras.layers.Dense(1, input_shape= (3,), activation = 'sigmoid'
))

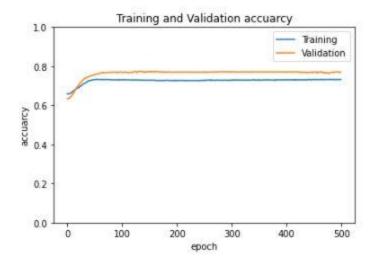
Epoch 498/500
12/12[========] - 0s 6ms/step - loss: 0.5420 - binary_accuracy: 0.7263 - val_loss: 0.5190 - val_binary_accuracy: 0.7634
Epoch 499/500
12/12[========] - 0s 5ms/step - loss: 0.5420 - binary_accuracy: 0.7263 - val_loss: 0.5190 - val_binary_accuracy: 0.7634
Epoch 500/500
12/12[=========] - 0s 5ms/step - loss: 0.5420 - binary_accuracy: 0.7263 - val_loss: 0.5190 - val_binary_accuracy: 0.7634
[21] eval = model.evaluate(x = x_test, y = y_test)
```

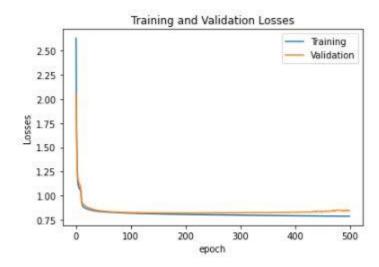




#### By adding hidden layers (binary\_accuracy: 0.7702)

```
model = keras.Sequential()
model.add(keras.layers.Dense(256, input_shape= (4,), activation = 'relu'))
model.add(keras.layers.Dense(128, activation = 'relu'))
model.add(keras.layers.Dense(64, activation = 'relu'))
model.add(keras.layers.Dense(32, activation = 'relu'))
```



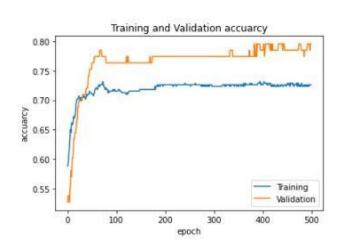


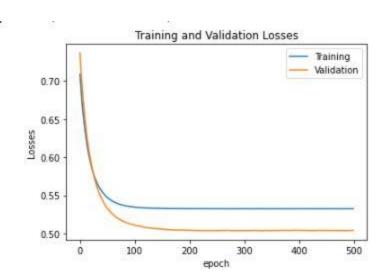
## By dropping 5 low features: (binary\_accuracy: 0.7957)

```
x.drop(['sbp','adiposity', 'obesity', 'typea', 'alcohol'],inplace=True,axi
s=1)

model = keras.Sequential()
model.add(keras.layers.Dense(1, input_shape= (4,), activation = 'sigmoid'
))

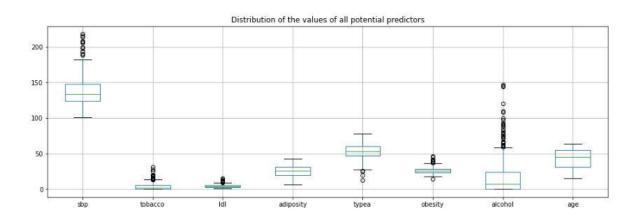
Epoch 498/500
12/12 [========] - 0s 5ms/step - loss: 0.5324 - binary_accuracy: 0.7263 - val_loss: 0.5040 - val_binary_accuracy: 0.7849
Epoch 499/500
12/12 [=======] - 0s 5ms/step - loss: 0.5324 - binary_accuracy: 0.7263 - val_loss: 0.5041 - val_binary_accuracy: 0.7957
Epoch 500/500
12/12 [========] - 0s 5ms/step - loss: 0.5325 - binary_accuracy: 0.7263 - val_loss: 0.5040 - val_binary_accuracy: 0.7957
[21] eval = model.evaluate(x = x_test, y = y_test)
3/3 [==========] - 0s 4ms/step - loss: 0.5040 - binary_accuracy: 0.7957
```



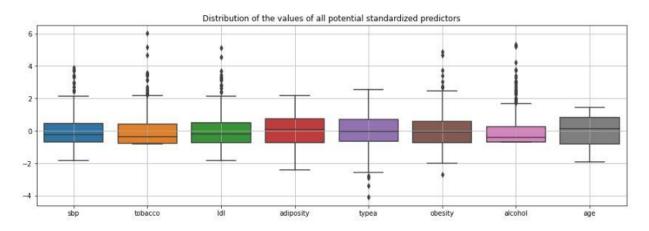


## **Using the traditional ML**

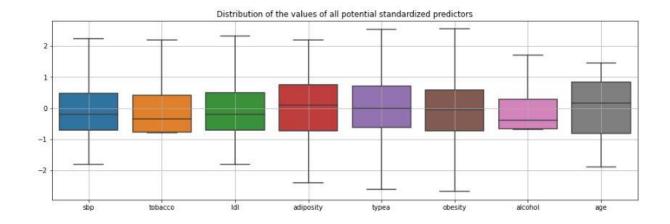
```
#import Libraries
from tensorflow import keras
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler , StandardScaler
from sklearn.model selection import train test split
import matplotlib.pyplot as plt
import seaborn as sns
#import data
chd data=pd.read csv('/content/CHDdata diagnosis.csv')
chd data
#check for null value
chd data.isnull().sum()
#check data types
chd data.dtypes
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(chd data.iloc[:,4])
chd data.iloc[:,4]=le.transform(chd data.iloc[:,4])
chd data
Index = np.r [0:4,5:9]
plt.figure(figsize=(16,5))
chd data.iloc[:,Index].boxplot()
plt.title("Distribution of the values of all potential predictors")
plt.show()
```



```
#rescaling
scaler = StandardScaler()
chd_data.iloc[:,Index] = scaler.fit_transform(chd_data.iloc[:,Index])
chd_data.iloc[0:5,:]
plt.figure(figsize=(16,5))
sns.boxplot(data=chd_data.iloc[:,Index])
plt.title("Distribution of the values
of all potential standardized predictors")
plt.grid()
plt.show()
```



```
outliers = ['sbp', 'tobacco', 'ldl', 'typea', 'obesity', 'alcohol']
for column in outliers:
   Q1,Q3 = np.percentile(chd_data[column],[25,75])
   IQR = Q3 - Q1
   lower_fence = Q1 - (1.5*IQR)
    upper_fence = Q3 + (1.5*IQR)
    chd_data[column] = chd_data[column].apply(lambda x: upper_fence if x>upper_fence
   else lower_fence if x<lower_fence else x)
plt.figure(figsize=(16,5))
sns.boxplot(data=chd_data.iloc[:,Index])
plt.title("Distribution of the values
of all potential standardized predictors")
plt.grid()
plt.show()</pre>
```



```
#spliting data
x=chd data.iloc[:,:-1]
y=chd data.iloc[:,-1]
x train, x test, y train, y test = train test split(x, y, test size=0.25,
random state=23)
x train.iloc[0,:]
from sklearn.linear model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy score, recall score
classifiers = []
classifiers.append(("LR",LogisticRegression(random state=0)))
classifiers.append(("NB", GaussianNB()))
classifiers.append(("DT", DecisionTreeClassifier(random state = 0)))
classifiers.append(("RF", RandomForestClassifier(random state = 0)))
classifiers.append(("SVM",SVC()))
classifiers.append(("KNN", KNeighborsClassifier()))
scores = []
clf names = []
```

```
my list = [ 0.2, 0.25, 0.33, 0.4]
    for clf in classifiers:
      score = 0
      recall = 0
      for p in my list:
        for i in range (101):
          X train, X test, y train, y test = train test split(x, y, test size
    = p, random state = i)
          classifier = clf[1]
          classifier.fit(X train, y train)
          y pred = classifier.predict(X test)
          acc score = (accuracy score(y test,y pred)*100).round(2)
          rec score = recall score(y test, y pred)
          if acc score > score:
              score = acc score
               recall = rec score
               paramters = (p, i, score, recall)
      p, i, score, recall = paramters
      print("classifier = {}, P = {}, i = {}, score = {}, recall = {}".format(
    classifier, p,i,score, recall))
classifier = GaussianNB(), P = 0.2, i = 33, score = 79.57, recall = 0.7894736842105263
classifier = DecisionTreeClassifier(random_state=0), P = 0.2, i = 0, score = 74.19, recall = 0.625
classifier = RandomForestClassifier(random_state=0), P = 0.2, i = 69, score = 78.49, recall = 0.6176470588235294
classifier = SVC(), P = 0.2, i = 62, score = 81.72, recall = 0.6296296296296297
classifier = KNeighborsClassifier(), P = 0.2, i = 80, score = 75.27, recall = 0.4642857142857143
    my list = [0.2, 0.25, 0.33, 0.4]
    for clf in classifiers:
      score = 0
      recall = 0
      for p in my_list:
        for i in range (101):
          X train, X test, y train, y test = train test split(x, y, test size
    = p, random state = i)
          classifier = clf[1]
          classifier.fit(X train, y train)
          y pred = classifier.predict(X test)
          acc score = (accuracy_score(y_test,y_pred)*100).round(2)
          rec score = recall score(y test,y pred)
          if rec score > recall:
               score = acc score
               recall = rec score
```

```
paramters = (p, i, score, recall)
   p, i, score, recall = paramters
   print("classifier = {}, P = {}, i = {}, score = {}, recall = {}".format(
 classifier, p,i,score, recall))
classifier = LogisticRegression(random_state=0), P = 0.25, i = 67, score = 79.31, recall = 0.7241379310344828
classifier = GaussianNB(), P = 0.2, i = 62, score = 78.49, recall = 0.888888888888888888
classifier = RandomForestClassifier(random_state=0), P = 0.25, i = 25, score = 73.28, recall = 0.6785714285714286
classifier = SVC(), P = 0.2, i = 54, score = 79.57, recall = 0.7142857142857143
classifier = KNeighborsClassifier(), P = 0.25, i = 78, score = 66.38, recall = 0.6285714285714286
 # Applying GridSearch on the dataset to Check the best paramters for our C
 lassification
 from sklearn.model selection import RepeatedStratifiedKFold, GridSearchCV
 for classifier name, classifier in classifiers:
     cv = RepeatedStratifiedKFold(n splits=5, n repeats=3, random state=0)
     if classifier name == "LR" :
          parameters = [{'solver' : ['newton-
 cg', 'lbfgs'], 'penalty' : ['12'],
                          'C':[100, 10, 1, 0.1, 0.01], 'multi class':['auto',
 'ovr', 'multinomial']},
                         {'solver': ['liblinear'], 'penalty' : ['11', '12'],
                          'C':[100, 10, 1, 0.1, 0.01], 'multi class':['auto',
 'ovr'], 'random state': [0,1,42]}]
     elif classifier name == "NB" :
         continue
     elif classifier name == "DT" :
          parameters = [{'criterion' : ['gini', 'entropy'], 'random state':[
 0, 1, 12, 42],
                           'splitter':['best', 'random'], 'max features': ['s
 qrt', 'log2']}]
     elif classifier name == "RF" :
          parameters = [{'bootstrap':[True], 'criterion' : ['gini', 'entropy
 '], 'n estimators':[10,15,20,25],
                           'max depth':[110,130,150,170], 'random_state':[ 0,
  1 , 42],
                          'min samples leaf':[7,9,11,13], 'min samples split':
 [8,12,14], 'max features': ['sqrt', 'log2']}]
     elif classifier name == "SVM" :
          parameters = [{'C':[100, 10, 1, 0.1, 0.01], 'gamma' : ['auto', 'sc
 ale'],
                          'kernel': ['poly', 'rbf', 'sigmoid']},
                         {'C':[100, 10, 1, 0.1, 0.01], 'kernel': ['linear']}]
```

```
best parameters : {'C': 0.1, 'multi_class': 'auto', 'penalty': '12', 'solver': 'newton-cg'}
DT (best score): 0.6495247000155836
best parameters : {'criterion': 'entropy', 'max_features': 'sqrt', 'random_state': 1, 'splitter': 'best'}
RF (best score) : 0.7158017765310892
RF (best score): 0.715801705310892
best parameters: {'bootstrap': True, 'criterion': 'entropy', 'max_depth': 110, 'max_features': 'sqrt', 'min_samples_leaf': 11, 'min_samples_split': 8, 'n_estimators': 25, 'random_s
SVM (best score): 0.7251908991740688
best parameters: {'C': 1, 'gamma': 'auto', 'kernel': 'rbf'}
KNW (best score): 0.7251908991740688
best parameters: {'C': 1, 'gamma': 'auto', 'kernel': 'rbf'}
best parameters: {'algorithm': 'auto', 'n_jobs': -1, 'n_neighbors': 13, 'weights': 'distance'}
classifiers = []
classifiers.append(("LR", LogisticRegression(C = 0.1, multi class = 'auto'
, penalty = '12', solver = 'newton-cq')))
classifiers.append(("NB", GaussianNB()))
classifiers.append(("DT", DecisionTreeClassifier(criterion = 'entropy', max
features ='sqrt', random state = 1, splitter = 'best')))
classifiers.append(("RF", RandomForestClassifier(bootstrap = True, criterio
n = 'entropy', max depth = 110, max features = 'sqrt',
                                                                     min samples leaf = 11, min
samples split = 8, n estimators = 25, random state = 42)))
classifiers.append(("SVM",SVC(C = 1, gamma = 'auto', kernel = 'rbf')))
classifiers.append(("KNN", KNeighborsClassifier(algorithm = 'auto', n jobs
 = -1, n neighbors = 13, weights = 'distance')))
my list = [0.2, 0.25, 0.33, 0.4]
for clf in classifiers:
   score = 0
   recall = 0
   for p in my list:
      for i in range (101):
         X train, X test, y train, y test = train test split(x, y, test size
= p, random state = i)
         classifier = clf[1]
         classifier.fit(X train,y_train)
         y pred = classifier.predict(X test)
         acc score = (accuracy score(y test,y pred)*100).round(2)
         rec score = recall score(y test,y pred)
         if acc score > score:
              score = acc score
              recall = rec_score
              paramters = (p, i, score, recall)
   p, i, score, recall = paramters
   print("classifier = {}, P = {}, i = {}, score = {}, recall = {}".format(
classifier, p, i, score, recall))
```

```
my list = [0.2, 0.25, 0.33, 0.4]
for clf in classifiers:
  score = 0
  recall = 0
  for p in my list:
     for i in range(101):
       X train, X test, y train, y test = train test split(x, y, test size
= p, random state = i)
       classifier = clf[1]
       classifier.fit(X train, y train)
       y pred = classifier.predict(X test)
       acc score = (accuracy score(y test,y pred)*100).round(2)
       rec_score = recall_score(y_test,y_pred)
       if rec_score > recall:
            score = acc score
            recall = rec_score
            paramters = (p, i, score, recall)
  p, i, score, recall = paramters
  print("classifier = {}, P = {}, i = {}, score = {}, recall = {}".format(
classifier, p,i,score, recall))
classifier = LogisticRegression(C=0.1, solver='newton-cg'), P = 0.25, i = 67, score = 81.9, recall = 0.7241379310344828
classifier = DecisionTreeClassifier(criterion='entropy', max_features='sqrt', random_state=1), P = 0.2, i = 28, score = 70.97, recall = 0.7 classifier = RandomForestClassifier(criterion='entropy', max_depth=110, max_features='sqrt',
                min_samples_leaf=11, min_samples_split=8,
n_estimators=25, random_state=42), P = 0.25, i = 43, score = 68.97, recall = 0.6904761904761905 classifier = SVC(C=1, gamma='auto'), P = 0.2, i = 54, score = 80.65, recall = 0.7142857142857143 classifier = KNeighborsClassifier(n_jobs=-1, n_neighbors=13, weights='distance'), P = 0.25, i = 78, score = 72.41, recall = 0.6
```

#### Datasets 2

## **CHD Prediction**"

## Its content 15 Features and 1 output

	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose	TenYearCHD
0	1	39	4.0	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0	0
1	0	46	2.0	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0	0
2	1	48	1.0	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0	0
3	0	61	3.0	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0	1
4	0	46	3.0	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0	0

#### Features

```
(male)
(age)
(education)
(currentsmoker)---(0 or 1)
(cigsperday) ---(cigarettes per day)
(BPMeds)---(Blood pressure medications)
(prevalentstroke)---( prevalence stroke, 0 or 1)
(prevalenthyp)---( prevalent hypertension, 0 or 1)
(diabetes)---(0 or 1)
(totchol)---(Total cholesterol)
(SysBP)---( Systolic Blood Pressure)
(diaBP)---( Diastolic blood pressure)
(BMI)---(body mass index)
(heartrate)
(glucose)|
```

## **Output**

## **Coronary Heart Disease Prediction (0 or 1).**

## Models' analysis using Neural Network

```
# import pakcages and libraries needed for the project
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set style('darkgrid')
```

## **Feature scaling**

```
# Scaling for making close variables values from each other
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
# choose index for only scaling numerical data
index = np.r_[1,4,9:15]
X_train[:, index] = sc_X.fit_transform(X_train[:, index]) # apply fit() on
    X_train and transform fit on X_train
X_test[:, index] = sc_X.transform(X_test[:, index]) # because we already f
it() on x_train we only transform fit on X_test
```

# **Model Building**

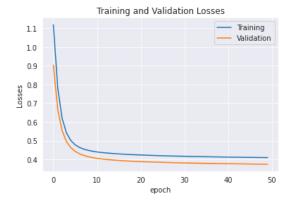
```
from tensorflow import keras
model = keras.Sequential()

# # First Hidden Layer
#model.add(keras.layers.Dense(32, input_shape= (15,), activation = 'relu'))

model.add(keras.layers.Dense(1, input_shape= (15,), activation = 'sigmoid'))
```

#### The results:-

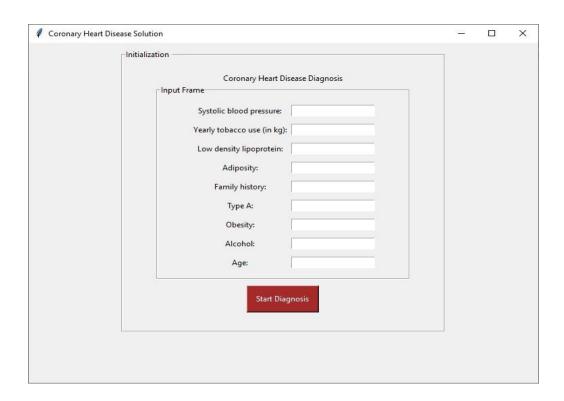
```
27/27 [====
                       ========] - 0s 9ms/step - loss: 0.4241 - binary_accuracy: 0.8410 - val_loss: 0.3889 - val_binary_accuracy: 0.8679
Epoch 22/50
27/27 [====
                                       - 0s 7ms/step - loss: 0.4232 - binary_accuracy: 0.8410 - val_loss: 0.3879 - val_binary_accuracy: 0.8691
Epoch 23/50
                                       - 0s 8ms/step - loss: 0.4224 - binary_accuracy: 0.8416 - val_loss: 0.3871 - val_binary_accuracy: 0.8691
27/27 [====
Epoch 24/50
                                       - 0s 7ms/step - loss: 0.4216 - binary_accuracy: 0.8413 - val_loss: 0.3863 - val_binary_accuracy: 0.8691
27/27 [====
Epoch 25/50
                                       - 0s 8ms/step - loss: 0.4208 - binary_accuracy: 0.8410 - val_loss: 0.3856 - val_binary_accuracy: 0.8691
27/27 [====
Epoch 26/50
                                       - 0s 7ms/step - loss: 0.4202 - binary_accuracy: 0.8413 - val_loss: 0.3849 - val_binary_accuracy: 0.8691
Epoch 27/50
                          =======] - 0s 9ms/step - loss: 0.4195 - binary_accuracy: 0.8416 - val_loss: 0.3842 - val_binary_accuracy: 0.8691
27/27 [====
Epoch 28/50
                         ========] - 0s 7ms/step - loss: 0.4189 - binary_accuracy: 0.8416 - val_loss: 0.3836 - val_binary_accuracy: 0.8691
Epoch 29/50
                        ========] - 0s 9ms/step - loss: 0.4183 - binary_accuracy: 0.8413 - val_loss: 0.3830 - val_binary_accuracy: 0.8691
27/27 [=====
```





# CUI

Coronary Heart Disease Risk	*-	×
Test risk for 10 years!		
-Initialization		
Gender (0,1):		
Age:		
Education:		
Current smoker (0,1):		
Number of Cigs per day:		
Blood pressure medicine (0,1):		
Prevalent stroke (0,1):		
Prevalent hypertension (0,1):		
Diabetes (0,1):		
Cholesterol:		
Systolic blood pressure:		
Diastolic blood pressure:		
Body mass index:		
Heart rate:		
Glucose:		



## **Conclusion**

In this project we used two datasets for CHD to diagnosis and prediction for 10 years. First the previous projects maximum accuracy was 69%using traditional Machine Learning models. we managed to increase it using (SVM) traditional Machine Learning to 82.8, and by applying neural network to the model the accuracy did not exceed 79% that mean that the dataset is not complicated enough to apply MLP.

The second dataset we used to get higher percentage, by using traditional Machine Learning models the (SVM) got high score of 87.45% and by applying neural network to the model the accuracy did not exceed 86.6

#### References

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