

Heart attack

September 15, 2020

```
[1]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import time
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score, confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.feature_selection import RFE
from sklearn.datasets import make_regression

def read_data(csv_file):
    try:
        return pd.read_csv(csv_file)
    except:
        print("The file is not found")
        return None

Heart_attack_data_set = read_data("C:/Users/omri1/PycharmProjects/untitled2/
↳heart_attack.csv")
```

```
[2]: Heart_attack_data_set
```

```
[2]:
```

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	\
0	75.0	0	582	0	20	
1	55.0	0	7861	0	38	
2	65.0	0	146	0	20	
3	50.0	1	111	0	20	
4	65.0	1	160	1	20	
..	
294	62.0	0	61	1	38	
295	55.0	0	1820	0	38	

296	45.0	0		2060	1	60
297	45.0	0		2413	0	38
298	50.0	0		196	0	45

	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	\
0		1	265000.00	1.9	130	1
1		0	263358.03	1.1	136	1
2		0	162000.00	1.3	129	1
3		0	210000.00	1.9	137	1
4		0	327000.00	2.7	116	0
..	
294		1	155000.00	1.1	143	1
295		0	270000.00	1.2	139	0
296		0	742000.00	0.8	138	0
297		0	140000.00	1.4	140	1
298		0	395000.00	1.6	136	1

	smoking	time	DEATH_EVENT
0	0	4	1
1	0	6	1
2	1	7	1
3	0	7	1
4	0	8	1
..
294	1	270	0
295	0	271	0
296	0	278	0
297	1	280	0
298	1	285	0

[299 rows x 13 columns]

```
[3]: # Statistical analysis
```

```
Heart_attack_data_set.describe()
```

	age	anaemia	creatinine_phosphokinase	diabetes	\
count	299.000000	299.000000	299.000000	299.000000	
mean	60.833893	0.431438	581.839465	0.418060	
std	11.894809	0.496107	970.287881	0.494067	
min	40.000000	0.000000	23.000000	0.000000	
25%	51.000000	0.000000	116.500000	0.000000	
50%	60.000000	0.000000	250.000000	0.000000	
75%	70.000000	1.000000	582.000000	1.000000	
max	95.000000	1.000000	7861.000000	1.000000	

ejection_fraction	high_blood_pressure	platelets	\
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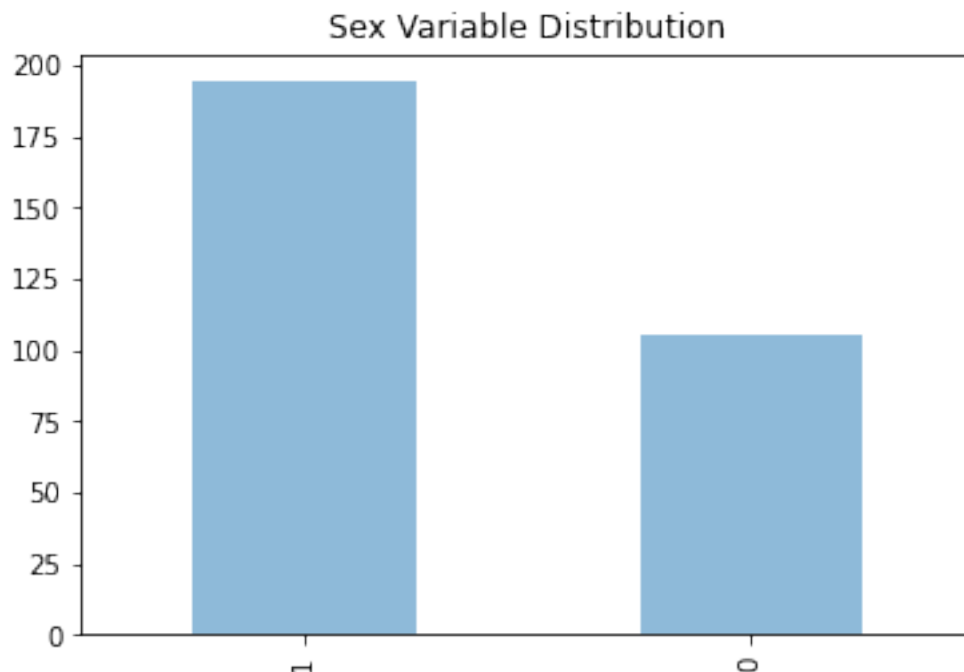
count	299.000000	299.000000	299.000000
mean	38.083612	0.351171	263358.029264
std	11.834841	0.478136	97804.236869
min	14.000000	0.000000	25100.000000
25%	30.000000	0.000000	212500.000000
50%	38.000000	0.000000	262000.000000
75%	45.000000	1.000000	303500.000000
max	80.000000	1.000000	850000.000000

	serum_creatinine	serum_sodium	sex	smoking	time \
count	299.00000	299.000000	299.000000	299.00000	299.000000
mean	1.39388	136.625418	0.648829	0.32107	130.260870
std	1.03451	4.412477	0.478136	0.46767	77.614208
min	0.50000	113.000000	0.000000	0.00000	4.000000
25%	0.90000	134.000000	0.000000	0.00000	73.000000
50%	1.10000	137.000000	1.000000	0.00000	115.000000
75%	1.40000	140.000000	1.000000	1.00000	203.000000
max	9.40000	148.000000	1.000000	1.00000	285.000000

	DEATH_EVENT
count	299.00000
mean	0.32107
std	0.46767
min	0.00000
25%	0.00000
50%	0.00000
75%	1.00000
max	1.00000

```
[4]: # From the first analysis I can conclude that most of the ages are on their 60,
      ↪with a little deviation.
      # To most of the examined there no diabetes, blood pressure, or smoking issues.
```

```
[5]: Heart_attack_data_set['sex'].value_counts().plot(kind="bar", title="Sex
      ↪Variable Distribution", alpha=0.5)
      plt.show()
```



[6]: *# There are almost two times male tested than female tested.*

```
[7]: def data_shape(data, label):
    print('Rows number of ' + label + " is: ", data.shape[0])
    print('Columns number of ' + label + ' is: ', data.shape[1])

    def data_columns(data):
        return list(data.columns)

    def describe_data(data):
        return data.describe()

    data_shape(Heart_attack_data_set, 'Heart attack data set')
    data_columns(Heart_attack_data_set)
    describe_data(Heart_attack_data_set)
```

Rows number of Heart attack data set is: 299

Columns number of Heart attack data set is: 13

```
[7]:
```

	age	anaemia	creatinine_phosphokinase	diabetes \
count	299.000000	299.000000	299.000000	299.000000
mean	60.833893	0.431438	581.839465	0.418060
std	11.894809	0.496107	970.287881	0.494067
min	40.000000	0.000000	23.000000	0.000000
25%	51.000000	0.000000	116.500000	0.000000

50%	60.000000	0.000000	250.000000	0.000000
75%	70.000000	1.000000	582.000000	1.000000
max	95.000000	1.000000	7861.000000	1.000000

	ejection_fraction	high_blood_pressure	platelets \
count	299.000000	299.000000	299.000000
mean	38.083612	0.351171	263358.029264
std	11.834841	0.478136	97804.236869
min	14.000000	0.000000	25100.000000
25%	30.000000	0.000000	212500.000000
50%	38.000000	0.000000	262000.000000
75%	45.000000	1.000000	303500.000000
max	80.000000	1.000000	850000.000000

	serum_creatinine	serum_sodium	sex	smoking	time \
count	299.000000	299.000000	299.000000	299.000000	299.000000
mean	1.39388	136.625418	0.648829	0.32107	130.260870
std	1.03451	4.412477	0.478136	0.46767	77.614208
min	0.50000	113.000000	0.000000	0.00000	4.000000
25%	0.90000	134.000000	0.000000	0.00000	73.000000
50%	1.10000	137.000000	1.000000	0.00000	115.000000
75%	1.40000	140.000000	1.000000	1.00000	203.000000
max	9.40000	148.000000	1.000000	1.00000	285.000000

	DEATH_EVENT
count	299.000000
mean	0.32107
std	0.46767
min	0.00000
25%	0.00000
50%	0.00000
75%	1.00000
max	1.00000

```
[8]: Smoking = Heart_attack_data_set[Heart_attack_data_set['smoking'] == 1]['smoking'].sum()
Diabetes = Heart_attack_data_set[Heart_attack_data_set['diabetes'] == 1]['diabetes'].sum()
High_blood_pressure = Heart_attack_data_set[Heart_attack_data_set['high_blood_pressure'] == 1]['high_blood_pressure'].sum()
anaemia = Heart_attack_data_set[Heart_attack_data_set['anaemia'] == 1]['anaemia'].sum()

print('Reasons for heart attack: \nSmoking = ' + str(Smoking) + '\nDiabetes = ' + str(Diabetes) + '\nHigh blood pressure = ' + str(High_blood_pressure) + '\nAnemia = ' + str(anaemia))
```

```

fig, ax = plt.subplots(figsize=(6, 3), subplot_kw=dict(aspect="equal"))

reasons = ['Smoking', 'Diabetes', 'High_blood_pressure', 'Anemia']

data = [Smoking, Diabetes, High_blood_pressure, anaemia]

wedges, texts = ax.pie(data, wedgeprops=dict(width=0.5), startangle=-40)

bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
kw = dict(arrowprops=dict(arrowstyle="-"), bbox=bbox_props, zorder=0,
        ↪va="center")

for i, p in enumerate(wedges):
    ang = (p.theta2 - p.theta1) / 2. + p.theta1
    y = np.sin(np.deg2rad(ang))
    x = np.cos(np.deg2rad(ang))
    horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
    connectionstyle = "angle,angleA=0,angleB={}".format(ang)
    kw["arrowprops"].update({"connectionstyle": connectionstyle})
    ax.annotate(reasons[i], xy=(x, y), xytext=(1.35 * np.sign(x), 1.4 *
    ↪y),horizontalalignment=horizontalalignment, **kw)

ax.set_title('Reasons for heart attack')
plt.show()

```

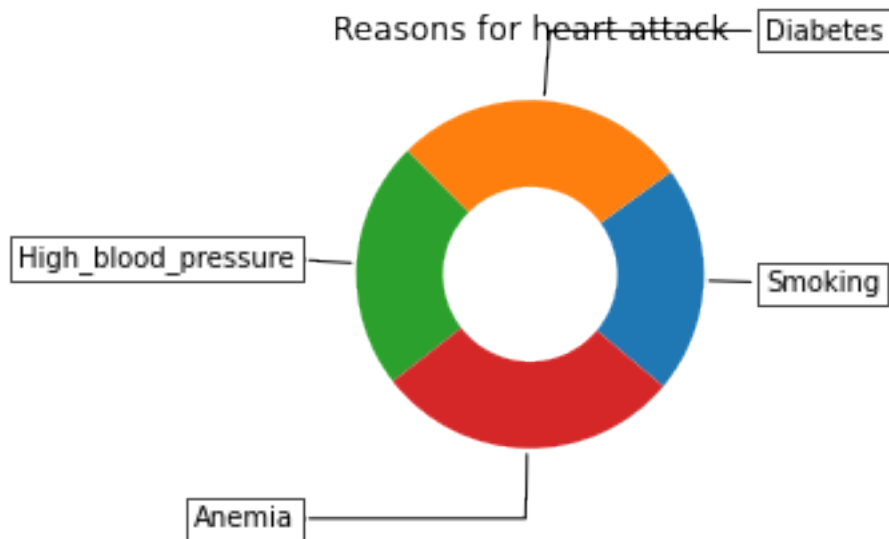
Reasons for heart attack:

Smoking = 96

Diabetes = 125

High blood pressure = 105

Anemia = 129



```
[9]: # Most of the heart attacks were caused by anemia but all the numbers are very
      ↪close to the mentioned reasons.
```

```
[10]: Smokers = Heart_attack_data_set[Heart_attack_data_set['smoking'] ==
      ↪1]['DEATH_EVENT'].sum()
      Non_smokers = Heart_attack_data_set[Heart_attack_data_set['smoking'] ==
      ↪0]['DEATH_EVENT'].sum()

      High_blood_pressure =
      ↪Heart_attack_data_set[Heart_attack_data_set['high_blood_pressure'] ==
      ↪1]['DEATH_EVENT'].sum()
      Non_high_blood_pressure =
      ↪Heart_attack_data_set[Heart_attack_data_set['high_blood_pressure'] ==
      ↪0]['DEATH_EVENT'].sum()

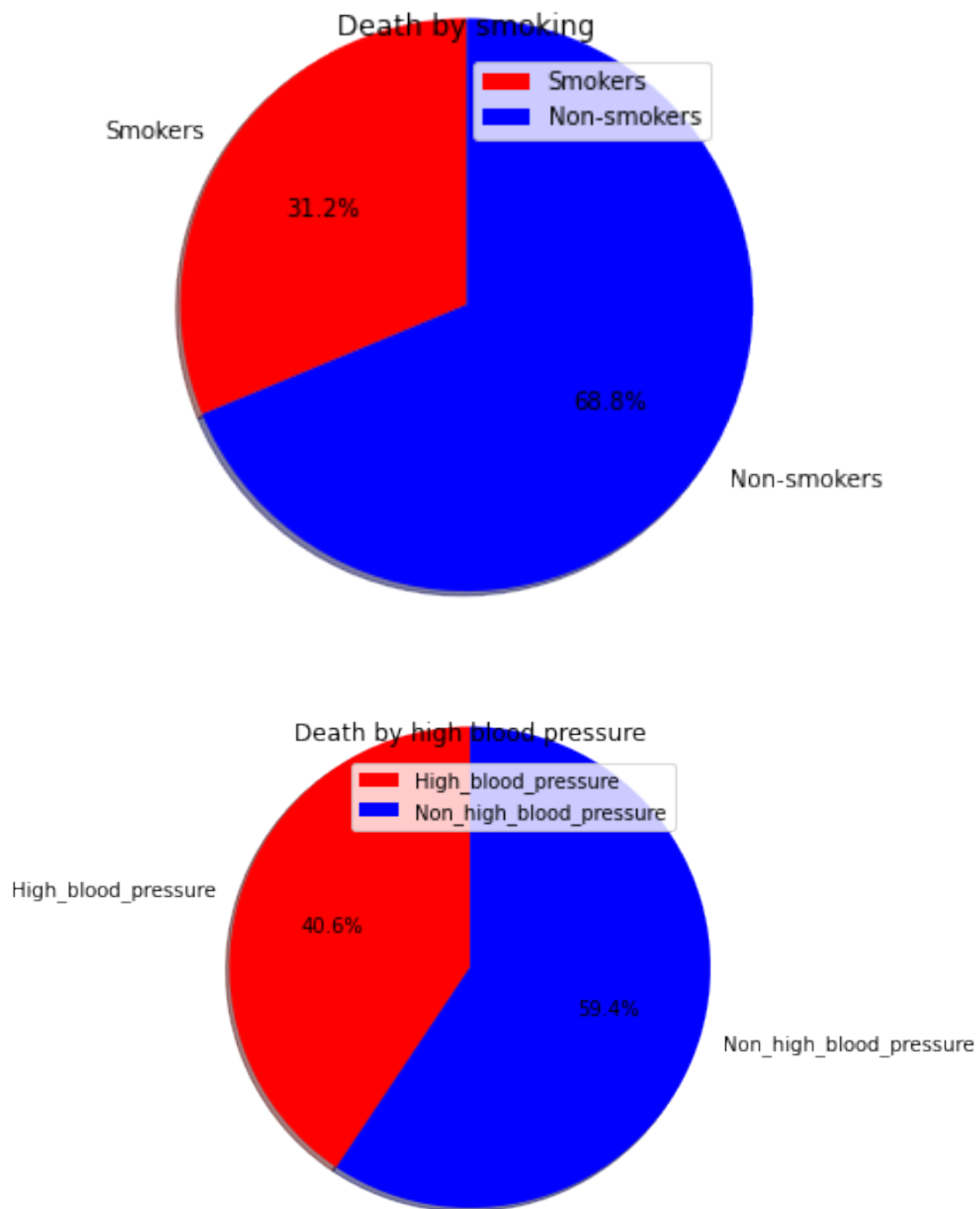
      Diabetes = Heart_attack_data_set[Heart_attack_data_set['diabetes'] ==
      ↪1]['DEATH_EVENT'].sum()
      Non_diabetes = Heart_attack_data_set[Heart_attack_data_set['diabetes'] ==
      ↪0]['DEATH_EVENT'].sum()

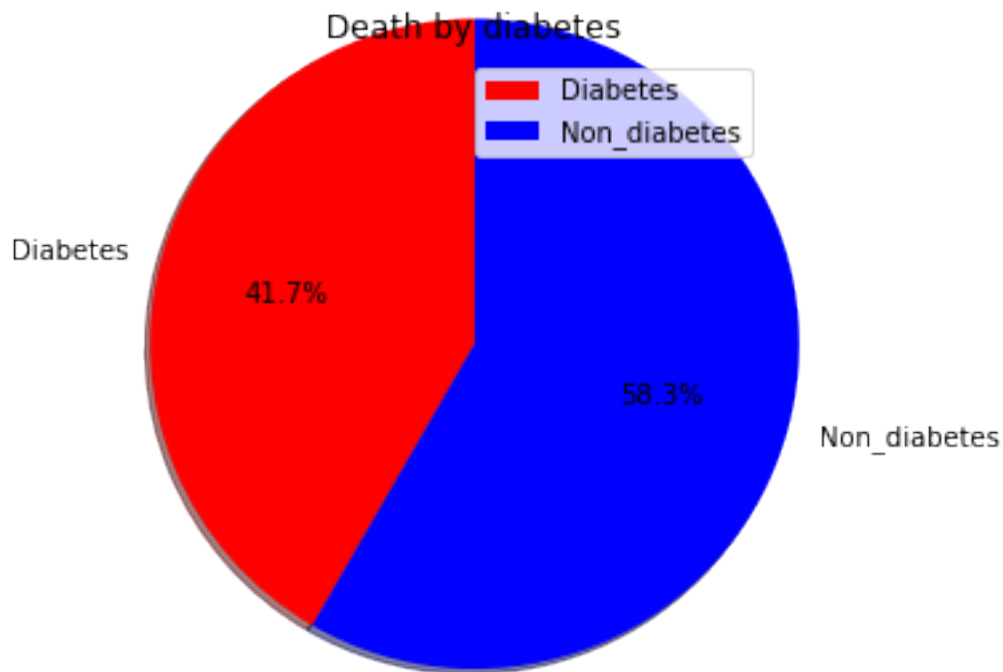
      Deaths = ['Smokers', 'Non-smokers']
      slices = [Smokers, Non_smokers]
      colors = ['r', 'b']
      plt.pie(slices, labels= Deaths, colors=colors, startangle=90, shadow=True,
      ↪explode=(0, 0), radius=1.4, autopct='%1.1f%%')
      plt.legend()
      plt.title('Death by smoking')
      plt.show()

      Deaths = ['High_blood_pressure', 'Non_high_blood_pressure']
      slices = [High_blood_pressure, Non_high_blood_pressure]
      colors = ['r', 'b']
      plt.pie(slices, labels= Deaths, colors=colors, startangle=90, shadow=True,
      ↪explode=(0, 0), radius=1.4, autopct='%1.1f%%')
      plt.legend()
      plt.title('Death by high blood pressure')
      plt.show()

      Deaths = ['Diabetes', 'Non_diabetes']
      slices = [Diabetes, Non_diabetes]
      colors = ['r', 'b']
      plt.pie(slices, labels= Deaths, colors=colors, startangle=90, shadow=True,
      ↪explode=(0, 0), radius=1.4, autopct='%1.1f%%')
      plt.legend()
      plt.title('Death by diabetes')
```

```
plt.show()
```





```
[11]: #Smoking, diabetes and high blood pressure do not necessarily affect death from
      ↪ a heart attack.
```

```
[12]: sns.set(style="whitegrid", palette="muted")
new_data = (Heart_attack_data_set - Heart_attack_data_set.mean()) /
      ↪ (Heart_attack_data_set.std())
new_data = pd.concat([Heart_attack_data_set['DEATH_EVENT'], new_data.iloc[:,0:
      ↪ 12]], axis=1)
new_data
```

```
[12]:
```

	DEATH_EVENT	age	anaemia	creatinine_phosphokinase	diabetes	\
0	1	1.190949	-0.869647	0.000165	-0.846161	
1	1	-0.490457	-0.869647	7.502063	-0.846161	
2	1	0.350246	-0.869647	-0.449186	-0.846161	
3	1	-0.910808	1.146046	-0.485257	-0.846161	
4	1	0.350246	1.146046	-0.434757	1.177856	
..	
294	0	0.098035	-0.869647	-0.536789	1.177856	
295	0	-0.490457	-0.869647	1.276075	-0.846161	
296	0	-1.331160	-0.869647	1.523425	1.177856	
297	0	-1.331160	-0.869647	1.887234	-0.846161	
298	0	-0.910808	-0.869647	-0.397655	-0.846161	

ejection_fraction high_blood_pressure platelets serum_creatinine \

0	-1.527998	1.356997	1.678834e-02	0.489237
1	-0.007065	-0.734457	7.523047e-09	-0.284076
2	-1.527998	-0.734457	-1.036336e+00	-0.090748
3	-1.527998	-0.734457	-5.455595e-01	0.489237
4	-1.527998	-0.734457	6.507077e-01	1.262550
..
294	-0.007065	1.356997	-1.107907e+00	-0.284076
295	-0.007065	-0.734457	6.791087e-02	-0.187412
296	1.851853	-0.734457	4.893878e+00	-0.574068
297	-0.007065	-0.734457	-1.261275e+00	0.005916
298	0.584409	-0.734457	1.345974e+00	0.199244

	serum_sodium	sex	smoking	time
0	-1.501519	0.734457	-0.686531	-1.626775
1	-0.141739	0.734457	-0.686531	-1.601007
2	-1.728149	0.734457	1.451727	-1.588122
3	0.084892	0.734457	-0.686531	-1.588122
4	-4.674340	-1.356997	-0.686531	-1.575238
..
294	1.444672	0.734457	1.451727	1.800432
295	0.538152	-1.356997	-0.686531	1.813317
296	0.311522	-1.356997	-0.686531	1.903506
297	0.764782	0.734457	1.451727	1.929275
298	-0.141739	0.734457	1.451727	1.993696

[299 rows x 13 columns]

```
[13]: new_data = pd.melt(new_data, id_vars="DEATH_EVENT", var_name="features",
    ↪value_name='value')
new_data
```

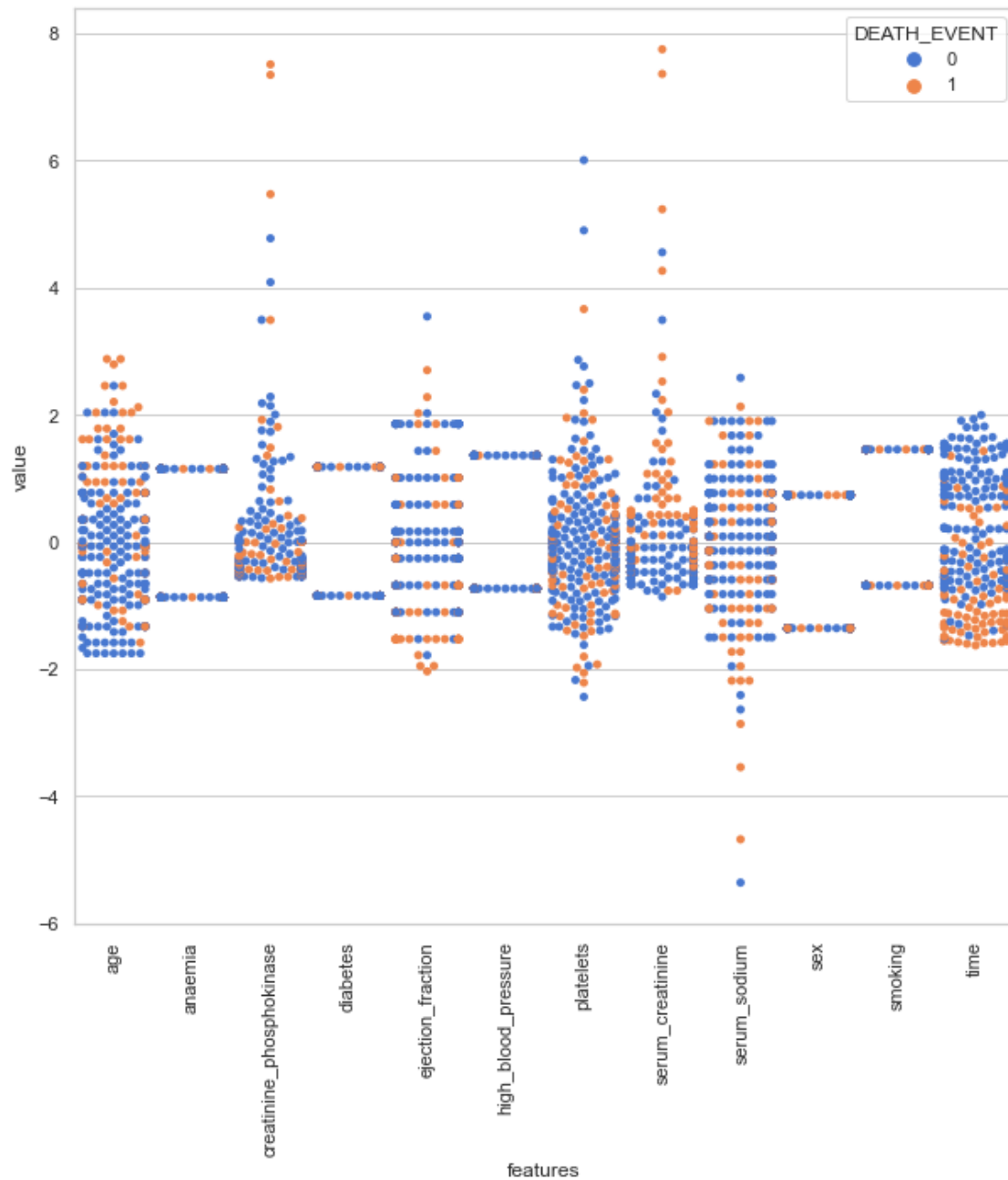
```
[13]:
```

	DEATH_EVENT	features	value
0	1	age	1.190949
1	1	age	-0.490457
2	1	age	0.350246
3	1	age	-0.910808
4	1	age	0.350246
...
3583	0	time	1.800432
3584	0	time	1.813317
3585	0	time	1.903506
3586	0	time	1.929275
3587	0	time	1.993696

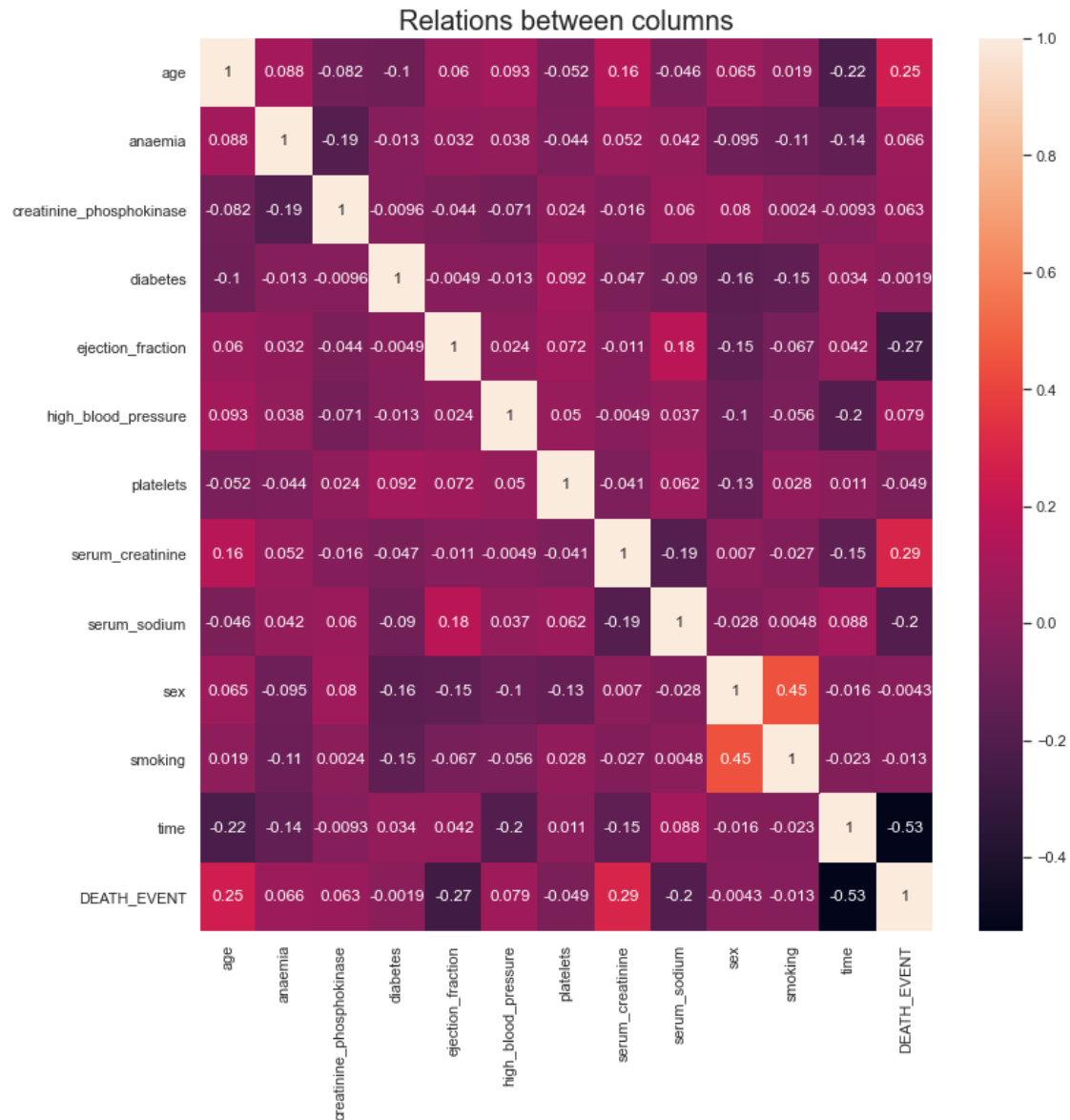
[3588 rows x 3 columns]

```
[14]: # 0 = Death
plt.figure(figsize=(10,10))
sns.swarmplot(x="features", y="value", hue="DEATH_EVENT", data=new_data)
plt.xticks(rotation=90)
```

```
[14]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11]),
      [Text(0, 0, 'age'),
       Text(1, 0, 'anaemia'),
       Text(2, 0, 'creatinine_phosphokinase'),
       Text(3, 0, 'diabetes'),
       Text(4, 0, 'ejection_fraction'),
       Text(5, 0, 'high_blood_pressure'),
       Text(6, 0, 'platelets'),
       Text(7, 0, 'serum_creatinine'),
       Text(8, 0, 'serum_sodium'),
       Text(9, 0, 'sex'),
       Text(10, 0, 'smoking'),
       Text(11, 0, 'time')])
```



```
[15]: fig, ax = plt.subplots(figsize=(12,12))
sns.heatmap(Heart_attack_data_set.corr(), annot = True, ax=ax)
plt.title('Relations between columns', fontsize = 20)
plt.show()
```



```
[16]: #There is a high relation between the sex of the individual to smoking but the
      ↪ interesting conclusion is
      #that have a very strong relationship between the serum sodium and age to heart
      ↪ attacks
      #and negative relation between ejection fraction to heart attacks.
```

```
[17]: drop_list = ['time', 'DEATH_EVENT']
fs_corr = Heart_attack_data_set.drop(columns=drop_list)
fs_corr.head()
```

```
[17]:
```

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	\
0	75.0	0	582	0	20	
1	55.0	0	7861	0	38	
2	65.0	0	146	0	20	
3	50.0	1	111	0	20	
4	65.0	1	160	1	20	

	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	\
0		1	265000.00	1.9	130	1
1		0	263358.03	1.1	136	1
2		0	162000.00	1.3	129	1
3		0	210000.00	1.9	137	1
4		0	327000.00	2.7	116	0

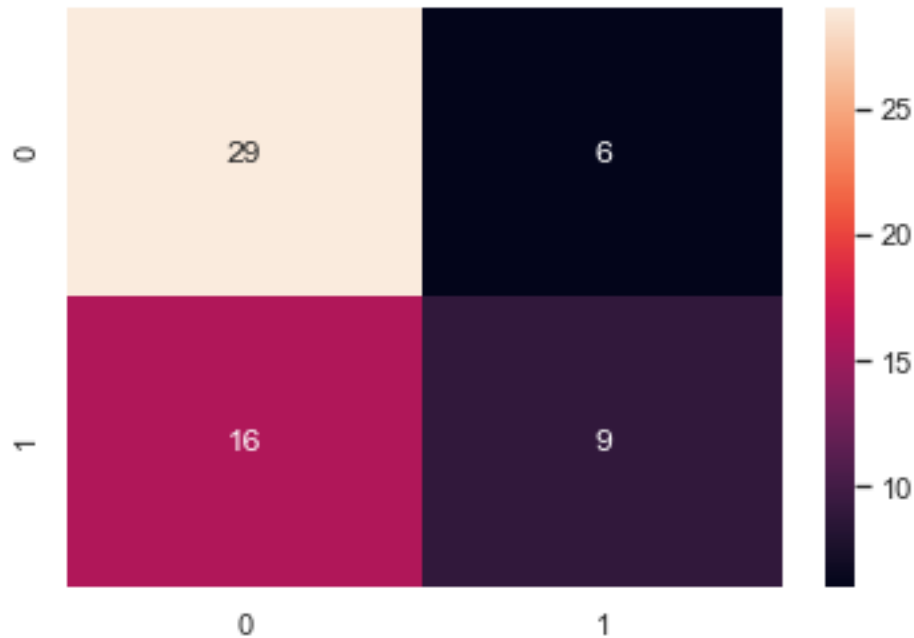
	smoking
0	0
1	0
2	1
3	0
4	0

```
[18]: y = Heart_attack_data_set['DEATH_EVENT']
x_train, x_test, y_train, y_test = train_test_split(fs_corr, y, test_size=0.
↪2, random_state=42)
clf_rf = RandomForestClassifier(n_estimators=20)
clr_rf = clf_rf.fit(x_train, y_train)
```

```
[19]: print('Accuracy', accuracy_score(y_test, clf_rf.predict(x_test)))
cm = confusion_matrix(y_test, clf_rf.predict(x_test))
sns.heatmap(cm, annot=True, fmt="d")
```

Accuracy 0.6333333333333333

```
[19]: <AxesSubplot:>
```



```
[ ]: #The algorithm has 63.3 success percent in the prediction if the heart attack,
      ↳will be fatal
      #according to the personal details of the individual (smoking/non-smoking, sex,
      ↳age, etc).
```

```
[20]: K = range(1, len(x_train.columns))
      for k in K:
          select_feature = SelectKBest(chi2, k=k).fit(x_train, y_train)
          scores = zip(x_train.columns, select_feature.scores_)
          print("Selected K:", k)
          for i, (column, score) in enumerate(scores):
              if i < k:
                  print("Feature:", column, ", Score:", score)
          print("-----")
```

```
Selected K: 1
Feature: age , Score: 46.9889849693994
-----
Selected K: 2
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
-----
Selected K: 3
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
```

```

-----
Selected K: 4
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
Feature: diabetes , Score: 0.0016732698597080864
-----
Selected K: 5
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
Feature: diabetes , Score: 0.0016732698597080864
Feature: ejection_fraction , Score: 55.896406551208116
-----
Selected K: 6
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
Feature: diabetes , Score: 0.0016732698597080864
Feature: ejection_fraction , Score: 55.896406551208116
Feature: high_blood_pressure , Score: 0.5289514866979651
-----
Selected K: 7
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
Feature: diabetes , Score: 0.0016732698597080864
Feature: ejection_fraction , Score: 55.896406551208116
Feature: high_blood_pressure , Score: 0.5289514866979651
Feature: platelets , Score: 27714.885624462317
-----
Selected K: 8
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
Feature: diabetes , Score: 0.0016732698597080864
Feature: ejection_fraction , Score: 55.896406551208116
Feature: high_blood_pressure , Score: 0.5289514866979651
Feature: platelets , Score: 27714.885624462317
Feature: serum_creatinine , Score: 18.105974482139235
-----
Selected K: 9
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
Feature: diabetes , Score: 0.0016732698597080864
Feature: ejection_fraction , Score: 55.896406551208116
Feature: high_blood_pressure , Score: 0.5289514866979651

```



```

Feature: platelets , Score: 27714.885624462317
Feature: serum_creatinine , Score: 18.105974482139235
Feature: serum_sodium , Score: 1.2352740846996069
-----
Selected K: 10
Feature: age , Score: 46.9889849693994
Feature: anaemia , Score: 0.44381997110870225
Feature: creatinine_phosphokinase , Score: 460.053375481774
Feature: diabetes , Score: 0.0016732698597080864
Feature: ejection_fraction , Score: 55.896406551208116
Feature: high_blood_pressure , Score: 0.5289514866979651
Feature: platelets , Score: 27714.885624462317
Feature: serum_creatinine , Score: 18.105974482139235
Feature: serum_sodium , Score: 1.2352740846996069
Feature: sex , Score: 0.23498621599728284
-----

```

```

[21]: clf_rf_ = RandomForestClassifier(n_estimators=20)
      rfe = RFE(estimator=clf_rf_, n_features_to_select=5, step=1)
      rfe = rfe.fit(x_train, y_train)

```

```

[22]: print('Chosen best 5 feature by RFE:',x_train.columns[rfe.support_])

```

```

Chosen best 5 feature by RFE: Index(['age', 'creatinine_phosphokinase',
    'ejection_fraction', 'platelets',
    'serum_creatinine'],
    dtype='object')

```

```

[23]: clf_rf_ = RandomForestClassifier(n_estimators=20)
      clr_rf_ = clf_rf_.fit(x_train,y_train)
      importances = clr_rf_.feature_importances_
      std = np.std([tree.feature_importances_ for tree in clf_rf.estimators_],axis=0)
      indices = np.argsort(importances)[::-1]

```

```

[24]: print("Feature ranking:")
      for f in range(x_train.shape[1]):
          print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

```

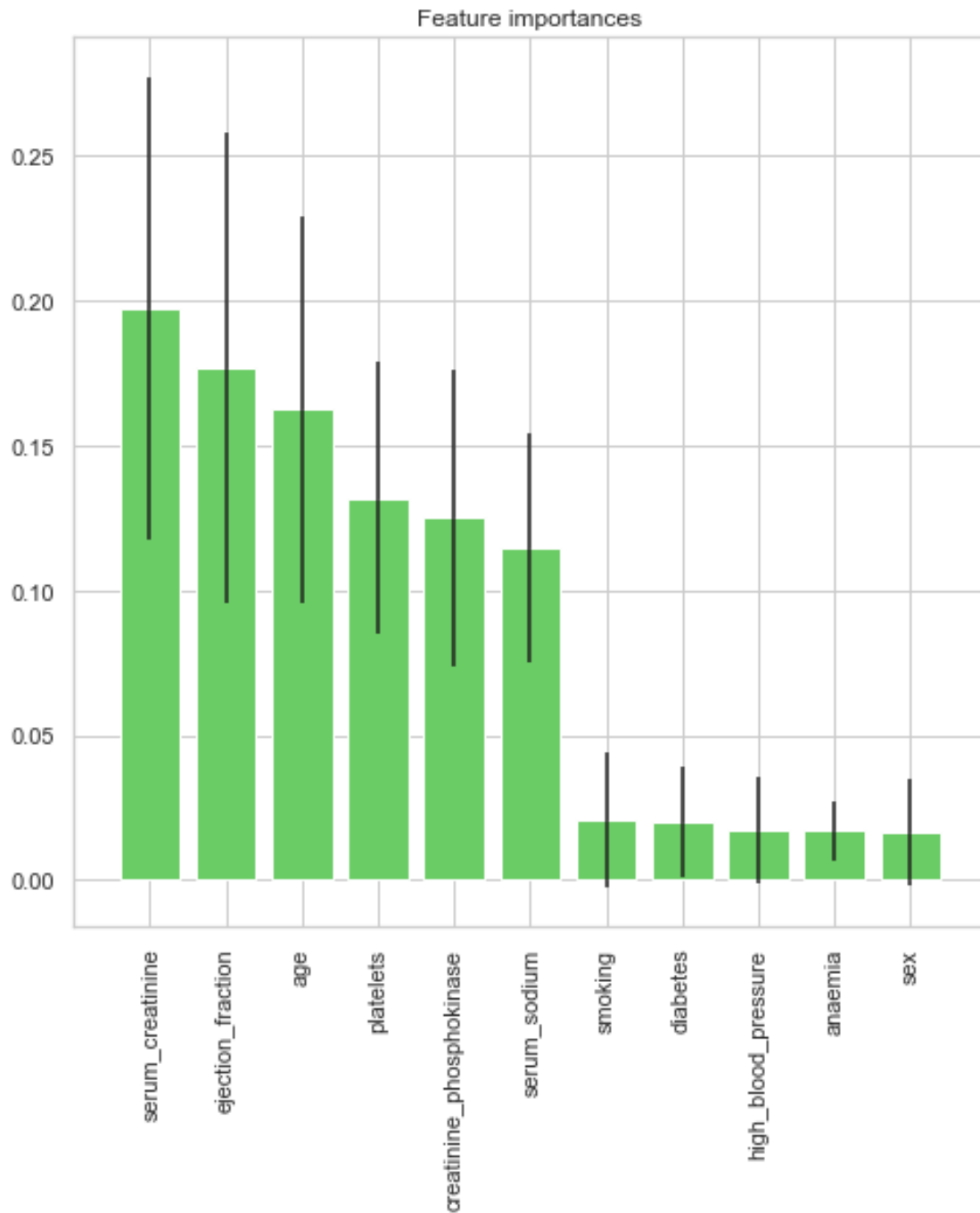
```

Feature ranking:
1. feature 7 (0.197355)
2. feature 4 (0.176655)
3. feature 0 (0.162451)
4. feature 6 (0.131765)
5. feature 2 (0.125157)
6. feature 8 (0.114812)
7. feature 10 (0.021037)
8. feature 3 (0.020357)
9. feature 5 (0.017075)

```

10. feature 1 (0.017006)
11. feature 9 (0.016331)

```
[25]: plt.figure(1, figsize=(8, 8))
plt.title("Feature importances")
plt.bar(range(x_train.shape[1]), importances[indices],
color="g", yerr=std[indices], align="center")
plt.xticks(range(x_train.shape[1]), x_train.columns[indices],rotation=90)
plt.xlim([-1, x_train.shape[1]])
plt.show()
```



```
[ ]: #The attribute which affects death from a heart attack most is the level of
      ↳serum creatinine in the blood.
```

```
[26]: #SVM algorithm
      from sklearn.svm import SVC
      from sklearn.metrics import classification_report, confusion_matrix
```

```
df_feat = Heart_attack_data_set
df_feat.info()
X_train, X_test, y_train, y_test = train_test_split(df_feat, np.ravel(y),
↳test_size=0.30, random_state=101)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 13 columns):
age                299 non-null float64
anaemia            299 non-null int64
creatinine_phosphokinase  299 non-null int64
diabetes            299 non-null int64
ejection_fraction  299 non-null int64
high_blood_pressure  299 non-null int64
platelets           299 non-null float64
serum_creatinine    299 non-null float64
serum_sodium        299 non-null int64
sex                 299 non-null int64
smoking             299 non-null int64
time                299 non-null int64
DEATH_EVENT         299 non-null int64
dtypes: float64(3), int64(10)
memory usage: 30.5 KB
```

```
[27]: model = SVC()
      model.fit(X_train,y_train)
```

```
[27]: SVC()
```

```
[28]: predictions = model.predict(X_test)
      print(confusion_matrix(y_test,predictions))
```

```
[[62  0]
 [28  0]]
```

```
[29]: print(classification_report(y_test,predictions))
```

	precision	recall	f1-score	support
0	0.69	1.00	0.82	62
1	0.00	0.00	0.00	28
accuracy			0.69	90
macro avg	0.34	0.50	0.41	90
weighted avg	0.47	0.69	0.56	90

```
C:\Users\omri1\Anaconda3\lib\site-
```

packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
[30]: #Gridsearch
from sklearn.model_selection import GridSearchCV
param_grid = {'C': [0.1,1, 10, 100, 1000], 'gamma': [1,0.1,0.01,0.001,0.0001],
              ↪ 'kernel': ['rbf']}
grid = GridSearchCV(SVC(),param_grid,refit=True,verbose=3)
grid.fit(X_train,y_train)
```

Fitting 5 folds for each of 25 candidates, totalling 125 fits

```
[CV] C=0.1, gamma=1, kernel=rbf ...
[CV] ... C=0.1, gamma=1, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=1, kernel=rbf ...
[CV] ... C=0.1, gamma=1, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=1, kernel=rbf ...
[CV] ... C=0.1, gamma=1, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=1, kernel=rbf ...
[CV] ... C=0.1, gamma=1, kernel=rbf, score=0.690, total= 0.0s
[CV] C=0.1, gamma=1, kernel=rbf ...
[CV] ... C=0.1, gamma=1, kernel=rbf, score=0.683, total= 0.0s
[CV] C=0.1, gamma=0.1, kernel=rbf ...
[CV] ... C=0.1, gamma=0.1, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=0.1, kernel=rbf ...
[CV] ... C=0.1, gamma=0.1, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=0.1, kernel=rbf ...
[CV] ... C=0.1, gamma=0.1, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=0.1, kernel=rbf ...
[CV] ... C=0.1, gamma=0.1, kernel=rbf, score=0.690, total= 0.0s
[CV] C=0.1, gamma=0.1, kernel=rbf ...
[CV] ... C=0.1, gamma=0.1, kernel=rbf, score=0.683, total= 0.0s
[CV] C=0.1, gamma=0.01, kernel=rbf ...
[CV] ... C=0.1, gamma=0.01, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=0.01, kernel=rbf ...
[CV] ... C=0.1, gamma=0.01, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=0.01, kernel=rbf ...
```

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 0.0s remaining: 0.0s

[Parallel(n_jobs=1)]: Done 2 out of 2 | elapsed: 0.0s remaining: 0.0s

```
[CV] ... C=0.1, gamma=0.01, kernel=rbf, score=0.667, total= 0.0s
[CV] C=0.1, gamma=0.01, kernel=rbf ...
[CV] ... C=0.1, gamma=0.01, kernel=rbf, score=0.690, total= 0.0s
[CV] C=0.1, gamma=0.01, kernel=rbf ...
[CV] ... C=0.1, gamma=0.01, kernel=rbf, score=0.683, total= 0.0s
[CV] C=0.1, gamma=0.001, kernel=rbf ...
```

[illegible]

[illegible]


```

[CV] ... C=1000, gamma=0.01, kernel=rbf, score=0.667, total= 0.0s
[CV] C=1000, gamma=0.01, kernel=rbf ...
[CV] ... C=1000, gamma=0.01, kernel=rbf, score=0.667, total= 0.0s
[CV] C=1000, gamma=0.01, kernel=rbf ...
[CV] ... C=1000, gamma=0.01, kernel=rbf, score=0.690, total= 0.0s
[CV] C=1000, gamma=0.01, kernel=rbf ...
[CV] ... C=1000, gamma=0.01, kernel=rbf, score=0.683, total= 0.0s
[CV] C=1000, gamma=0.001, kernel=rbf ...
[CV] ... C=1000, gamma=0.001, kernel=rbf, score=0.667, total= 0.0s
[CV] C=1000, gamma=0.001, kernel=rbf ...
[CV] ... C=1000, gamma=0.001, kernel=rbf, score=0.667, total= 0.0s
[CV] C=1000, gamma=0.001, kernel=rbf ...
[CV] ... C=1000, gamma=0.001, kernel=rbf, score=0.667, total= 0.0s
[CV] C=1000, gamma=0.001, kernel=rbf ...
[CV] ... C=1000, gamma=0.001, kernel=rbf, score=0.714, total= 0.0s
[CV] C=1000, gamma=0.001, kernel=rbf ...
[CV] ... C=1000, gamma=0.001, kernel=rbf, score=0.707, total= 0.0s
[CV] C=1000, gamma=0.0001, kernel=rbf ...
[CV] ... C=1000, gamma=0.0001, kernel=rbf, score=0.667, total= 0.0s
[CV] C=1000, gamma=0.0001, kernel=rbf ...
[CV] ... C=1000, gamma=0.0001, kernel=rbf, score=0.690, total= 0.0s
[CV] C=1000, gamma=0.0001, kernel=rbf ...
[CV] ... C=1000, gamma=0.0001, kernel=rbf, score=0.690, total= 0.0s
[CV] C=1000, gamma=0.0001, kernel=rbf ...
[CV] ... C=1000, gamma=0.0001, kernel=rbf, score=0.762, total= 0.0s
[CV] C=1000, gamma=0.0001, kernel=rbf ...
[CV] ... C=1000, gamma=0.0001, kernel=rbf, score=0.683, total= 0.0s

[Parallel(n_jobs=1)]: Done 125 out of 125 | elapsed: 1.6s finished

```

```

[30]: GridSearchCV(estimator=SVC(),
                  param_grid={'C': [0.1, 1, 10, 100, 1000],
                              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                              'kernel': ['rbf']},
                  verbose=3)

```

```

[31]: grid.best_params_
      grid.best_estimator_
      grid_predictions = grid.predict(X_test)
      print(confusion_matrix(y_test, grid_predictions))
      print(classification_report(y_test, grid_predictions))

```

```

[[60  2]
 [26  2]]

      precision    recall  f1-score   support

0         0.70        0.97        0.81         62
1         0.50        0.07        0.12         28

```

accuracy			0.69	90
macro avg	0.60	0.52	0.47	90
weighted avg	0.64	0.69	0.60	90

```
[ ]: # The SVM and Grid Search algorithms gave 69 percent for success in the  
      ↳ prediction.  
      # It is a really great prediction in consider to the few amount of data we got  
      ↳ from the CSV sheet.
```

```
[ ]:
```