Health Care

Cardiovascular diseases are the leading cause of death globally. It is therefore necessary to identify the causes and develop a system to predict heart attacks in an effective manner. The data below has the information about the factors that might have an impact on cardiovascular health.

datasets

Variable Description Age Age in years Sex 1 = male; 0 = female cp| Chest pain type trestbps Resting blood pressure (in mm Hg on admission to the hospital) chol Serum cholesterol in mg/dl fbs Fasting blood sugar > 120 mg/dl (1 = true; 0 = false) restecg Resting electrocardiographic results thalach Maximum heart rate achieved exang Exercise induced angina (1 = yes; 0 = no) oldpeak ST depression induced by exercise relative to rest slope Slope of the peak exercise ST segment

importing libraries

```
import numpy as np
           import pandas as pd
           import matplotlib.pyplot as plt
           import seaborn as sns
           %matplotlib inline
           import warnings
           warnings.filterwarnings('ignore')
           # import dataset
 In [2]:
           df = pd.read_excel(r'D:\family\eswar\simplilearn\ml datasets health care.xlsx')
           df.shape
 In [3]:
           # sahpe of dataset
           (303, 14)
 Out[3]:
 In [4]: df.head()
           # printing head columns
                                                                     oldpeak
 Out[4]:
                       ср
                          trestbps
                                    chol
                                         fbs
                                              restecg
                                                      thalach
                                                              exang
                                                                             slope
                                                                                    ca
                                                                                        thal
                                                                                             target
                               145
                                     233
                                                         150
                        2
                                           0
                                                         187
                                                                  0
                                                                         3.5
                                                                                     0
                                                                                          2
              37
                               130
                                    250
                                                   1
                                                                                 0
           2
               41
                    0
                               130
                                    204
                                           0
                                                   0
                                                         172
                                                                  0
                                                                         1.4
                                                                                 2
                                                                                     0
                                                                                          2
                                                         178
                                                                  0
                                                                                     0
                               120
                                     236
                                                                         0.8
                    0
                        0
                                                         163
                                                                         0.6
                                                                                     0
                                                                                          2
               57
                               120
                                    354
                                           0
                                                                   1
                                                                                 2
In [67]: df.tail()
           # printing
                       tail columns
Out[67]:
                    sex
                         ср
                             trestbps chol
                                           fbs
                                               restecg
                                                        thalach
                                                                exang
                                                                       oldpeak
                                                                                slope
                                                                                      ca
                                                                                          thal
                                      241
                                                                           0.2
                                                                                       0
                                                                                            3
                                                                                                   0
           298
                      0
                                 140
                                                                                                   0
           299
                          3
                                 110
                                      264
                                             0
                                                            132
                                                                    0
                                                                           1.2
                                                                                       0
                                                                                            3
                45
           300
                 68
                      1
                          0
                                 144
                                       193
                                             1
                                                     1
                                                            141
                                                                    0
                                                                           3.4
                                                                                   1
                                                                                       2
                                                                                            3
                                                                                                   0
           301
                57
                                 130
                                       131
                                             0
                                                            115
                                                                            1.2
                                                                                            3
                                                                                                   0
                      0
                                      236
                                             0
                                                            174
                                                                    0
                                                                           0.0
                                                                                                   0
           302
                57
                                 130
 In [5]: df.describe()
           # description
```

```
trestbps
                                                                                               thalach
                                             ср
                                                                 chol
                                                                             fbs
                                                                                    restecg
                                                                                                           exang
                                                                                                                     oldpeak
                                                                                                                                 slope
                       age
                                  sex
          count 303.000000 303.000000
                                      303.000000
                                                 303.000000 303.000000 303.000000
                                                                                 303.000000 303.000000
                                                                                                       303.000000
                                                                                                                  303.000000
                                                                                                                             303.000000
          mean
                  54.366337
                             0.683168
                                        0.966997 131.623762 246.264026
                                                                         0.148515
                                                                                    0.528053
                                                                                            149.646865
                                                                                                         0.326733
                                                                                                                    1.039604
                                                                                                                               1.399340
            std
                  9.082101
                             0.466011
                                        1.032052
                                                  17.538143
                                                            51.830751
                                                                         0.356198
                                                                                   0.525860
                                                                                             22.905161
                                                                                                         0.469794
                                                                                                                    1.161075
                                                                                                                               0.616226
            min
                  29.000000
                             0.000000
                                        0.000000
                                                  94.000000 126.000000
                                                                         0.000000
                                                                                   0.000000
                                                                                             71.000000
                                                                                                         0.000000
                                                                                                                    0.000000
                                                                                                                               0.000000
            25%
                  47.500000
                             0.000000
                                        0.000000
                                                 120.000000 211.000000
                                                                         0.000000
                                                                                    0.000000
                                                                                            133.500000
                                                                                                         0.000000
                                                                                                                    0.000000
                                                                                                                               1.000000
            50%
                  55.000000
                             1.000000
                                        1.000000
                                                 130.000000 240.000000
                                                                         0.000000
                                                                                    1.000000
                                                                                            153.000000
                                                                                                         0.000000
                                                                                                                    0.800000
                                                                                                                               1.000000
            75%
                  61.000000
                             1.000000
                                        2.000000
                                                 140.000000
                                                           274.500000
                                                                         0.000000
                                                                                    1.000000
                                                                                            166.000000
                                                                                                         1.000000
                                                                                                                    1.600000
                                                                                                                               2.000000
                  77.000000
                             1.000000
                                        3.000000 \ 200.000000 \ 564.000000
                                                                         1.000000
                                                                                    2.000000
                                                                                            202.000000
                                                                                                         1.000000
                                                                                                                    6.200000
                                                                                                                               2.000000
 In [6]: df.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 303 entries, 0 to 302
          Data columns (total 14 columns):
           #
                Column
                           Non-Null Count Dtype
           0
                age
                           303 non-null
                                             int64
                           303 non-null
                                             int64
           1
                sex
           2
                           303 non-null
                                             int64
           3
                trestbps
                           303 non-null
                                             int64
           4
                           303 non-null
                                             int64
                chol
           5
                fbs
                           303 non-null
                                             int64
           6
                restecq
                           303 non-null
                                             int64
           7
                thalach
                           303 non-null
                                             int64
           8
                exang
                           303 non-null
                                             int64
           9
                oldpeak
                           303 non-null
                                             float64
           10
                           303 non-null
              slope
                                             int64
                           303 non-null
           11
                                             int64
                ca
           12
                thal
                           303 non-null
                                             int64
           13 target
                           303 non-null
                                             int64
          dtypes: float64(1), int64(13)
          memory usage: 33.3 KB
 In [7]: info = ["age","1: male, 0: female", "chest pain type, 1: typical angina, 2: atypical angina, 3: non-anginal pain
 In [8]: for i in range(len(info)):
               print(df.columns[i]+":\t\t\t"+info[i])
          age:
                                     1: male, 0: female
          sex:
                                     chest pain type, 1: typical angina, 2: atypical angina, 3: non-anginal pain, 4: asympto
          cp:
          matic
          trestbps:
                                              resting blood pressure
                                     Serum cholesterol in mg/dl
          chol:
                                     fasting blood sugar > 120 \text{ mg/dl}
          fbs:
          restecg:
                                              resting electrocardiographic results (values 0,1,2)
          thalach:
                                              maximum heart rate achieved
          exang:
                                     exercise induced angina
                                              ST depression induced by exercise relative to rest
          oldpeak:
          slope:
                                     Slope of the peak exercise ST segment
 In [9]: df["target"].describe()
          # analyzing the target variables
                    303.000000
          count
 Out[9]:
          mean
                      0.544554
          std
                      0.498835
          min
                      0.000000
          25%
                      0.000000
          50%
                       1.000000
          75%
                      1.000000
          max
                      1.000000
          Name: target, dtype: float64
In [10]: df["target"].unique()
          array([1, 0], dtype=int64)
Out[10]:
```

print(df.corr()["target"].abs().sort_values(ascending=False))

checking correlation between columns

In [111]:

```
target
            1.000000
            0.436757
exang
            0.433798
ср
oldpeak
            0.430696
thalach
            0.421741
ca
            0.391724
slope
            0.345877
thal
            0.344029
sex
            0.280937
age
            0.225439
trestbps
            0.144931
restecg
            0.137230
chol
            0.085239
fbs
            0.028046
Name: target, dtype: float64
```

fbs is weakly correlated

exploratory data analysis (EDA)

sex

array([3, 2, 1, 0], dtype=int64)

<AxesSubplot:xlabel='cp', ylabel='target'>

sns.barplot(df["cp"],y)

In [16]: df["cp"].unique()

Out[16]:

In [17]:

Out[17]:

```
y = df["target"]
In [12]:
           sns.countplot(y)
           target_temp = df.target.value_counts()
           print(target_temp)
           # analyzing the target variables
           1
                 165
           0
                 138
           Name: target, dtype: int64
              160
              140
              120
              100
               80
               60
               40
               20
                0
                                                         i
                                          target
In [13]: print("Percentage of patience without heart problems: "+str(round(target_temp[0]*100/303,2)))
print("Percentage of patience with heart problems: "+str(round(target_temp[1]*100/303,2)))
           Percentage of patience without heart problems: 45.54
           Percentage of patience with heart problems: 54.46
In [14]: df["sex"].unique()
           array([1, 0], dtype=int64)
Out[14]:
In [15]:
           sns.barplot(df["sex"],y)
           <AxesSubplot:xlabel='sex', ylabel='target'>
Out[15]:
              0.8
              0.7
              0.6
              0.5
             0.4
              0.3
              0.2
              0.1
              0.0
```

```
0.8 - 0.6 - 0.6 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 - 0.0 -
```

In [23]: df["exang"].unique()

Out[23]:

In [24]:

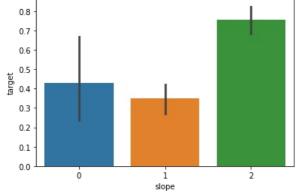
array([0, 1], dtype=int64)

sns.barplot(df["exang"],y)

```
In [18]: df["fbs"].describe()
          count
                   303.000000
Out[18]:
                      0.148515
          mean
                      0.356198
          std
          min
                      0.00000
                      0.000000
          25%
          50%
                      0.000000
          75%
                      0.000000
                      1.000000
          max
          Name: fbs, dtype: float64
In [19]: df["fbs"].unique()
          array([1, 0], dtype=int64)
Out[19]:
In [20]: sns.barplot(df["fbs"],y)
          <AxesSubplot:xlabel='fbs', ylabel='target'>
Out[20]:
            0.6
            0.5
            0.4
          0.3
            0.2
            0.1
            0.0
                                                 i
                          Ó
                                     fbs
          df["restecg"].unique()
In [21]:
          array([0, 1, 2], dtype=int64)
Out[21]:
          sns.barplot(df["restecg"],y)
In [22]:
          <AxesSubplot:xlabel='restecg', ylabel='target'>
Out[22]:
            0.7
            0.6
            0.5
          parget
0.4
            0.3
            0.2
            0.1
            0.0
                       ó
                                      i
                                    restecg
```

```
Out[24]: <AxesSubplot:xlabel='exang', ylabel='target'>
              0.7
              0.6
              0.5
           parget
0.4
              0.3
              0.2
              0.1
              0.0
                                                       i
```

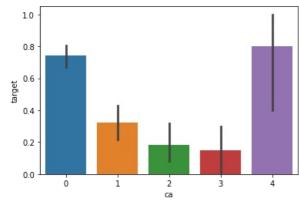
```
exang
In [25]: df["slope"].unique()
         array([0, 2, 1], dtype=int64)
Out[25]:
         sns.barplot(df["slope"],y)
In [26]:
         <AxesSubplot:xlabel='slope', ylabel='target'>
Out[26]:
```



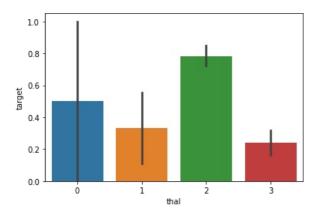
```
df["ca"].unique()
In [27]:
         array([0, 2, 1, 3, 4], dtype=int64)
Out[27]:
```

```
sns.barplot(df["ca"],y)
In [28]:
```

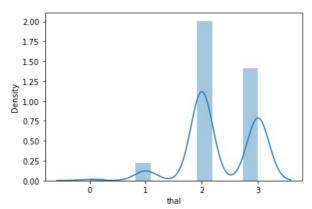
<AxesSubplot:xlabel='ca', ylabel='target'> Out[28]:



```
In [29]: df["thal"].unique()
         array([1, 2, 3, 0], dtype=int64)
Out[29]:
In [30]:
         sns.barplot(df["thal"],y)
         <AxesSubplot:xlabel='thal', ylabel='target'>
Out[30]:
```



```
In [31]: sns.distplot(df["thal"])
Out[31]: <AxesSubplot:xlabel='thal', ylabel='Density'>
```



TRAIN TEST SPLIT

```
In [32]: from sklearn.model_selection import train_test_split
    predictors = df.drop("target" , axis=1)
    target = df["target"]
    X_train,X_test,Y_train,Y_test = train_test_split(predictors,target,test_size=0.20,random_state=0)

In [33]: X_train.shape
Out[33]: (242, 13)

In [34]: X_test.shape
Out[34]: (61, 13)

In [35]: Y_train.shape
Out[35]: (242,)

In [36]: Y_test.shape
```

MODEL FITTING

(61,)

Out[36]:

```
In [37]: from sklearn.metrics import accuracy_score
In [38]: from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X_train,Y_train)
Y_pred_lr = lr.predict(X_test)
```

```
In [39]: | Y_pred_tr.shape
Out[39]: (61,)
         score_lr = round(accuracy_score(Y_pred_lr,Y_test)*100,2)
In [40]:
         print("The accuracy score achieved using Logistic Regression is: "+str(score_lr)+" %")
         The accuracy score achieved using Logistic Regression is: 85.25 %
In [41]: from sklearn.naive bayes import GaussianNB
         nb = GaussianNB()
         nb.fit(X train,Y train)
         Y_pred_nb = nb.predict(X_test)
In [42]: Y_pred_nb.shape
Out[42]: (61,)
         score_nb = round(accuracy_score(Y_pred_nb,Y_test)*100,2)
In [43]:
         print("The accuracy score achieved using Naive Bayes is: "+str(score nb)+" %")
         The accuracy score achieved using Naive Bayes is: 85.25 %
In [44]: from sklearn import svm
         sv = svm.SVC(kernel='linear')
         sv.fit(X train, Y train)
         Y_pred_svm = sv.predict(X_test)
In [45]: Y_pred_svm.shape
Out[45]: (61,)
In [46]:
         score_svm = round(accuracy_score(Y_pred_svm,Y_test)*100,2)
         print("The accuracy score achieved using Linear SVM is: "+str(score_svm)+" %")
         The accuracy score achieved using Linear SVM is: 81.97 \%
         from sklearn.neighbors import KNeighborsClassifier
In [47]:
         knn = KNeighborsClassifier(n_neighbors=7)
         knn.fit(X_train,Y_train)
         Y pred knn=knn.predict(X test)
In [48]: Y_pred_knn.shape
         (61,)
Out[48]:
In [49]:
         score_knn = round(accuracy_score(Y_pred_knn,Y_test)*100,2)
         print("The accuracy score achieved using KNN is: "+str(score knn)+" %")
         The accuracy score achieved using KNN is: 67.21 %
```

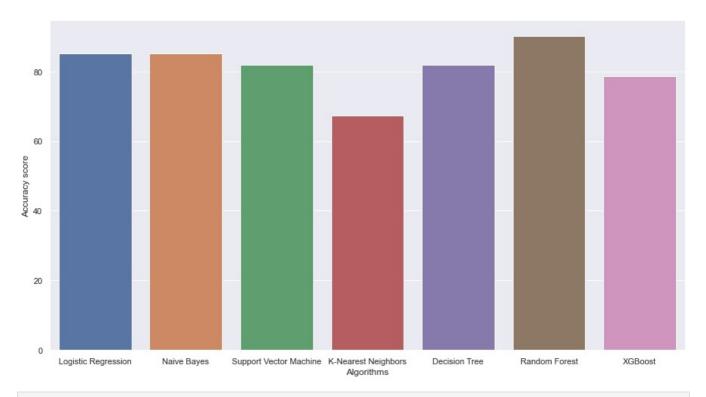
Decision Tree

```
In [50]: from sklearn.tree import DecisionTreeClassifier
         max_accuracy = 0
         for x in range(200):
             dt = DecisionTreeClassifier(random_state=x)
             dt.fit(X train,Y train)
             Y_pred_dt = dt.predict(X_test)
             current_accuracy = round(accuracy_score(Y_pred_dt,Y_test)*100,2)
             if(current_accuracy>max_accuracy):
                 max accuracy = current accuracy
                 best_x = x
         dt = DecisionTreeClassifier(random_state=best_x)
         dt.fit(X_train,Y_train)
         Y pred dt = dt.predict(X test)
In [51]: print(Y_pred_dt.shape)
         (61,)
         score dt = round(accuracy score(Y pred dt,Y test)*100,2)
In [52]:
         print("The accuracy score achieved using Decision Tree is: "+str(score_dt)+" %")
         The accuracy score achieved using Decision Tree is: 81.97 \%
```

Random Forest

```
for x in range(2000):
             rf = RandomForestClassifier(random state=x)
             rf.fit(X_train,Y_train)
             Y_pred_rf = rf.predict(X_test)
             current_accuracy = round(accuracy_score(Y_pred_rf,Y_test)*100,2)
             if(current_accuracy>max_accuracy):
                 max_accuracy = current_accuracy
                 best x = x
         #print(max accuracy)
         #print(best_x)
         rf = RandomForestClassifier(random_state=best_x)
         rf.fit(X_train,Y_train)
         Y_pred_rf = rf.predict(X_test)
In [54]: Y_pred_rf.shape
         (61,)
Out[54]:
In [55]: score_rf = round(accuracy_score(Y_pred_rf,Y_test)*100,2)
         print("The accuracy score achieved using Decision Tree is: "+str(score_rf)+" %")
         The accuracy score achieved using Decision Tree is: 90.16 \%
         xg boost
In [61]: pip install xgboost
         Collecting xgboost
           Using cached xgboost-1.6.2-py3-none-win amd64.whl (125.4 MB)
         Requirement already satisfied: numpy in c:\users\eswar\anaconda3\lib\site-packages (from xgboost) (1.21.5)
         Installing collected packages: xgboost
         Successfully installed xgboost-1.6.2
         Note: you may need to restart the kernel to use updated packages.
In [62]: import xgboost as xgb
         xgb model = xgb.XGBClassifier(objective="binary:logistic", random state=42)
         xgb model.fit(X train, Y train)
         Y pred xgb = xgb model.predict(X test)
In [63]: Y_pred_xgb.shape
         (61,)
Out[63]:
In [64]: score_xgb = round(accuracy_score(Y_pred_xgb,Y_test)*100,2)
         print("The accuracy score achieved using XGBoost is: "+str(score_xgb)+" %")
         The accuracy score achieved using XGBoost is: 78.69 %
In [65]: scores = [score_lr,score_nb,score_svm,score_knn,score_dt,score_rf,score_xgb]
         algorithms = ["Logistic Regression", "Naive Bayes", "Support Vector Machine", "K-Nearest Neighbors", "Decision Tree
         for i in range(len(algorithms)):
         print("The accuracy score achieved using "+algorithms[i]+" is: "+str(scores[i])+" %")
         The accuracy score achieved using Logistic Regression is: 85.25 \%
         The accuracy score achieved using Naive Bayes is: 85.25 %
         The accuracy score achieved using Support Vector Machine is: 81.97 \%
         The accuracy score achieved using K-Nearest Neighbors is: 67.21 %
         The accuracy score achieved using Decision Tree is: 81.97 \mbox{\%}
         The accuracy score achieved using Random Forest is: 90.16 \%
         The accuracy score achieved using XGBoost is: 78.69 %
In [66]: sns.set(rc={'figure.figsize':(15,8)})
         plt.xlabel("Algorithms")
plt.ylabel("Accuracy score")
         sns.barplot(algorithms, scores)
Out[66]: <AxesSubplot:xlabel='Algorithms', ylabel='Accuracy score'>
```

max accuracy = 0



In []:

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