In [49]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Loading dataset

In [50]:
```python
df = pd.read_csv('Heart Failure prediction.csv')
```

In [51]:
```python
df
```

Out[51]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	
0	75.0	0	582	0	20	1	2
1	55.0	0	7861	0	38	0	2
2	65.0	0	146	0	20	0	1
3	50.0	1	111	0	20	0	2
4	65.0	1	160	1	20	0	3
...	...	...	...	...	...	...	
294	62.0	0	61	1	38	1	1
295	55.0	0	1820	0	38	0	2
296	45.0	0	2060	1	60	0	7
297	45.0	0	2413	0	38	0	1
298	50.0	0	196	0	45	0	3

299 rows × 13 columns

In [52]:
```python
df.head()
```

Out[52]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	pl
0	75.0	0	582	0	20	1	265
1	55.0	0	7861	0	38	0	263
2	65.0	0	146	0	20	0	162
3	50.0	1	111	0	20	0	210
4	65.0	1	160	1	20	0	327

In [53]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   age                       299 non-null    float64
 1   anaemia                   299 non-null    int64  
 2   creatinine_phosphokinase  299 non-null    int64  
 3   diabetes                  299 non-null    int64  
 4   ejection_fraction         299 non-null    int64  
 5   high_blood_pressure       299 non-null    int64  
 6   platelets                 299 non-null    float64
 7   serum_creatinine          299 non-null    float64
 8   serum_sodium              299 non-null    int64  
 9   sex                       299 non-null    int64  
 10  smoking                   299 non-null    int64  
 11  time                      299 non-null    int64  
 12  DEATH_EVENT               299 non-null    int64  
dtypes: float64(3), int64(10)
memory usage: 30.5 KB
```

In [54]:
```
1 df.describe().T
```

Out[54]:

	count	mean	std	min	25%	50%	
age	299.0	60.833893	11.894809	40.0	51.0	60.0	
anaemia	299.0	0.431438	0.496107	0.0	0.0	0.0	
creatinine_phosphokinase	299.0	581.839465	970.287881	23.0	116.5	250.0	5
diabetes	299.0	0.418060	0.494067	0.0	0.0	0.0	
ejection_fraction	299.0	38.083612	11.834841	14.0	30.0	38.0	
high_blood_pressure	299.0	0.351171	0.478136	0.0	0.0	0.0	
platelets	299.0	263358.029264	97804.236869	25100.0	212500.0	262000.0	3035
serum_creatinine	299.0	1.393880	1.034510	0.5	0.9	1.1	
serum_sodium	299.0	136.625418	4.412477	113.0	134.0	137.0	1
sex	299.0	0.648829	0.478136	0.0	0.0	1.0	
smoking	299.0	0.321070	0.467670	0.0	0.0	0.0	
time	299.0	130.260870	77.614208	4.0	73.0	115.0	2
DEATH_EVENT	299.0	0.321070	0.467670	0.0	0.0	0.0	

In [55]:
```
1 df.shape
```

Out[55]: (299, 13)

In [56]:
```
df.columns
```
Out[56]:
```
Index(['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes',
       'ejection_fraction', 'high_blood_pressure', 'platelets',
       'serum_creatinine', 'serum_sodium', 'sex', 'smoking', 'time',
       'DEATH_EVENT'],
      dtype='object')
```

In [57]:
```
for col in df.columns:
    print(f'{col}, {len(df[col].unique())}')
```
```
age, 47
anaemia, 2
creatinine_phosphokinase, 208
diabetes, 2
ejection_fraction, 17
high_blood_pressure, 2
platelets, 176
serum_creatinine, 40
serum_sodium, 27
sex, 2
smoking, 2
time, 148
DEATH_EVENT, 2
```

In [58]:
```
cat_cols = ['anaemia', 'diabetes', 'high_blood_pressure', 'sex', 'smoking'
con_cols = ['age', 'creatinine_phosphokinase', 'ejection_fraction', 'plate
```

Summary statistics

In [59]:
```
df[con_cols].describe().T[['min', '50%','max']].rename(columns={'50%':'avg

```
Out[59]:

	min	avg	max
age	40.0	60.0	95.0
creatinine_phosphokinase	23.0	250.0	7861.0
ejection_fraction	14.0	38.0	80.0
platelets	25100.0	262000.0	850000.0
serum_creatinine	0.5	1.1	9.4
serum_sodium	113.0	137.0	148.0
time	4.0	115.0	285.0

3) Exploratory Data Analysis¶

Count plot of categorical features

Categorical DATA :

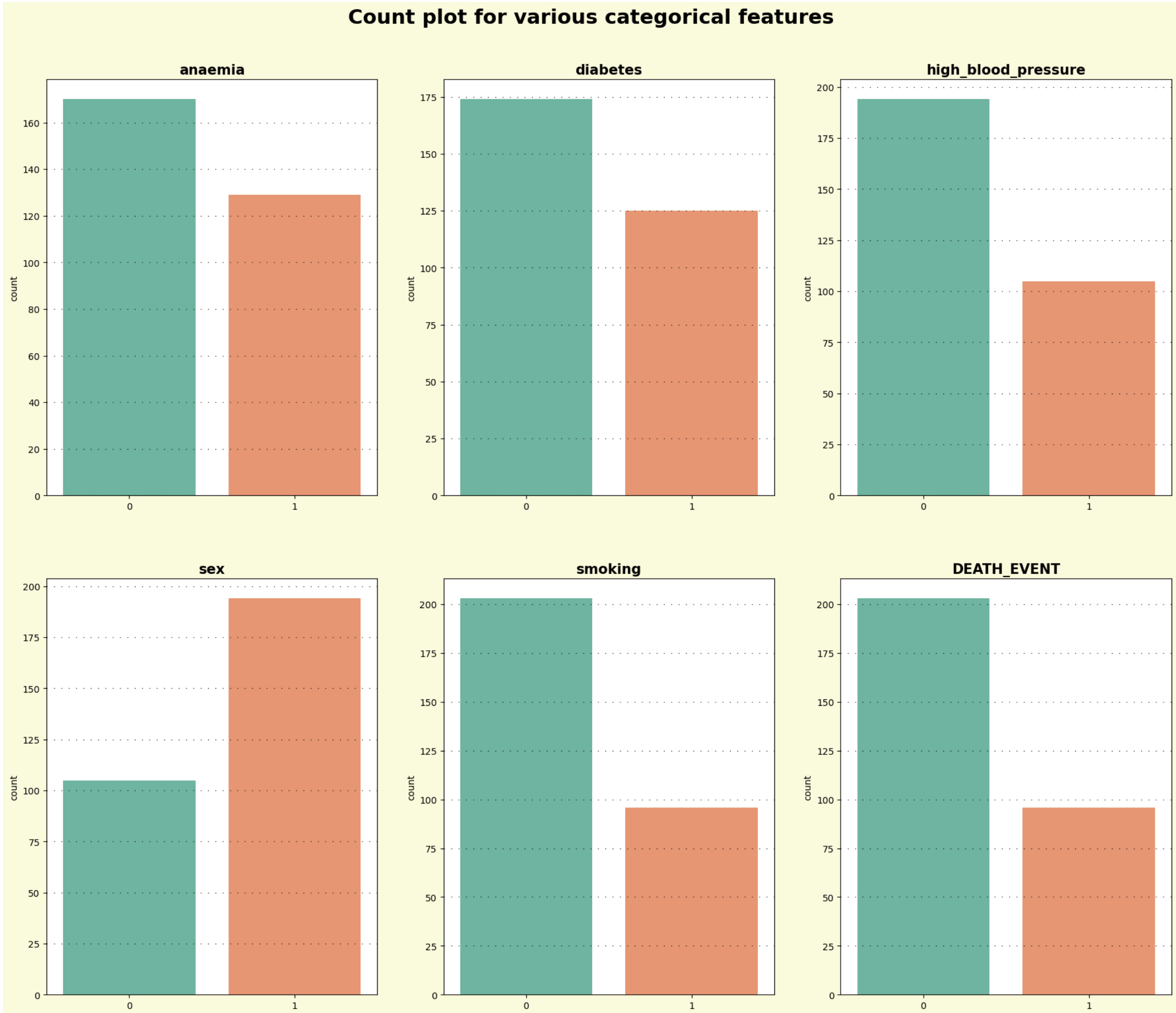
anaemia, diabetes, high_blood_pressure, sex, smoking, DEATH_EVENT (YES(1) / NO(0))

Numirical DATA :

age, creatinine_phosphokinase, ejection_fraction, platelets, serum_creatinine, serum_sodium, time

In [60]:

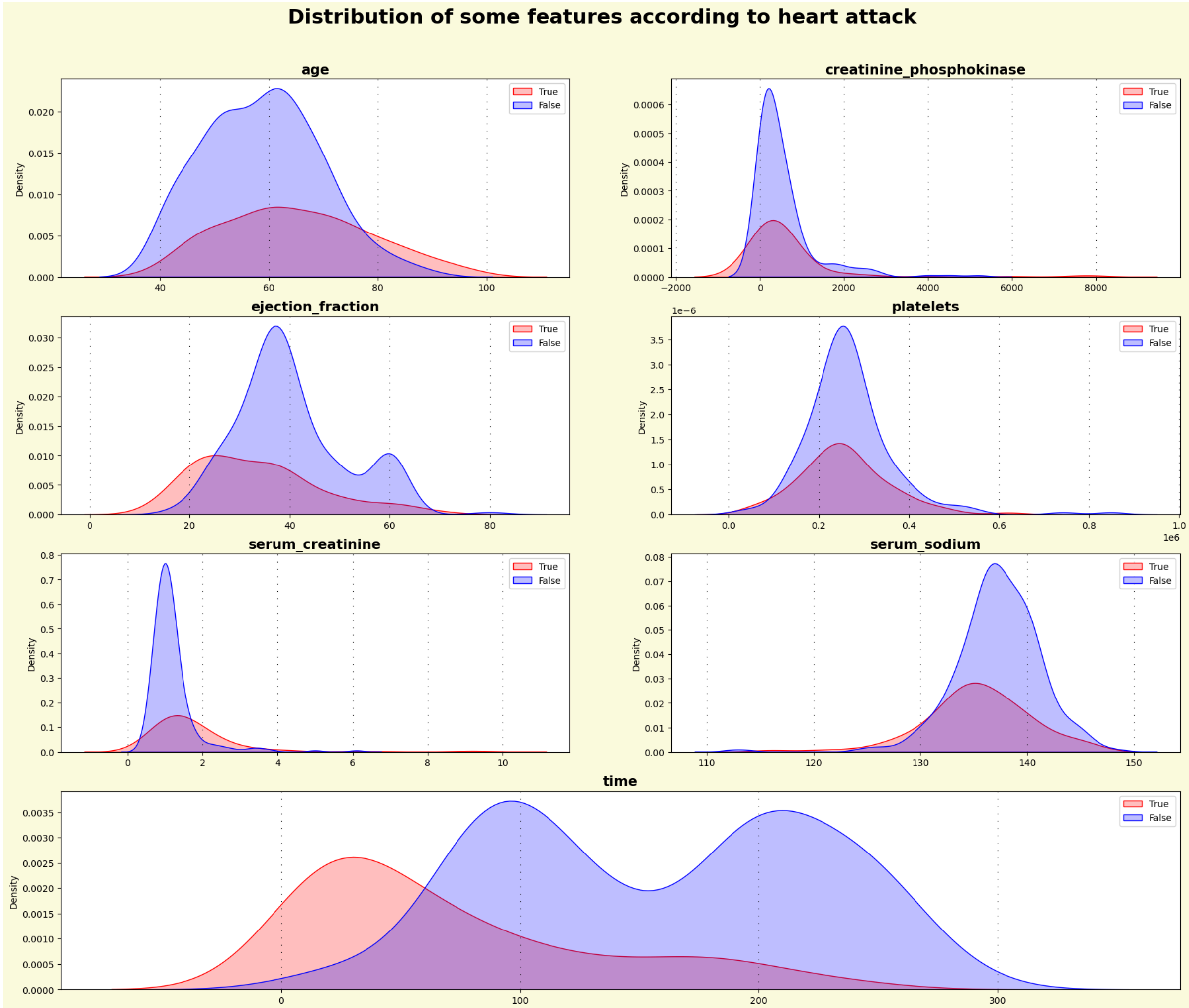
```
def plot_cate_feat(df, ax, col_name):
    ax.set_title(col_name,fontweight ="bold",fontsize=15)
    ax.grid(color='#000000', linestyle='dashed', axis='y',dashes=(1,9))
    sns.countplot(ax=ax,data=df,x=col_name,palette = 'Set2')
    ax.set_xlabel("")

fig = plt.figure(figsize=(22,18))
gs  = fig.add_gridspec(2,3)
ax1 = fig.add_subplot(gs[0,0])
ax2 = fig.add_subplot(gs[0,1])
ax3 = fig.add_subplot(gs[0,2])
ax4 = fig.add_subplot(gs[1,0])
ax5 = fig.add_subplot(gs[1,1])
ax6 = fig.add_subplot(gs[1,2])
axes = [ax1, ax2, ax3, ax4, ax5, ax6]


fig.suptitle(t='Count plot for various categorical features',y=0.94, fontw
fig.set_facecolor("#fefae0")

for ax,col_name in zip(axes,cat_cols):
    plot_cate_feat(df, ax, col_name)



plt.show()
```



Distribution of continuous features according to target variable

In [61]:

```

def plot_con_feat(df, ax, col_name, target='DEATH_EVENT'):
    ax.set_title(col_name,fontweight ="bold",fontsize=15)
    ax.grid(color='#000000', linestyle='dashed', axis='x',dashes=(1,9))
    sns.kdeplot(ax=ax,data=df,x=col_name, hue=target, fill=True, palette =
    ax.legend([True, False])
    ax.set_xlabel("")

fig = plt.figure(figsize=(22,18))
gs  = fig.add_gridspec(4,2)
ax1 = fig.add_subplot(gs[0,0])
ax2 = fig.add_subplot(gs[0,1])
ax3 = fig.add_subplot(gs[1,0])
ax4 = fig.add_subplot(gs[1,1])
ax5 = fig.add_subplot(gs[2,0])
ax6 = fig.add_subplot(gs[2,1])
ax7 = fig.add_subplot(gs[3,:])
axes = [ax1, ax2, ax3, ax4, ax5, ax6,ax7]


fig.suptitle(t='Distribution of some features according to heart attack',y
fig.set_facecolor("#fefae0")

for ax,col_name in zip(axes,con_cols):
    plot_con_feat(df, ax, col_name)

plt.show()
```



Correlation between features and 'DEATH_EVENT'

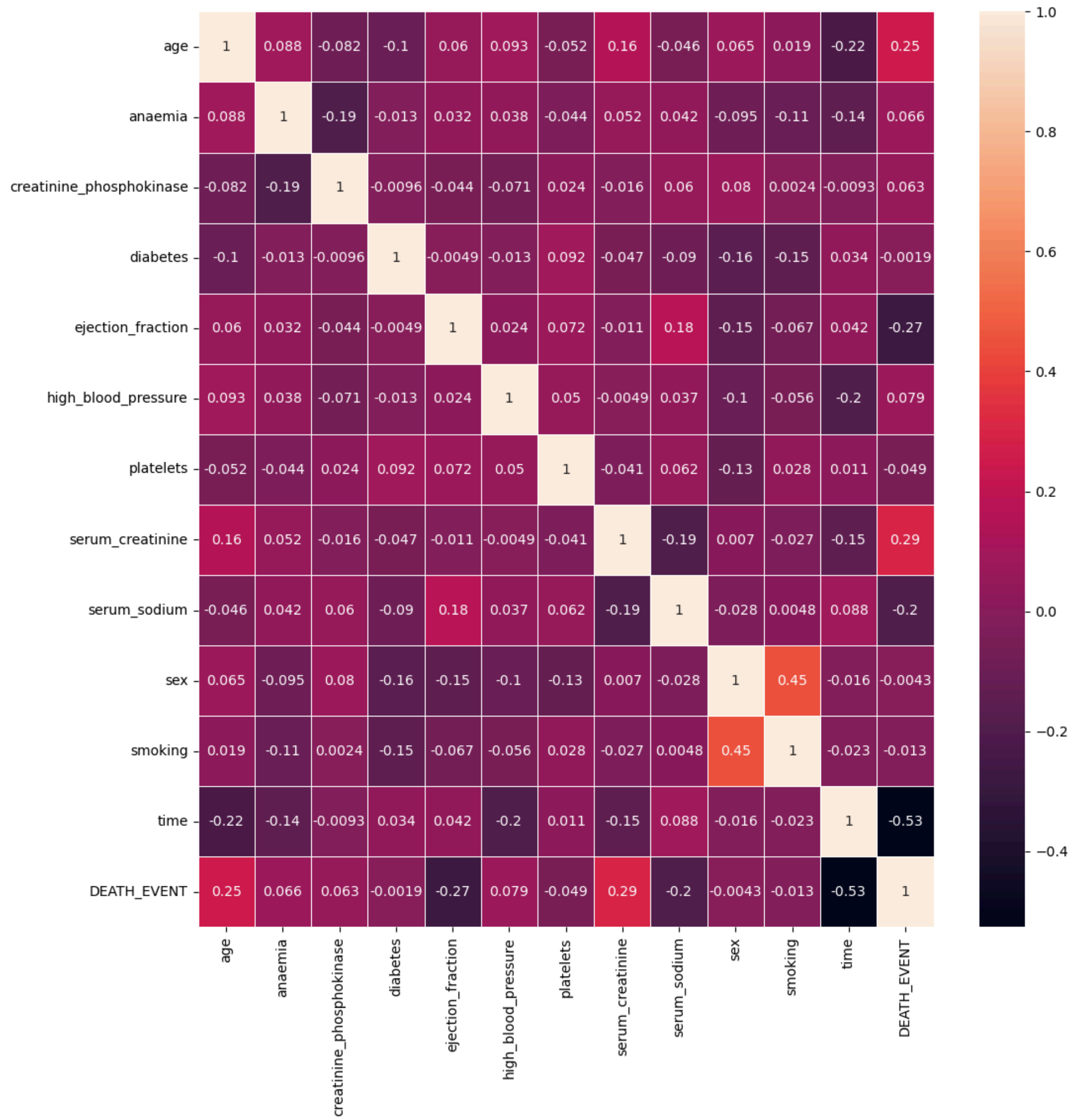
In [62]:
```
df_corr = df.corr()
df_corr['DEATH_EVENT'].sort_values()
```

Out[62]:
```
time                       -0.526964
ejection_fraction          -0.268603
serum_sodium               -0.195204
platelets                  -0.049139
smoking                    -0.012623
sex                        -0.004316
diabetes                   -0.001943
creatinine_phosphokinase    0.062728
anaemia                     0.066270
high_blood_pressure         0.079351
age                         0.253729
serum_creatinine            0.294278
DEATH_EVENT                 1.000000
Name: DEATH_EVENT, dtype: float64
```

In [63]:

```
import seaborn as sns
plt.figure(figsize=(12,12))
sns.heatmap(df.corr(),annot=True,linewidths=.5)
```

Out[63]: <AxesSubplot:>



4) Modeling

Importing Packages

In [64]:
```python
#Scaling
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler

# Train Test Split
from sklearn.model_selection import train_test_split

# Metrics
from sklearn.metrics import classification_report, accuracy_score

# Models
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import RidgeClassifier, LogisticRegression
from sklearn.svm import SVC
```

In [65]:
```python
X = df.drop('DEATH_EVENT', axis=1)
y = df['DEATH_EVENT']
x_train, x_test, y_train, y_test = train_test_split(X,y,test_size=0.2, ran
```

In [66]:
```python
X
```

Out[66]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure
0	75.0	0	582	0	20	1
1	55.0	0	7861	0	38	0
2	65.0	0	146	0	20	0
3	50.0	1	111	0	20	0
4	65.0	1	160	1	20	0
...	...	...	...	...	...	...
294	62.0	0	61	1	38	1
295	55.0	0	1820	0	38	0
296	45.0	0	2060	1	60	0
297	45.0	0	2413	0	38	0
298	50.0	0	196	0	45	0

In [67]:
```python
y
```

Out[67]:
```
0      1
1      1
2      1
3      1
4      1
      ..
294    0
295    0
296    0
297    0
298    0
Name: DEATH_EVENT, Length: 299, dtype: int64
```

In [68]:
```
mdl = make_pipeline(StandardScaler(), LogisticRegression())
mdl.fit(x_train,y_train)
y_pred = mdl.predict(x_test)
```

5) Validation

get classification report

In [69]:
```
classification_report(y_test,y_pred)
```

Out[69]:
```
'              precision    recall  f1-score   support\n\n           0
0.91      0.91      0.91        45\n           1       0.73      0.73      0.
73        15\n\n    accuracy                           0.87        60\n   mac
ro avg       0.82      0.82      0.82        60\nweighted avg       0.87
0.87      0.87        60\n'
```

Evaluated Score Train DataSet by Model

In [70]:
```
print('Score TrainDataSet: ',mdl.score(x_train,y_train))
```

```
Score TrainDataSet:  0.8493723849372385
```

Evaluated Score Test DataSet by Model

In [71]:
```
print('Score TestDataSet: ',mdl.score(x_test,y_test))
```

```
Score TestDataSet:  0.8666666666666667
```

Accuracy Score

In [72]:
```
print(f'Accuracy score of Logistic Regression is {accuracy_score(y_test, y
```

```
Accuracy score of Logistic Regression is 86.66666666666667%
```