```
In [1]:
         1 import numpy as np
         2 import pandas as pd
         3 from collections import Counter
            import seaborn as sns
          6 sns.set(rc={'figure.figsize':(6,4)})
            import matplotlib.pyplot as plt
            %matplotlib inline
         9
            from tadm import tadm
            import random
        12 import pickle
        13 import time
        14
            from sklearn.model selection import train test split
            from sklearn.preprocessing import LabelEncoder
        17
            from sklearn.preprocessing import MinMaxScaler
        19 from sklearn.preprocessing import StandardScaler
           from sklearn.preprocessing import MaxAbsScaler
        21 from sklearn.preprocessing import RobustScaler
        22 from sklearn.preprocessing import QuantileTransformer
         23 from sklearn.preprocessing import PowerTransformer
            from sklearn.preprocessing import Normalizer
         25
            from sklearn.linear model import LogisticRegression
            from sklearn.neighbors import KNeighborsClassifier
        28 from sklearn.naive bayes import GaussianNB
            from sklearn.tree import DecisionTreeClassifier
            from sklearn.ensemble import RandomForestClassifier
         31
            from sklearn.model selection import cross val score
         33 from sklearn.metrics import accuracy score
         34 from sklearn.metrics import log loss
        35 from sklearn.metrics import cohen kappa score
        36 from sklearn.metrics import confusion matrix
         37 from sklearn import metrics
         38
         39 # for ignore warnings
         40 import warnings
            warnings.filterwarnings("ignore")
         42
            plot data list = []
```

Out[2]:

	Age(years)	Weight(kg)	Height(cm)	ВМІ	Gender	Profession	smoke	Exercise	cereal	salad	 Poor and unplanned work	Lack of career development	Feeling of powerlessness	Lack of financial security	Unable to satisfy all stakeholders	
(	42	61.0	165	22.41	Male	Sitting-Job	No	Moderate	Once	Everyday	 Low	Low	Low	Low	Low	
	30	49.0	165	18.00	Female	Other	No	Inactive	Twice	Rarely	 Average	Average	Low	Low	Low	
:	. 52	60.0	159	23.73	Male	Moving-Job	Yes	Moderate	Twice	Rarely	 Very low	Very low	Very low	Very low	Very low	
;	46	61.0	172	20.62	Male	Other	No	Low	Thrice	Sometimes	 Average	Average	Very low	Average	Average	
4	45	65.0	155	27.06	Female	Moving-Job	No	Inactive	Twice	Everyday	 Very low	Very High	Average	Average	Low	

5 rows × 35 columns

In [3]: 1 df.shape

Out[3]: (375, 35)

### In [4]: 1 df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 375 entries, 0 to 374 Data columns (total 35 columns): # Column Non-Null Count Dtype \_\_\_\_\_ 0 Age(vears) 375 non-null int64 375 non-null 1 Weight(kg) float64 375 non-null int64 2 Height(cm) 3 BMT 375 non-null float64 Gender 375 non-null object 4 5 Profession 375 non-null object 6 smoke 375 non-null object 7 Exercise 375 non-null object cereal 375 non-null object 9 salad 375 non-null object vegetables 375 non-null object 10 11 grains 375 non-null object 12 sweets 375 non-null object 13 Sweets in a week 375 non-null object 14 Refined Sugar 375 non-null object 15 Milk Products consumption 375 non-null object 16 Milk Quantity(ml/day) 375 non-null object 375 non-null 17 Pregnancy object 18 History of Diabetes 375 non-null object 375 non-null 19 Anxiety object Stress Workload 20 375 non-null object 21 Poor family income 375 non-null object 22 Pressure of working 375 non-null object 23 Frequent travel 375 non-null object 24 Monotonus work 375 non-null object 25 Poor and unplanned work 375 non-null object Lack of career development 375 non-null object 27 Feeling of powerlessness 375 non-null object 28 Lack of financial security object 375 non-null 29 Unable to satisfy all stakeholders 375 non-null object 30 High Blood Pressure 375 non-null object 31 Blood\_Sugar\_Fasting 375 non-null object 375 non-null 32 Blood Sugar Post Meal object 33 HbA1c Glycated Haemoglobin 375 non-null object 34 Class 375 non-null object dtypes: float64(2), int64(2), object(31)

memory usage: 102.7+ KB

In [5]:

1 round(df.describe(),2)

# Out[5]:

	Age(years)	Weight(kg)	Height(cm)	BMI
count	375.00	375.00	375.00	375.00
mean	42.41	64.94	162.57	24.63
std	15.29	11.99	10.08	4.45
min	4.00	20.00	100.00	10.97
25%	30.00	57.00	155.50	22.20
50%	40.00	65.00	163.00	24.22
75%	53.00	72.00	168.00	27.15
max	90.00	102.00	193.00	52.00

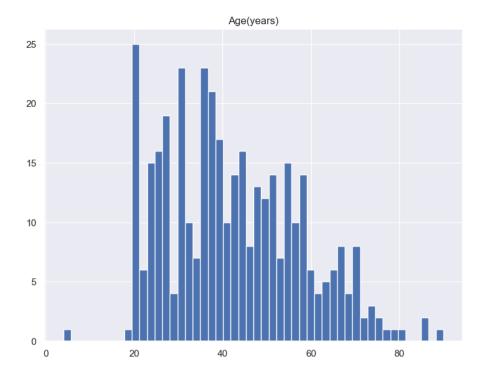
```
1 # check null
In [6]:
          2 df.isnull().sum()
Out[6]: Age(years)
                                              0
        Weight(kg)
                                              0
        Height(cm)
                                              0
        BMI
                                              0
                                              0
        Gender
        Profession
                                              0
        smoke
                                              0
        Exercise
                                              0
        cereal
                                              0
        salad
                                              0
        vegetables
                                              0
        grains
                                              0
        sweets
                                              0
        Sweets_in_a_week
                                              0
        Refined Sugar
                                              0
        Milk Products consumption
                                              0
        Milk Quantity(ml/day)
                                              0
        Pregnancy
                                              0
        History of Diabetes
                                              0
        Anxiety
                                              0
        Stress_Workload
                                              0
        Poor \nfamily income
                                              0
        Pressure of\n working
                                              0
        Frequent \ntravel
                                              0
        Monotonus\n work
                                              0
        Poor and unplanned work
                                              0
        Lack of career development
                                              0
        Feeling of powerlessness
                                              0
        Lack of financial security
                                              0
        Unable to satisfy all stakeholders
                                              0
        High Blood Pressure
                                              0
        Blood Sugar Fasting
                                              0
        Blood_Sugar_Post_Meal
                                              0
        HbA1c_Glycated_Haemoglobin
                                              0
        Class
        dtype: int64
```

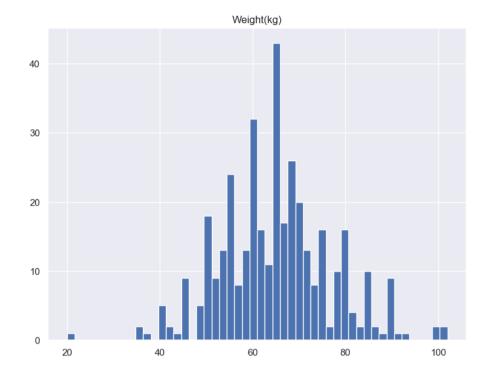
Number of numerical variables: 4

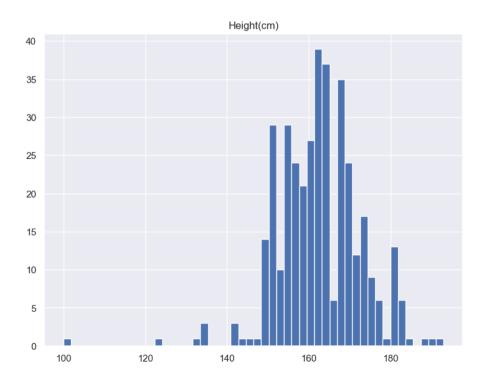
#### Out[7]:

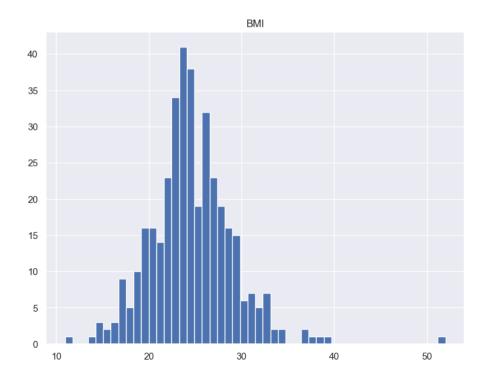
	Age(years)	Weight(kg)	Height(cm)	BMI
0	42	61.0	165	22.41
1	30	49.0	165	18.00
2	52	60.0	159	23.73
3	46	61.0	172	20.62
4	45	65.0	155	27.06

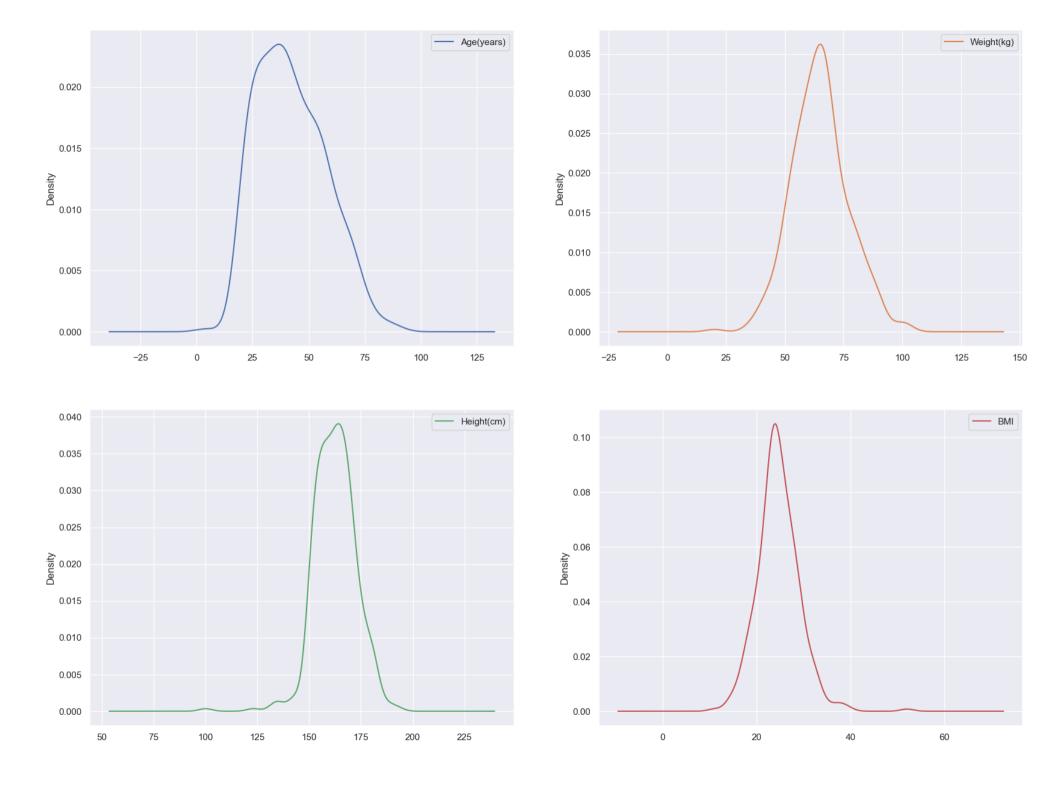
```
In [8]: 1 # Histogram:distribution of a single numerical variable
    numerical_variables_df.hist(bins=50, figsize=(20, 15))
    plt.show()
```

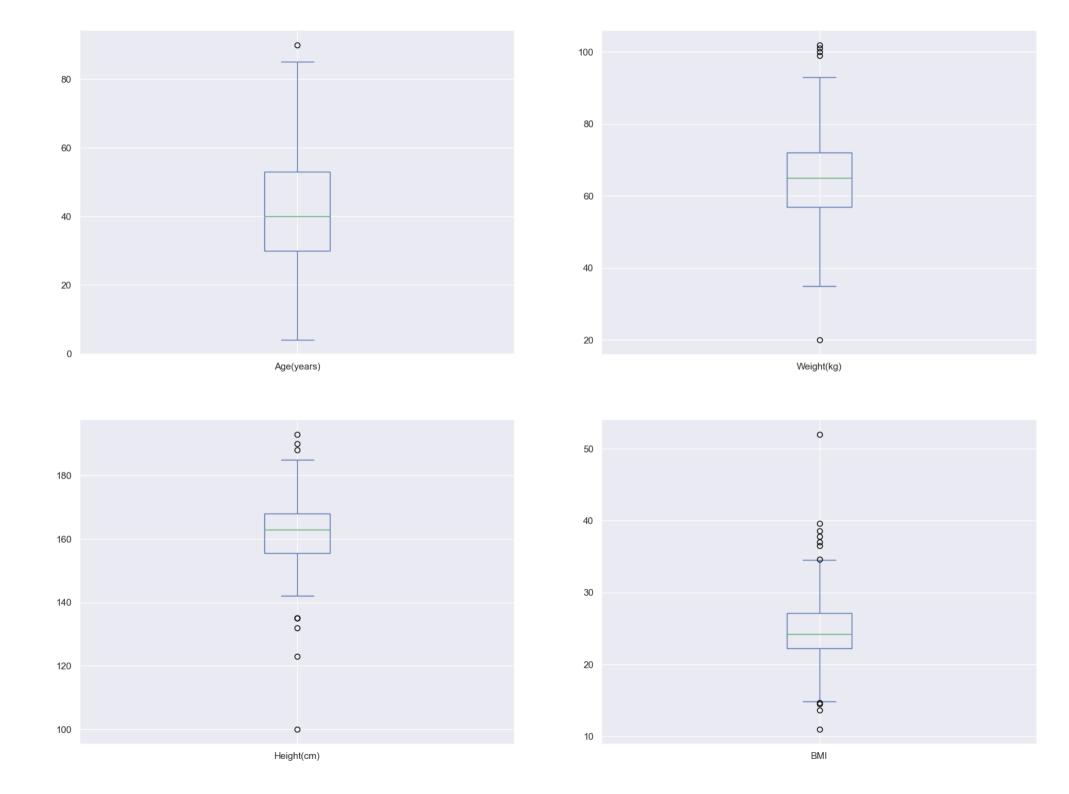








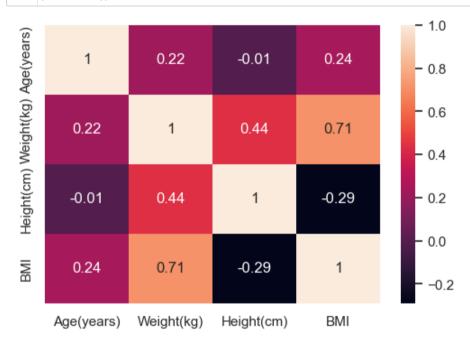


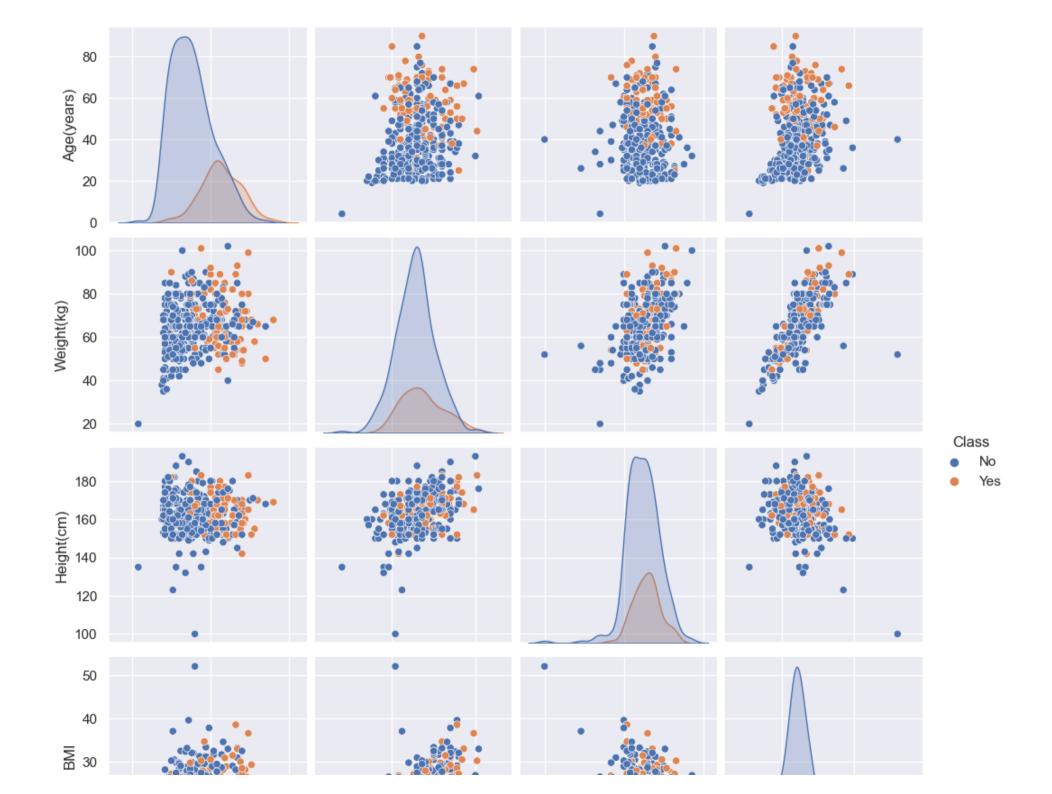


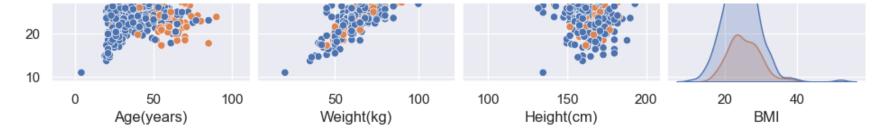
# observation: outlier is detected in all features

```
In [11]:
```

- 1 # Correlation between the different characteristics. Closer to 1 better is the correlation.
- 2 sns.heatmap(round(numerical\_variables\_df.corr(method='pearson'),2), annot = True)
- 3 plt.show()







Number of categorical variables: 31

### Out[37]:

	Gender	Profession	smoke	Exercise	cereal	salad	vegetables	grains	sweets	Sweets_in_a_week	 Poor and unplanned work	Lack of career development	Feeling of powerlessness	Lack of financial security	Unable to satisfy all stakeholders
0	Male	Sitting-Job	No	Moderate	Once	Everyday	Twice	Rice- Wheat	Yes	Weekly	 Low	Low	Low	Low	Low
1	Female	Other	No	Inactive	Twice	Rarely	Twice	Rice- Wheat- Maida	Yes	Weekly	 Average	Average	Low	Low	Low
2	Male	Moving-Job	Yes	Moderate	Twice	Rarely	Twice	Polished- Rice	Yes	Rarely	 Very low	Very low	Very low	Very low	Very low
3	Male	Other	No	Low	Thrice	Sometimes	Twice	Wheat	Yes	Weekly	 Average	Average	Very low	Average	Average
4	Female	Moving-Job	No	Inactive	Twice	Everyday	Twice	Brown- Rice	Yes	Weekly	 Very low	Very High	Average	Average	Low

5 rows × 31 columns

4

```
Unique values in Gender is : ['Female', 'Male'],
                                                                                                       Count : 2
Unique values in Profession is : ['Business', 'Business-sitting-job', 'Housewife', 'Moving-Job', 'Other', 'Sitting-Job', 'other'],
                                                                                                                                                                                                                                                        C
ount: 7
Unique values in smoke is : ['No', 'YES', 'Yes', 'yes'],
                                                                                                                     Count: 4
Unique values in Exercise is : ['High', 'Inactive', 'Intense', 'Low', 'Moderate', 'Very intense'],
                                                                                                                                                                                  Count : 6
Unique values in cereal is : ['More than three times', 'None', 'Once', 'Thrice', 'Thrice in a day', 'Twice'],
                                                                                                                                                                                                                  Count: 6
Unique values in salad is : ['1 bowl in lunch and/or dinner', '1/2 bowl in lunch and/or dinner', 'Everyday', 'Frequently', 'Never', 'None', 'R
arely', 'Rarely (Weekly)', 'Sometimes'],
                                                                                         Count: 9
Unique values in vegetables is : ['Daily', 'Never', 'None', 'Once', 'Once in a week', 'Sometimes', 'Twice', 'Twice a day', 'Weekly'],
Count: 9
Unique values in grains is : ['Brown-Rice', 'Brown-Rice-Millets', 'Brown-Rice-Millets-Maida', 'Brown-Rice-Wheat', 'Brown-Rice-Wheat-Millets',
'Millets', 'Polished-Rice', 'Polished-Rice-Brown-Rice-Wheat', 'Polished-Rice-Brown-Rice-Wheat-Millets', 'Polished-Rice-Maida', 'Polished-Rice-M
illets', 'Polished-Rice-Wheat', 'Polished-Rice-Wheat-Maida-Millets', 'Polished-Rice-Wheat-Millets', 'Rice-Wheat', 'Rice-Wheat-Brown-Rice', 'Ric
e-Wheat-Brown-Rice-Maida', 'Rice-Wheat-Maida', 'Rice-Wheat-Millets', 'Rice-Wheat-Millets-Maida', 'Wheat', 'Wheat-Brown-Rice', 
-Millets', 'Wheat-Maida', 'Wheat-Millets', 'Wheat-Millets-Maida'],
                                                                                                                                      Count: 26
Unique values in sweets is : ['No', 'Yes'],
                                                                                              Count : 2
Unique values in Sweets_in_a_week is : ['Daily', 'Monthly', 'Never', 'Rarely', 'Weekly'],
                                                                                                                                                                               Count : 5
Unique values in Refined Sugar is : ['No', 'Yes'],
                                                                                                           Count: 2
Unique values in Milk Products consumption is : ['No', 'Yes'],
                                                                                                                               Count : 2
Unique values in Milk Quantity(ml/day) is : ['100-200', '200-400', '400-600', 'More than 600'],
                                                                                                                                                                                           Count: 4
Unique values in Pregnancy is : ['No', 'Not-Applicable', 'Yes'],
                                                                                                                                   Count: 3
Unique values in History of Diabetes is : ['No', 'Yes'],
                                                                                                                     Count : 2
Unique values in Anxiety is : ['No', 'Yes'],
                                                                                                Count : 2
Unique values in Stress Workload is : [' Low', 'Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                                                                                                                     Count: 7
Unique values in Poor
family income is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                                                                      Count : 6
Unique values in Pressure of
 working is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                                                             Count: 6
Unique values in Frequent
```

```
travel is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                        Count: 6
Unique values in Monotonus
 work is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                      Count : 6
Unique values in Poor and unplanned work is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                         Count : 6
Unique values in Lack of career development is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                            Count : 6
Unique values in Feeling of powerlessness is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                          Count : 6
Unique values in Lack of financial security is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                            Count : 6
Unique values in Unable to satisfy all stakeholders is : ['Average', 'High', 'Low', 'Very High', 'Very high', 'Very low'],
                                                                                                                                    Count: 6
Unique values in High Blood Pressure is : ['No', 'Yes'],
                                                                   Count : 2
Unique values in Blood Sugar Fasting is : ['High', 'Low', 'Moderate'],
                                                                                Count : 3
Unique values in Blood_Sugar_Post_Meal is : ['High', 'Low', 'Moderate'],
                                                                                  Count : 3
Unique values in HbA1c Glycated Haemoglobin is : ['High', 'Low', 'Moderate'],
                                                                                       Count: 3
```

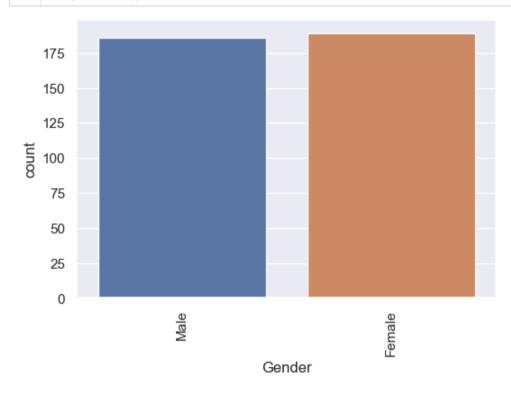
Count : 2

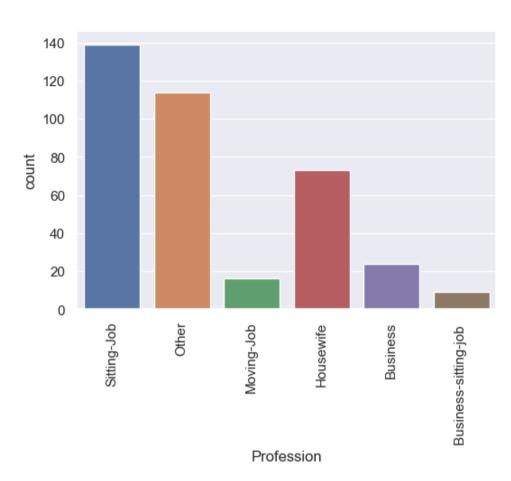
Unique values in Class is : ['No', 'Yes'],

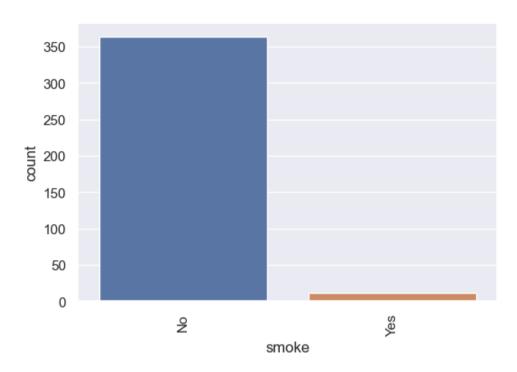
```
In [39]:
           1 replacement dict = {'other': 'Other'}
           2 categorical variables df['Profession'].replace(replacement dict, inplace=True)
             replacement dict = {'YES': 'Yes', 'yes': 'Yes'}
             categorical variables df['smoke'].replace(replacement dict, inplace=True)
             replacement dict = {'Thrice in a day': 'Thrice'}
             categorical variables df['cereal'].replace(replacement dict, inplace=True)
             replacement dict = {'None': 'Never', 'Rarely (Weekly)': 'Rarely', 'Sometimes': 'Rarely'}
             categorical variables df['salad'].replace(replacement dict, inplace=True)
          12
             replacement dict = {'None': 'Never', 'Once in a week': 'Once', 'Sometimes': 'Rarely', 'Twice a day': 'Twice'}
             categorical variables df['vegetables'].replace(replacement dict, inplace=True)
          15
          16 replacement dict = {' Low': 'Low', 'Very High': 'Very high'}
             categorical variables df['Stress Workload'].replace(replacement dict, inplace=True)
          18
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Poor \nfamily income'].replace(replacement dict, inplace=True)
          21
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Pressure of\n working'].replace(replacement dict, inplace=True)
          24
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Frequent \ntravel'].replace(replacement dict, inplace=True)
          27
          28 replacement dict = {'Very High': 'Very high'}
             categorical variables df['Monotonus\n work'].replace(replacement dict, inplace=True)
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Poor and unplanned work'].replace(replacement dict, inplace=True)
          33
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Lack of career development'].replace(replacement dict, inplace=True)
          36
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Feeling of powerlessness'].replace(replacement dict, inplace=True)
          39
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Lack of financial security'].replace(replacement dict, inplace=True)
          42
             replacement dict = {'Very High': 'Very high'}
             categorical variables df['Unable to satisfy all stakeholders'].replace(replacement dict, inplace=True)
          45
             for col in categorical variables df.columns:
                  print(f"Unique values in {col} is : {sorted(categorical variables df[col].unique())}, \
          47
```

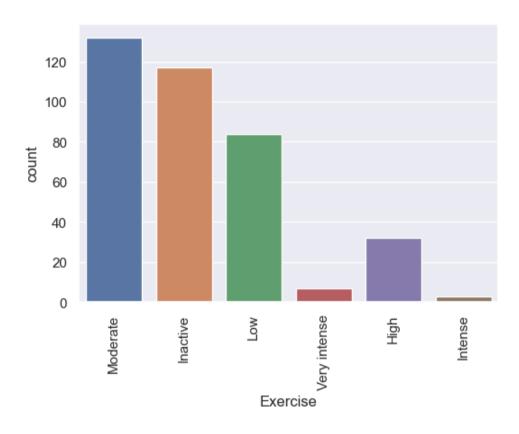
```
Unique values in Gender is : ['Female', 'Male'],
                                                                                                          Count : 2
Unique values in Profession is : ['Business', 'Business-sitting-job', 'Housewife', 'Moving-Job', 'Other', 'Sitting-Job'],
                                                                                                                                                                                                                                               Count: 6
Unique values in smoke is : ['No', 'Yes'],
                                                                                               Count : 2
Unique values in Exercise is : ['High', 'Inactive', 'Intense', 'Low', 'Moderate', 'Very intense'],
                                                                                                                                                                                                    Count: 6
Unique values in cereal is : ['More than three times', 'None', 'Once', 'Thrice', 'Twice'],
                                                                                                                                                                                      Count : 5
Unique values in salad is: ['1 bowl in lunch and/or dinner', '1/2 bowl in lunch and/or dinner', 'Everyday', 'Frequently', 'Never', 'Rarely'],
Count: 6
Unique values in vegetables is : ['Daily', 'Never', 'Once', 'Rarely', 'Twice', 'Weekly'],
                                                                                                                                                                                    Count: 6
Unique values in grains is : ['Brown-Rice', 'Brown-Rice-Millets', 'Brown-Rice-Millets', 'Brown-Rice-Wheat', 'Brown-Rice-Wheat-Millets',
'Millets', 'Polished-Rice', 'Polished-Rice-Brown-Rice-Wheat', 'Polished-Rice-Brown-Rice-Wheat-Millets', 'Polished-Rice-Maida', 'Polished-Rice-M
illets', 'Polished-Rice-Wheat', 'Polished-Rice-Wheat-Maida-Millets', 'Polished-Rice-Wheat-Millets', 'Rice-Wheat', 'Rice-Wheat-Brown-Rice', 'Ric
e-Wheat-Brown-Rice-Maida', 'Rice-Wheat-Maida', 'Rice-Wheat-Millets', 'Rice-Wheat-Millets-Maida', 'Wheat', 'Wheat-Brown-Rice', 'Wheat-Brown-Rice', 'Wheat-Brown-Rice', 'Wheat-Brown-Rice', 'Rice-Wheat-Millets', 'Rice-Wheat-Millets', 'Rice-Wheat-Millets', 'Rice-Wheat-Millets', 'Wheat', 'Wheat', 'Wheat-Brown-Rice', 'Wheat-Brown-R
-Millets', 'Wheat-Maida', 'Wheat-Millets', 'Wheat-Millets-Maida'],
                                                                                                                                          Count: 26
Unique values in sweets is : ['No', 'Yes'],
                                                                                                 Count : 2
Unique values in Sweets in a week is : ['Daily', 'Monthly', 'Never', 'Rarely', 'Weekly'],
                                                                                                                                                                                   Count : 5
Unique values in Refined Sugar is : ['No', 'Yes'],
                                                                                                              Count : 2
Unique values in Milk Products consumption is : ['No', 'Yes'],
                                                                                                                                   Count : 2
Unique values in Milk Quantity(ml/day) is : ['100-200', '200-400', '400-600', 'More than 600'],
                                                                                                                                                                                                Count: 4
Unique values in Pregnancy is : ['No', 'Not-Applicable', 'Yes'],
                                                                                                                                       Count: 3
Unique values in History of Diabetes is : ['No', 'Yes'],
                                                                                                                        Count : 2
Unique values in Anxiety is : ['No', 'Yes'],
                                                                                                   Count : 2
Unique values in Stress Workload is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                                                                                                      Count : 5
Unique values in Poor
family income is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                                                                   Count: 5
Unique values in Pressure of
 working is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                                                          Count : 5
Unique values in Frequent
travel is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                                                       Count: 5
```

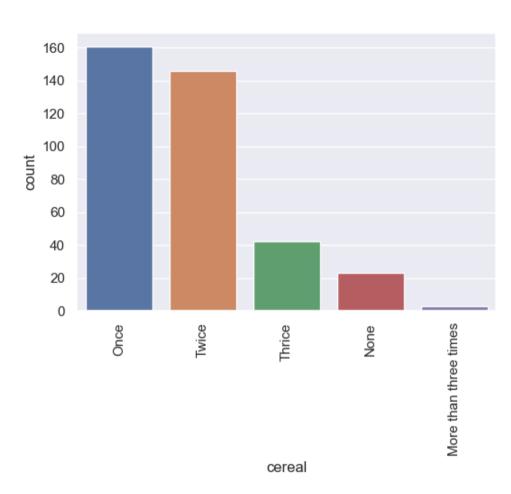
```
Unique values in Monotonus
 work is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                         Count : 5
Unique values in Poor and unplanned work is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                            Count : 5
Unique values in Lack of career development is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                               Count : 5
Unique values in Feeling of powerlessness is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                             Count : 5
Unique values in Lack of financial security is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                               Count : 5
Unique values in Unable to satisfy all stakeholders is : ['Average', 'High', 'Low', 'Very high', 'Very low'],
                                                                                                                       Count : 5
Unique values in High Blood Pressure is : ['No', 'Yes'],
                                                                  Count : 2
Unique values in Blood Sugar Fasting is : ['High', 'Low', 'Moderate'],
                                                                                Count : 3
Unique values in Blood Sugar Post Meal is : ['High', 'Low', 'Moderate'],
                                                                                  Count : 3
Unique values in HbA1c Glycated Haemoglobin is : ['High', 'Low', 'Moderate'],
                                                                                       Count: 3
Unique values in Class is : ['No', 'Yes'],
                                                    Count : 2
```

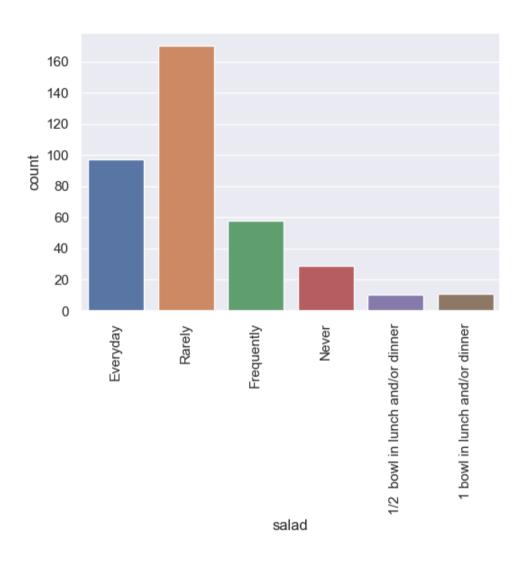


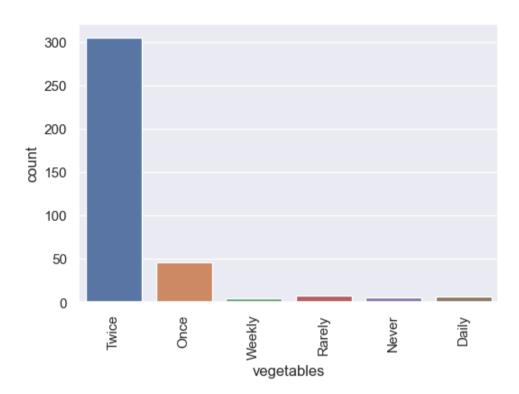


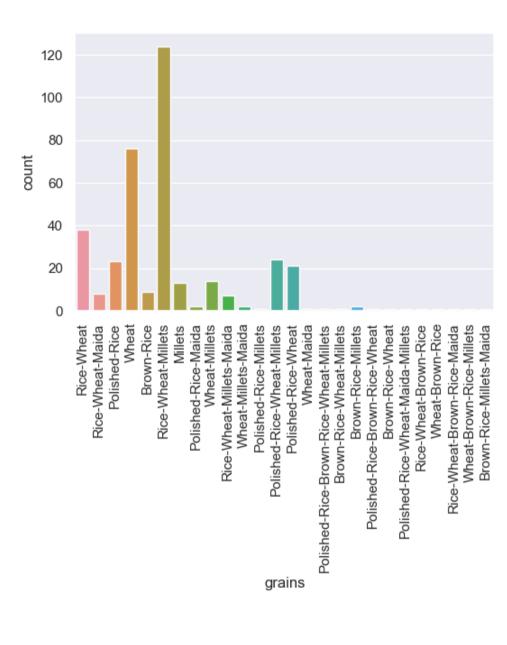


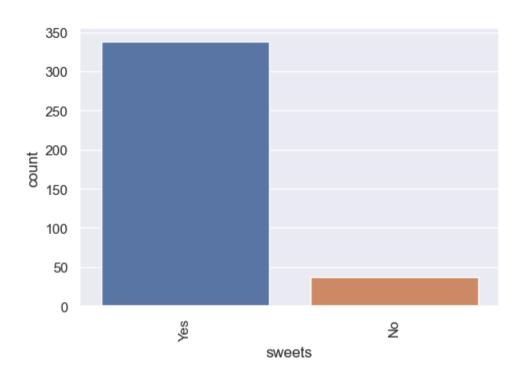


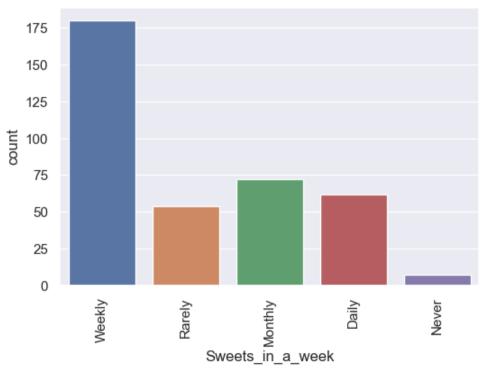


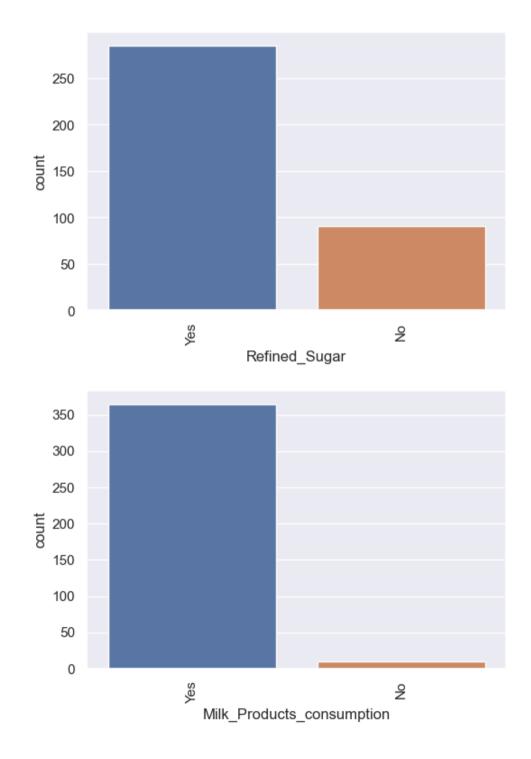


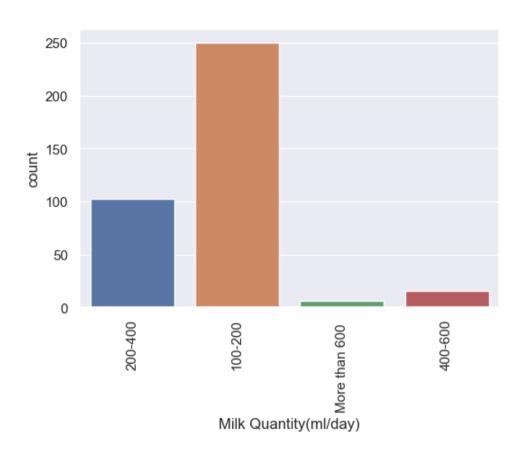


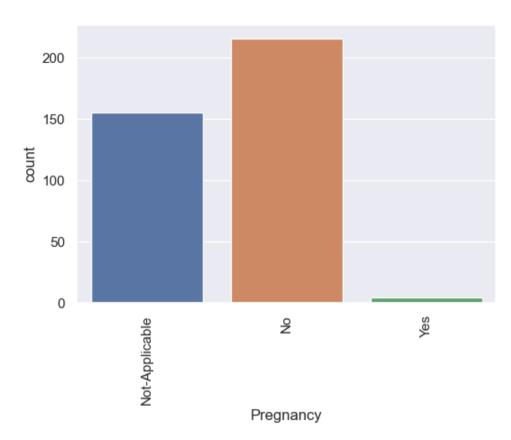


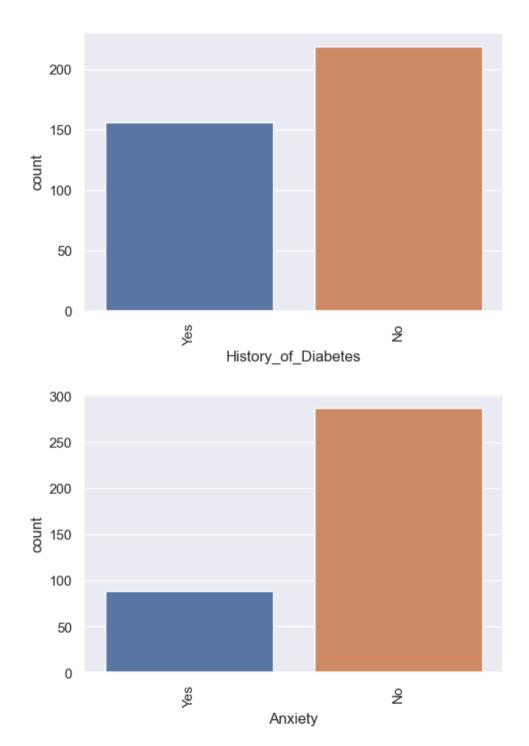


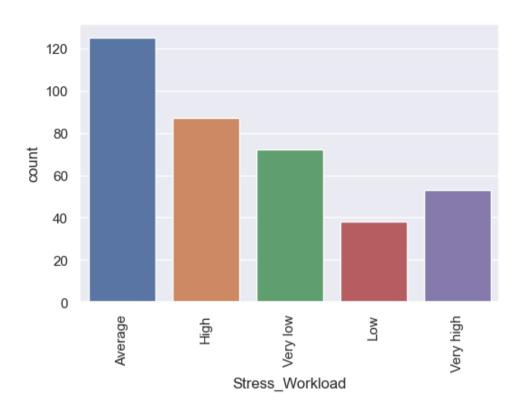


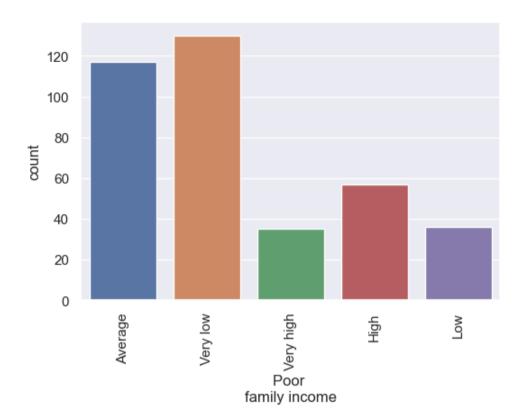


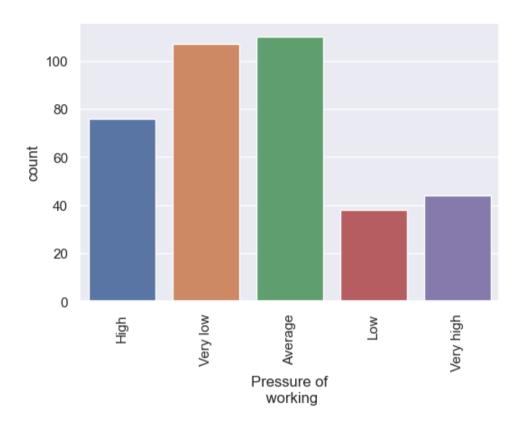


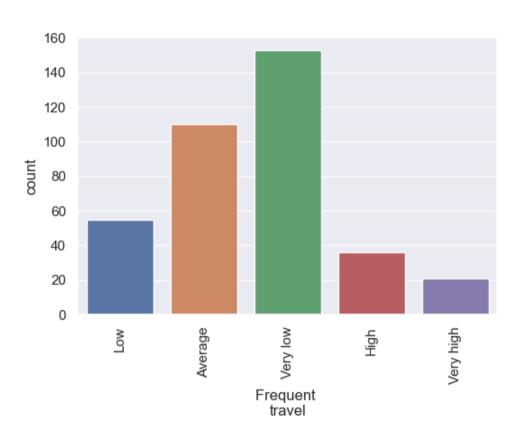


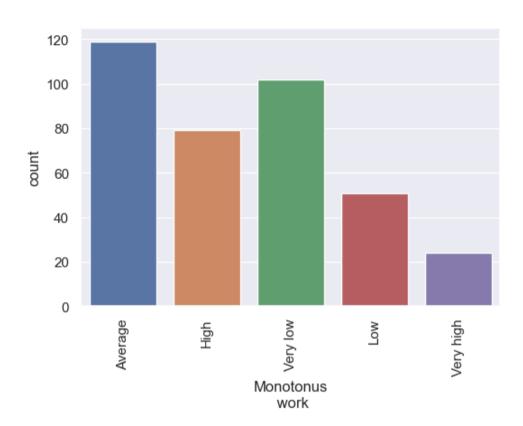


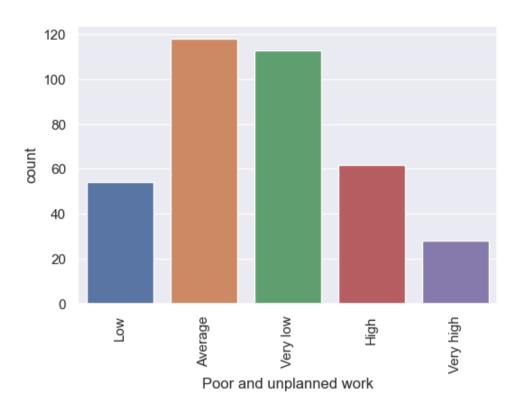


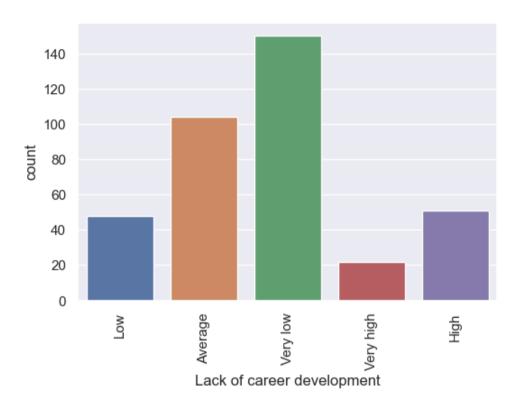


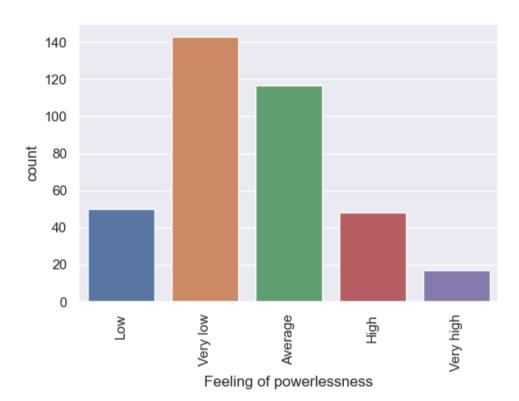


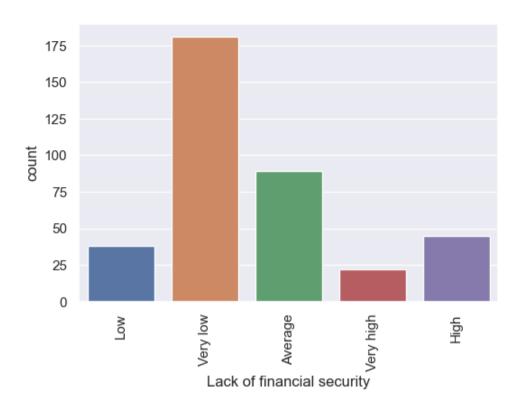


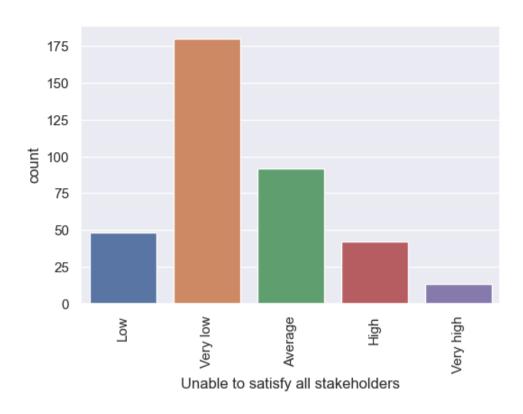


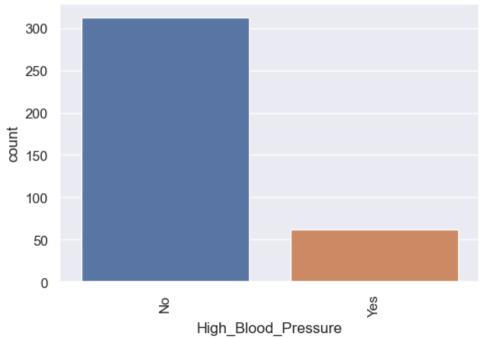


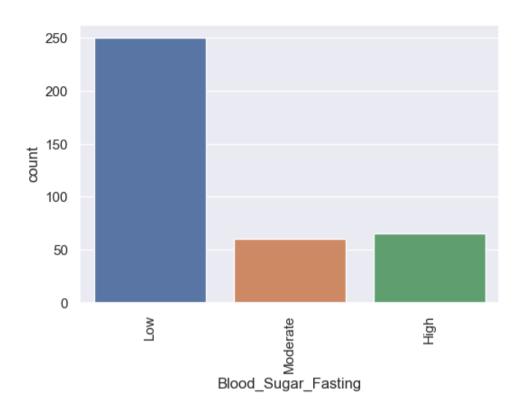


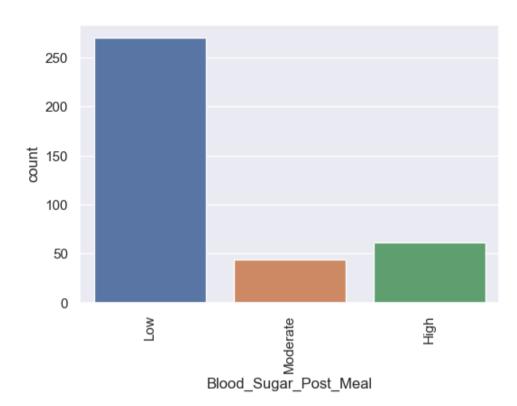


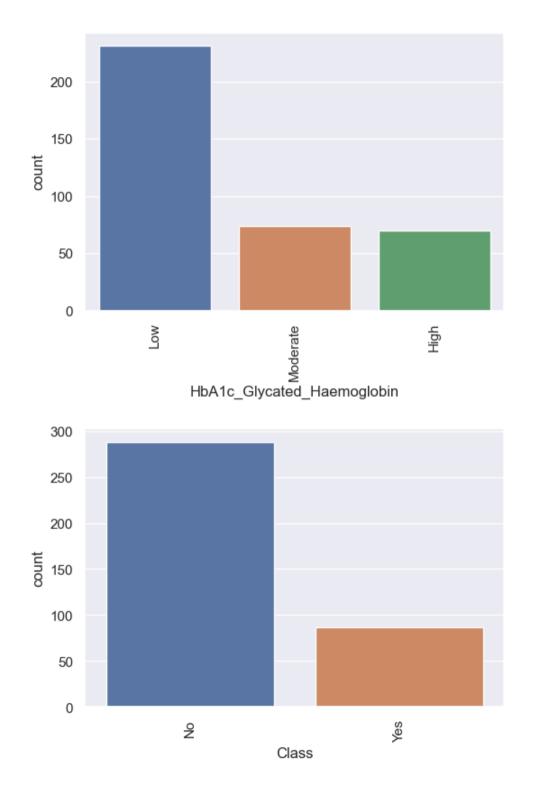


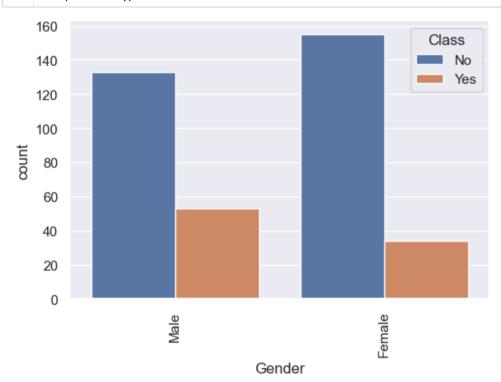


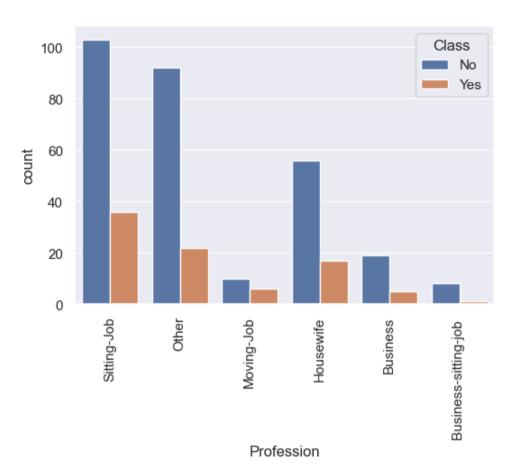


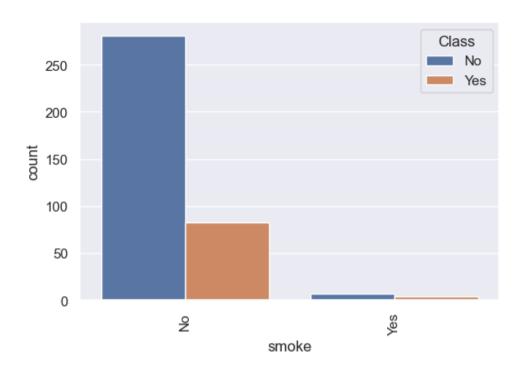


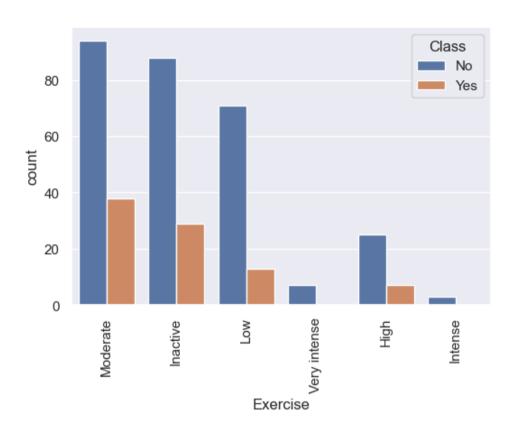


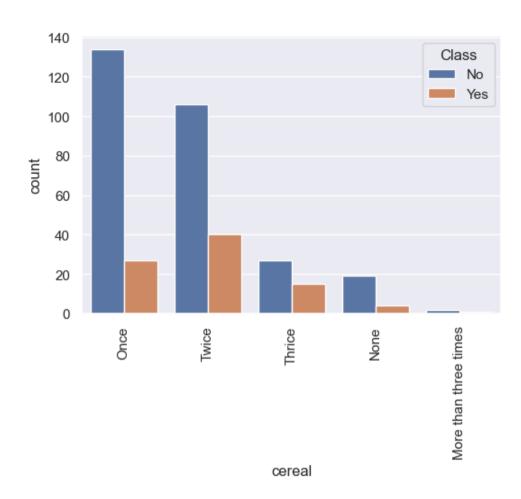


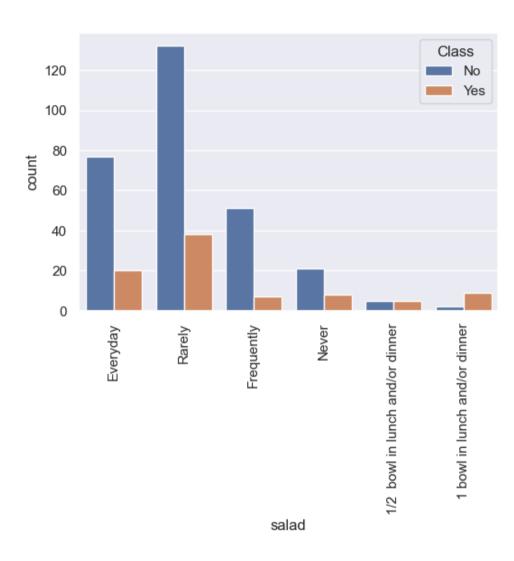


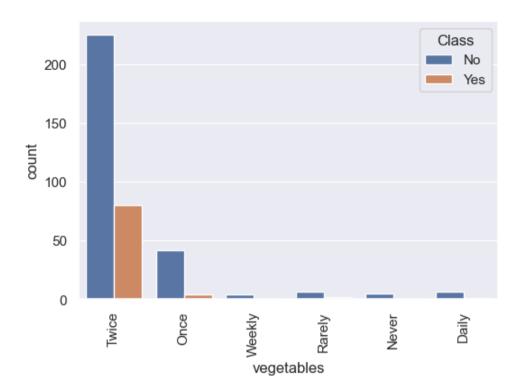


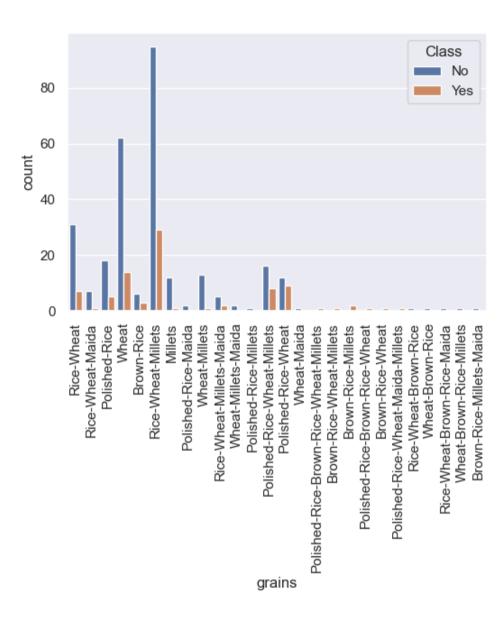


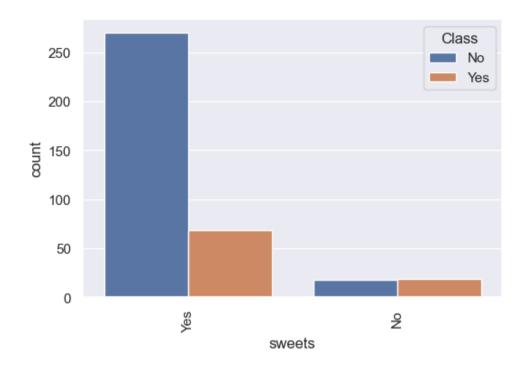


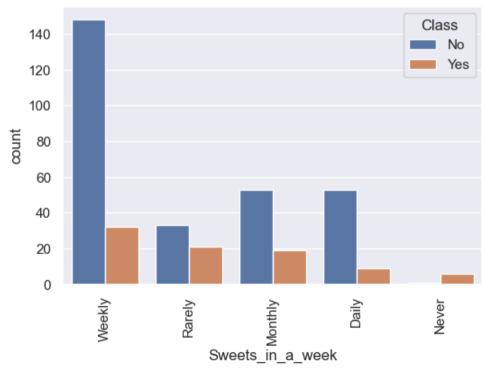


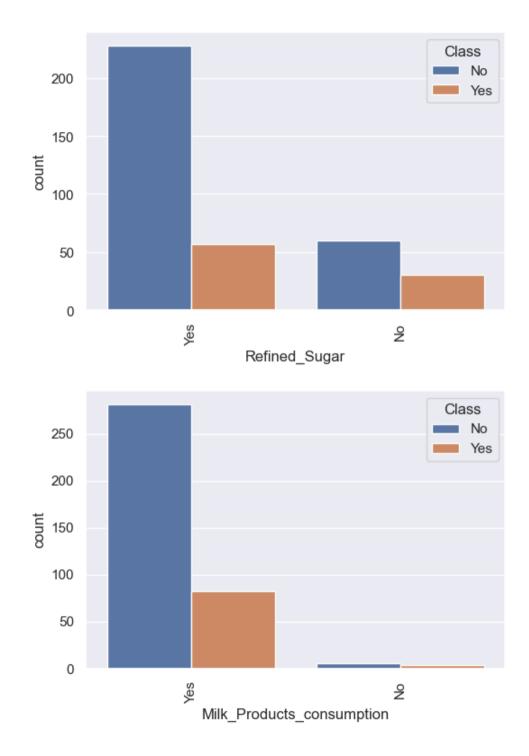


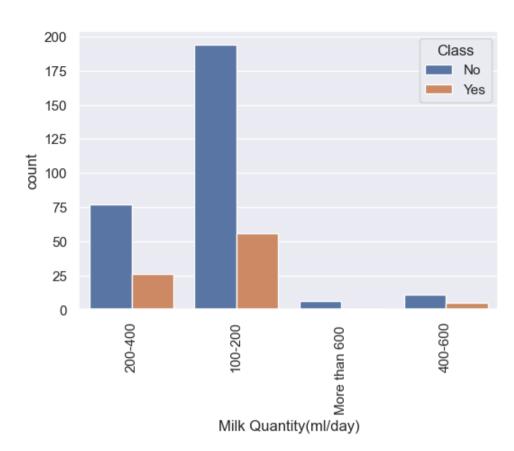


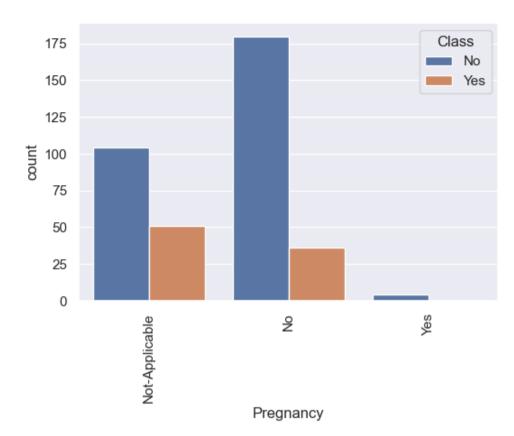


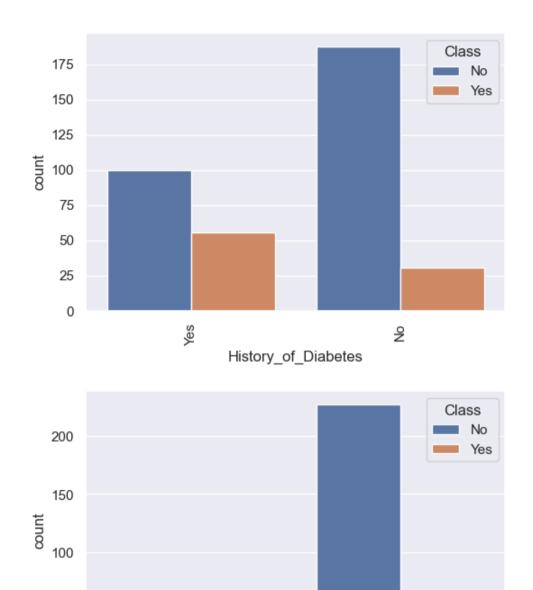












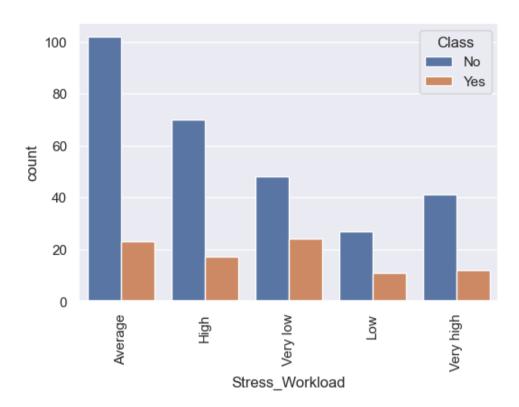
50

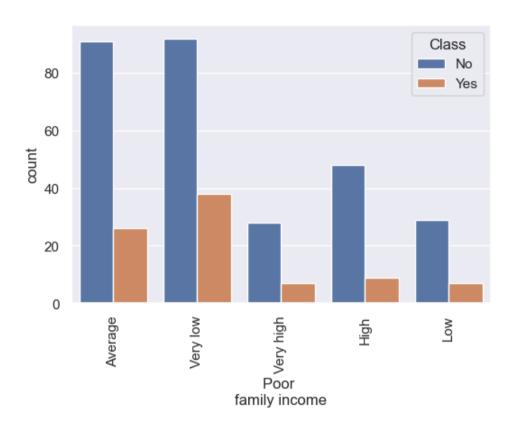
0

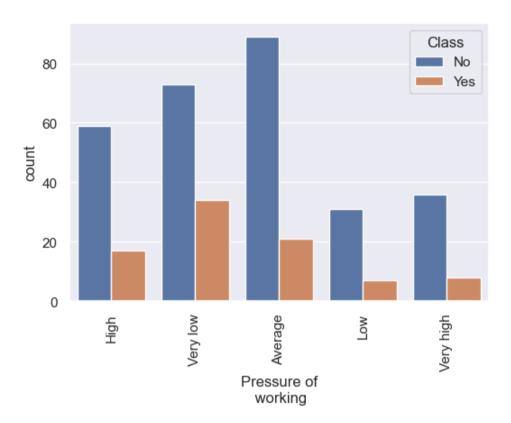
Yes

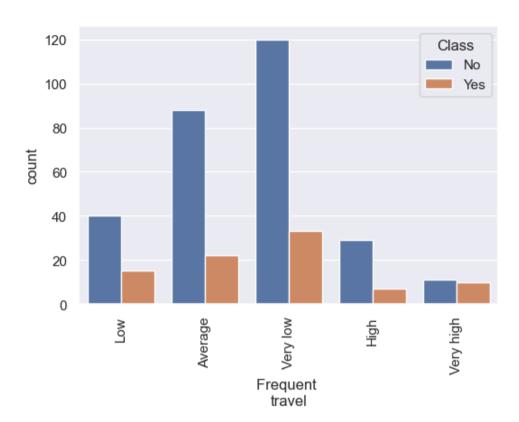
2

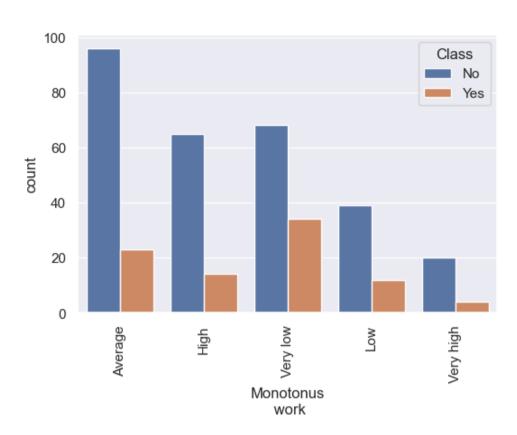
Anxiety

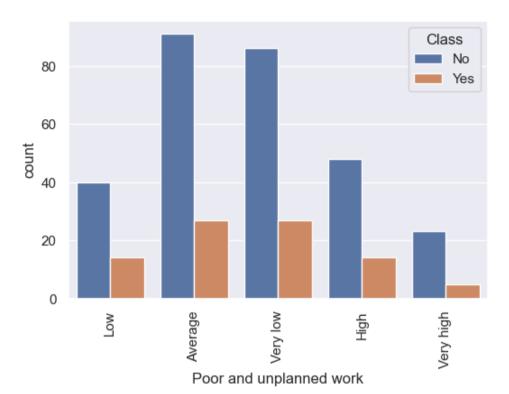


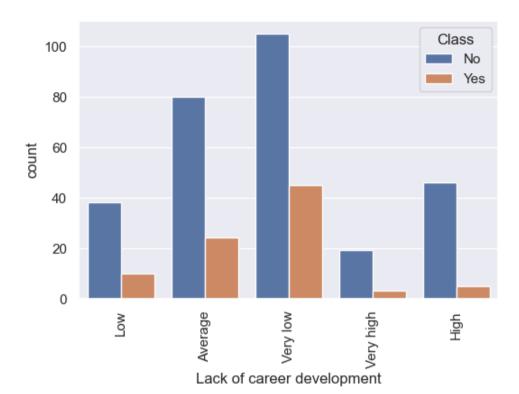


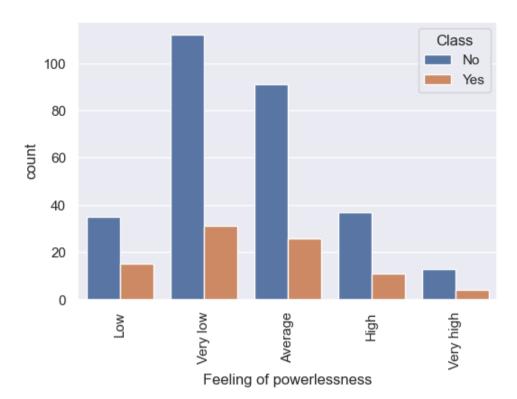


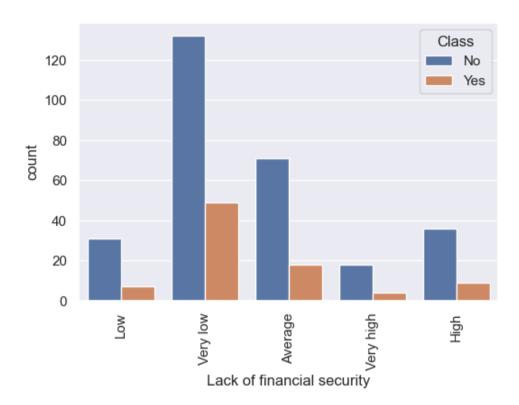


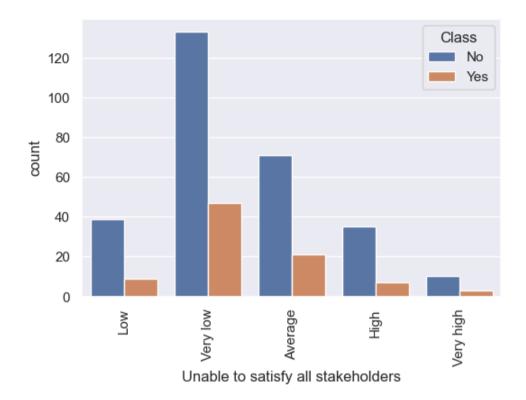


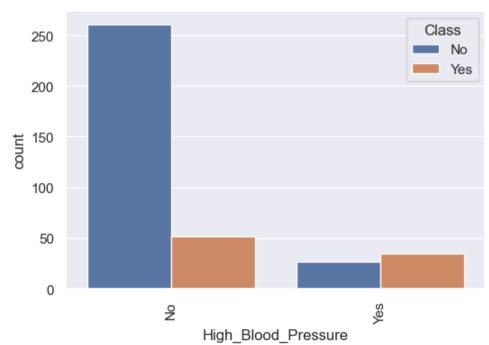


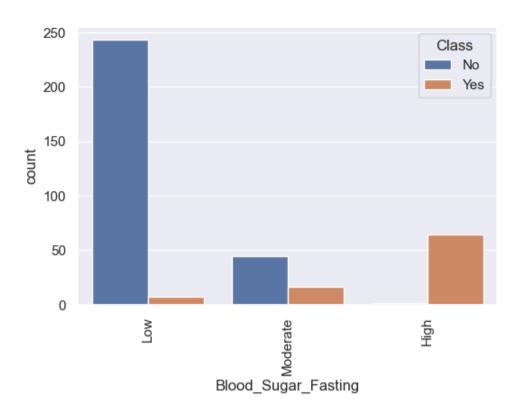


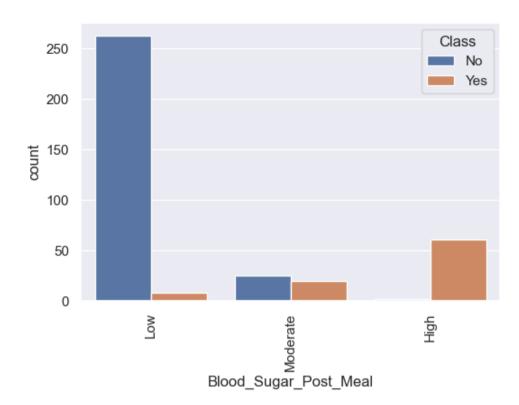


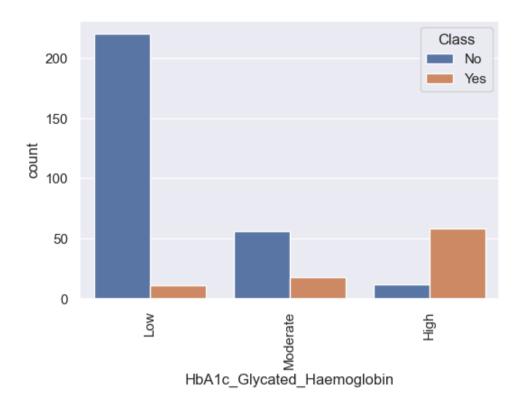












In [43]: 1 categorical\_variables\_df.head()

Out[43]:

	Gender	Profession	smoke	Exercise	cereal	salad	vegetables	grains	sweets	Sweets_in_a_week		Lack of career development	Feeling of powerlessness	Lack of financial security	Unable to satisfy all stakeholders	High_l
0	1	5	0	4	2	2	4	14	1	4	 2	2	2	2	2	
1	0	4	0	1	4	5	4	17	1	4	 0	0	2	2	2	
2	1	3	1	4	4	5	4	6	1	3	 4	4	4	4	4	
3	1	4	0	3	3	5	4	20	1	4	 0	0	4	0	0	
4	0	3	0	1	4	2	4	0	1	4	 4	3	0	0	2	

5 rows × 31 columns

In [44]: 1 dataset = pd.concat([numerical\_variables\_df, categorical\_variables\_df], axis=1)

2 dataset.head()

Out[44]:

Age(years)	Weight(kg)	Height(cm)	ВМІ	Gender	Profession	smoke	Exercise	cereal	salad	 •	Lack of career development	Feeling of powerlessness	Lack of financial security	Unable to satisfy all stakeholders	High_Blood
<b>0</b> 42	61.0	165	22.41	1	5	0	4	2	2	 2	2	2	2	2	
1 30	49.0	165	18.00	0	4	0	1	4	5	 0	0	2	2	2	
<b>2</b> 52	60.0	159	23.73	1	3	1	4	4	5	 4	4	4	4	4	
<b>3</b> 46	61.0	172	20.62	1	4	0	3	3	5	 0	0	4	0	0	
4 45	65.0	155	27.06	0	3	0	1	4	2	 4	3	0	0	2	

5 rows × 35 columns

In [45]:

1 | X, Y = dataset.drop(['Class'], axis = 1), dataset['Class']

2 # train\_test\_split 80/20

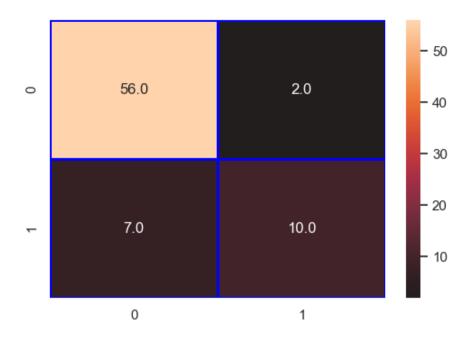
3 X\_train, X\_test, y\_train, y\_test = train\_test\_split(X,Y, test\_size = 0.2, random\_state = 42, stratify = Y)

```
1 # Model initialization
In [46]:
          2 lr Classifier = LogisticRegression()
          3 knn Classifier = KNeighborsClassifier()
          4 gnb Classifier = GaussianNB()
          5 dt Classifier = DecisionTreeClassifier()
          6 rf_Classifier = RandomForestClassifier()
          7 model list = [lr Classifier, knn Classifier, gnb Classifier, dt Classifier, rf Classifier]
          9 # Scaler initialization
         10 MinMax scaler = MinMaxScaler()
         11 Standard scaler = StandardScaler()
         12 MaxAbs_scaler = MaxAbsScaler()
         13 Robust scaler = RobustScaler()
         14 Quantile scaler = QuantileTransformer()
         15 Power scaler = PowerTransformer()
         16 Normalizer scaler = Normalizer()
         scaler list = [MinMax scaler, Standard scaler, MaxAbs scaler, Robust scaler,
                            Quantile_scaler, Power_scaler, Normalizer_scaler]
         18
```

```
In [47]:
           1 def run pipeline(X train, X test, y train, y test, scaler, classifier):
           2
                  # Model Information
           3
                  print(f"Modele name : {type(classifier). name }")
                  print(f"Scaler name : {type(scaler).__name__}")
           4
           5
           6
                  # process 1 : fit and transform X train data
           7
                  scaled X train = scaler.fit transform(X train)
           8
          9
                  # process 2 : train model
                  classifier.fit(scaled X train, y_train)
          10
          11
          12
                  # process 3 : transform X test data
         13
                  scaled X test = scaler.transform(X test)
         14
         15
                  # process 4 : test model
         16
                 y pred = classifier.predict(scaled X test)
         17
                  # print(y pred, le.inverse transform(y pred))
          18
         19
                  # process 5 : Perform k-fold cross-validation using cross val score
          20
                  scores = cross val score(classifier, scaled X train, y train, cv=10, scoring='accuracy')
          21
                  print(f"10 K-Fold Accuracy score : {np.round (scores,4)}")
          22
                  print(f"10 K-Fold Average Accuracy score : {round(np.average(scores)*100,2)} %")
          23
          24
                  # process 6 : model evalution
          25
                  print("Accuracy score:", round((accuracy score(y test, y pred))*100,2),'%')
          26
                  print("Loss:", round((1-accuracy score(y test, y pred))*100,2),'%')
                  print("Cohen kappa score:", round((cohen kappa score(y test, y pred))*100,2),'%')
          27
          28
                  print("Classification report:\n",metrics.classification report(y test, y pred))
          29
                  print("confusion matrix:\n", confusion matrix(y test, y pred))
          30
                  # plot confusion matrix
                 fig, ax = plt.subplots()
          31
          32
                  fig.set size inches(6,4) # WH
          33
                  sns.heatmap(confusion matrix(y test, y pred),
          34
                              annot=True,
          35
                              fmt=".1f",
          36
                              linewidths = 2,
          37
                              linecolor = "blue",
          38
                              center=0)
          39
                  plt.show()
          40
                  # process 7 : save model in pkl file
          41
          42
                  filename = f'Moduls\\{str(type(classifier). name )} {str(type(scaler). name )} 01 LS Disease Prediction.pkl'
          43
                  pickle.dump(classifier, open(filename, 'wb'))
          44
          45
                  # collect data for bar plot
          46
                  global plot data list
                  plot_data_list.append([str(type(classifier).__name__),
          47
                                         str(type(scaler). name ),
          48
```

```
In [48]:
           1 for model in model list:
                 for scaler in scaler list:
           3
                     run pipeline(X train, X test, y train, y test, scaler, model)
           4
           5
                 # plot data
           6
                  plot df = pd.DataFrame(plot data list, columns=['classifier', 'scaler', 'accuracy score'])
           7
                 plot df.to csv(f"Dataset\\{str(type(model). name )} accuracy score plot data 01 LS Disease Prediction.csv", index=False)
           8
                 sns.set(rc={'figure.figsize':(18.6)})
          9
                 ax = sns.barplot(data=plot df, x="classifier", y="accuracy score", hue="scaler")
         10
                  plt.title('Accuracy Score Plot')
         11
                  plt.xlabel('Classifier')
                 plt.ylabel('Accuracy Score')
         12
                 for i in ax.containers:
         13
                     ax.bar label(i,)
         14
         15
                 plt.show()
         16
         17
                 # empty list
         18
                 plot data list = []
                 print("\n\n")
         19
         20
          21 print("Done...")
```

```
Modele name : LogisticRegression
Scaler name : MinMaxScaler
10 K-Fold Accuracy score : [0.9667 0.9
                                          0.9667 0.8667 0.8667 0.8667 0.8667 0.9
                                                                                    0.8667 0.8667]
10 K-Fold Average Accuracy score: 89.33 %
Accuracy score: 88.0 %
Loss: 12.0 %
Cohen_kappa_score: 61.8 %
Classification report:
               precision
                            recall f1-score
                                             support
           0
                             0.97
                                                   58
                   0.89
                                       0.93
           1
                   0.83
                             0.59
                                       0.69
                                                   17
    accuracy
                                       0.88
                                                  75
                                                   75
   macro avg
                   0.86
                             0.78
                                       0.81
                                                   75
                   0.88
                             0.88
weighted avg
                                       0.87
confusion matrix:
 [[56 2]
 [ 7 10]]
```



Modele name : LogisticRegression Scaler name : StandardScaler

10 K-Fold Accuracy\_score : [0.9667 0.8667 0.8667 0.8667 0.9 0.8333 0.9 0.7667 0.8667]

10 K-Fold Average Accuracy\_score : 88.0 %

Accuracy score: 88.0 %

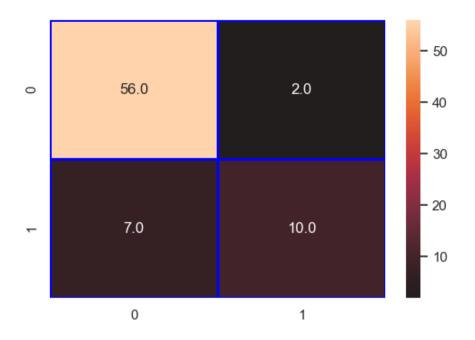
Loss: 12.0 %

Cohen\_kappa\_score: 61.8 %
Classification report:

precision recall f1-score support 0.89 0.97 0.93 0 58 0.83 0.69 1 0.59 17 accuracy 0.88 75 macro avg 0.86 0.81 75 0.78 weighted avg 0.88 0.88 75 0.87

confusion\_matrix:

[[56 2]



Modele name : LogisticRegression

Scaler name : MaxAbsScaler

10 K-Fold Accuracy\_score : [0.9333 0.9 0.9 0.8667 0.8667 0.8667 0.8667 0.8667 0.8333]

10 K-Fold Average Accuracy\_score : 88.0 %

Accuracy\_score: 88.0 %

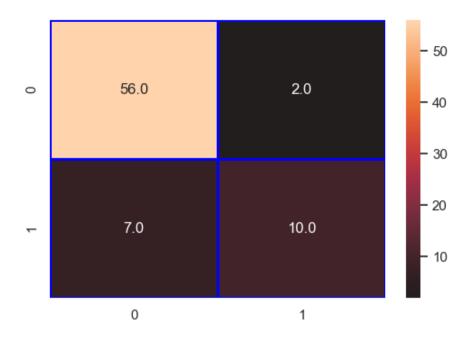
Loss: 12.0 %

Cohen\_kappa\_score: 61.8 %
Classification\_report:

	precision	recall	f1-score	support
0	0.89	0.97	0.93	58
1	0.83	0.59	0.69	17
accuracy			0.88	75
macro avg	0.86	0.78	0.81	75
weighted avg	0.88	0.88	0.87	75

confusion\_matrix:

[[56 2]



Modele name : LogisticRegression

Scaler name : RobustScaler

10 K-Fold Accuracy\_score : [0.9667 0.9333 0.9 0.9 0.8667 0.9 0.8333 0.9 0.8 0.8667]

10 K-Fold Average Accuracy\_score : 88.67 %

Accuracy\_score: 88.0 %

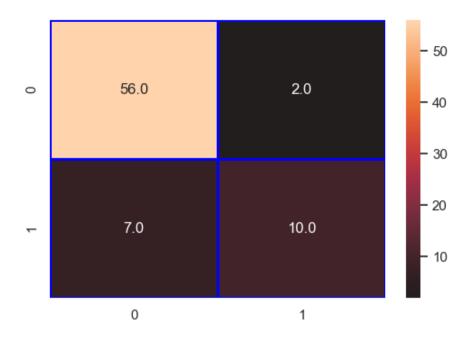
Loss: 12.0 %

Cohen\_kappa\_score: 61.8 %
Classification\_report:

		precision	recall	f1-score	support
	0	0.89	0.97	0.93	58
	1	0.83	0.59	0.69	17
accur	racy			0.88	75
macro	avg	0.86	0.78	0.81	75
weighted	avg	0.88	0.88	0.87	75

confusion\_matrix:

[[56 2]



Modele name : LogisticRegression Scaler name : QuantileTransformer

10 K-Fold Accuracy\_score : [0.9 0.9 0.9 0.9 0.8667 0.8667 0.8667 0.9 0.8667 0.8333]

10 K-Fold Average Accuracy\_score : 88.0 %

Accuracy\_score: 89.33 %

Loss: 10.67 %

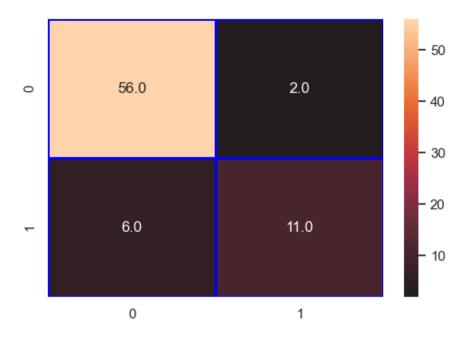
Cohen\_kappa\_score: 66.81 %
Classification\_report:

	precision	recall	f1-score	support
0	0.90	0.97	0.93	58
1	0.85	0.65	0.73	17
accuracy			0.89	75
macro avg	0.87	0.81	0.83	75
weighted avg	0.89	0.89	0.89	75

confusion\_matrix:

[[56 2]

[ 6 11]]



Modele name : LogisticRegression Scaler name : PowerTransformer

10 K-Fold Accuracy\_score : [0.9667 0.9667 0.9 0.8667 0.8333 0.9 0.8667 0.9 0.8667 0.8667]

10 K-Fold Average Accuracy\_score : 89.33 %

Accuracy\_score: 88.0 %

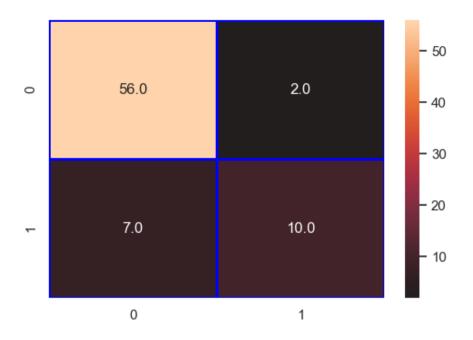
Loss: 12.0 %

Cohen\_kappa\_score: 61.8 %
Classification\_report:

	precision	recall	f1-score	support
0	0.89	0.97	0.93	58
1	0.83	0.59	0.69	17
accuracy			0.88	75
macro avg	0.86	0.78	0.81	75
weighted avg	0.88	0.88	0.87	75

confusion\_matrix:

[[56 2]



Modele name : LogisticRegression

Scaler name : Normalizer

10 K-Fold Accuracy\_score : [0.7667 0.7667 0.7667 0.7667 0.7667 0.7667 0.7667 0.7667 0.7667]

10 K-Fold Average Accuracy\_score : 76.67 %

Accuracy\_score: 77.33 %

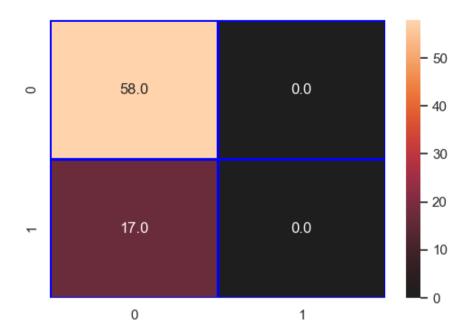
Loss: 22.67 %

Cohen\_kappa\_score: 0.0 %
Classification\_report:

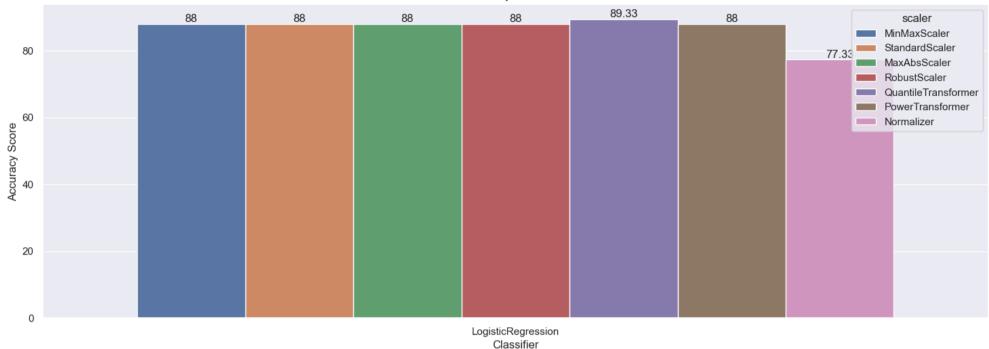
	precision	recall	f1-score	support
0	0.77	1.00	0.87	58
1	0.00	0.00	0.00	17
accuracy			0.77	75
macro avg	0.39	0.50	0.44	75
weighted avg	0.60	0.77	0.67	75

confusion\_matrix:

[[58 0] [17 0]]



## Accuracy Score Plot



Modele name : KNeighborsClassifier

Scaler name : MinMaxScaler

10 K-Fold Average Accuracy\_score : 85.67 %

Accuracy\_score: 88.0 %

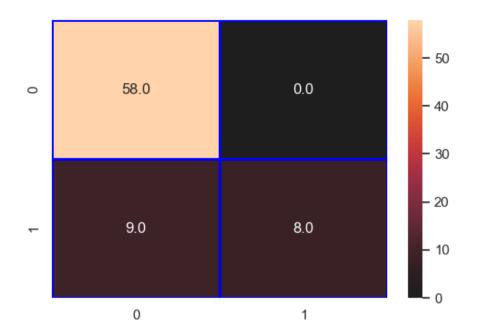
Loss: 12.0 %

Cohen\_kappa\_score: 57.89 %
Classification report:

		precision	recall	f1-score	support
	0	0.87	1.00	0.93	58
	1	1.00	0.47	0.64	17
accura	асу			0.88	75
macro a	avg	0.93	0.74	0.78	75
weighted a	avg	0.90	0.88	0.86	75

confusion\_matrix:

[[58 0] [ 9 8]]



Modele name : KNeighborsClassifier

Scaler name : StandardScaler

10 K-Fold Accuracy\_score : [0.8333 0.9333 0.9 0.8333 0.8667 0.8667 0.9 0.9 0.9333 0.8667]

10 K-Fold Average Accuracy\_score : 88.33 %

Accuracy\_score: 89.33 %

Loss: 10.67 %

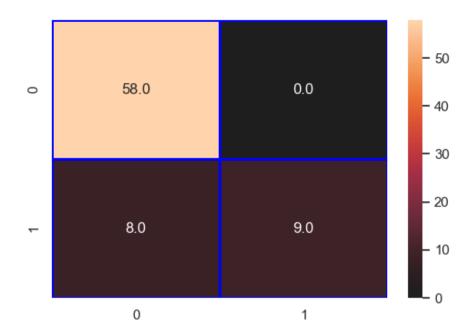
Cohen\_kappa\_score: 63.5 %
Classification report:

	precision	recall	f1-score	support
0	0.88	1.00	0.94	58
1	1.00	0.53	0.69	17
accuracy			0.89	75
macro avg	0.94	0.76	0.81	75
weighted avg	0.91	0.89	0.88	75

confusion\_matrix:

[[58 0]

[ 8 9]]



Modele name : KNeighborsClassifier

Scaler name : MaxAbsScaler

10 K-Fold Average Accuracy\_score : 85.67 %

Accuracy score: 88.0 %

Loss: 12.0 %

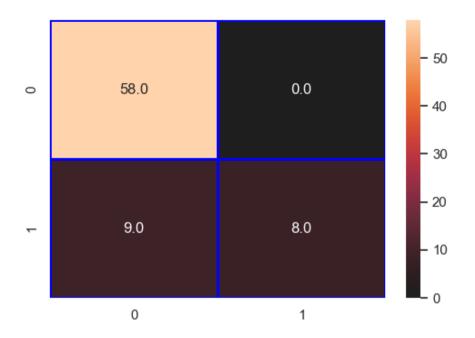
Cohen\_kappa\_score: 57.89 %
Classification report:

precision recall f1-score support 0.87 0.93 0 1.00 58 1.00 0.64 1 0.47 17 accuracy 0.88 75 macro avg 0.93 0.78 75 0.74 weighted avg 0.90 0.88 75 0.86

confusion\_matrix:

[[58 0]

[ 9 8]]



Modele name : KNeighborsClassifier

Scaler name : RobustScaler

10 K-Fold Average Accuracy\_score : 88.0 %

Accuracy\_score: 90.67 %

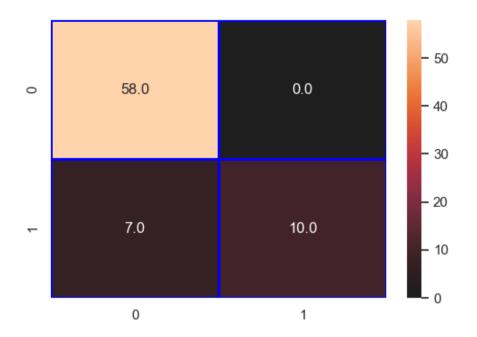
Loss: 9.33 %

Cohen\_kappa\_score: 68.84 %
Classification\_report:

	precision	recall	f1-score	support
0	0.89	1.00	0.94	58
1	1.00	0.59	0.74	17
accuracy			0.91	75
macro avg	0.95	0.79	0.84	75
weighted avg	0.92	0.91	0.90	75

confusion\_matrix:

[[58 0]



Modele name : KNeighborsClassifier Scaler name : QuantileTransformer

10 K-Fold Accuracy\_score : [0.8 0.9 0.9 0.8333 0.8333 0.8333 0.8333 0.8333 0.8333 0.8667]

10 K-Fold Average Accuracy\_score : 83.67 %

Accuracy\_score: 89.33 %

Loss: 10.67 %

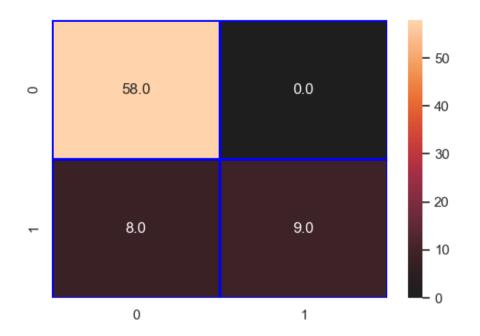
Cohen\_kappa\_score: 63.5 %
Classification report:

	precision	recall	f1-score	support
0	0.88	1.00	0.94	58
1	1.00	0.53	0.69	17
accuracy			0.89	75
macro avg	0.94	0.76	0.81	75
weighted avg	0.91	0.89	0.88	75

confusion\_matrix:

[[58 0]

[ 8 9]]



Modele name : KNeighborsClassifier Scaler name : PowerTransformer

10 K-Fold Accuracy\_score : [0.8333 0.9333 0.9333 0.8667 0.8667 0.8667 0.9 0.9 0.9 0.8667]

10 K-Fold Average Accuracy\_score : 88.67 %

Accuracy\_score: 89.33 %

Loss: 10.67 %

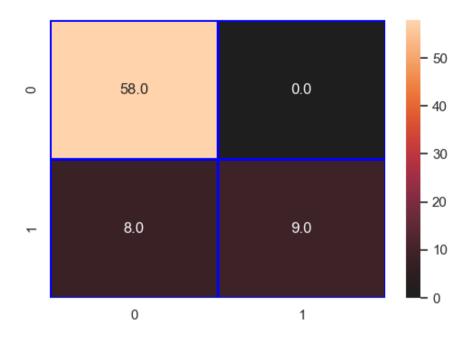
Cohen\_kappa\_score: 63.5 %
Classification report:

	precision	recall	f1-score	support
0	0.88	1.00	0.94	58
1	1.00	0.53	0.69	17
accuracy			0.89	75
macro avg	0.94	0.76	0.81	75
weighted avg	0.91	0.89	0.88	75

confusion\_matrix:

[[58 0]

[ 8 9]]



Modele name : KNeighborsClassifier

Scaler name : Normalizer

10 K-Fold Average Accuracy\_score : 77.67 %

Accuracy\_score: 76.0 %

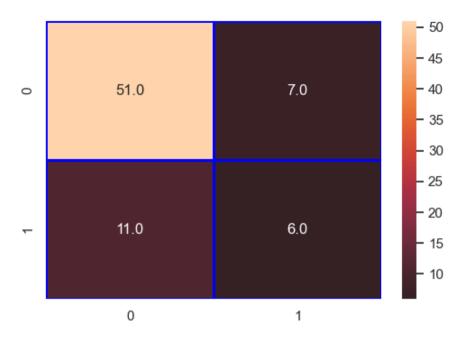
Loss: 24.0 %

Cohen\_kappa\_score: 25.33 %
Classification report:

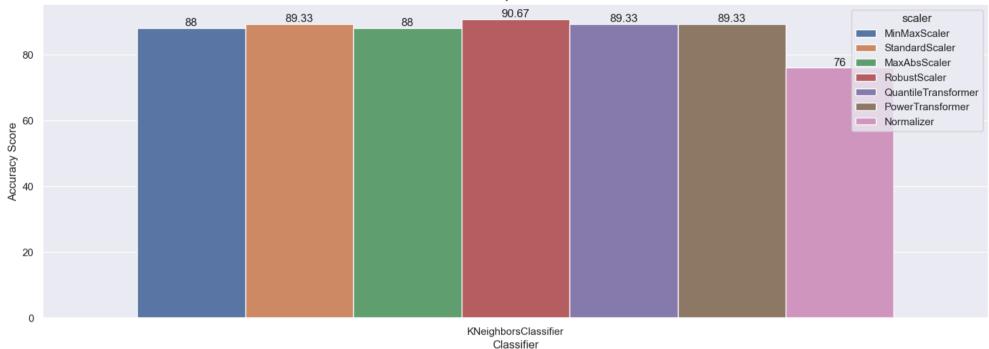
				<b>6</b> -	_
		precision	recall	f1-score	support
		•			
	0	0.82	0.88	0.85	58
	1	0.46	0.35	0.40	17
accur	racy			0.76	75
macro	avg	0.64	0.62	0.63	75
weighted	avg	0.74	0.76	0.75	75

confusion\_matrix:

[[51 7] [11 6]]



## Accuracy Score Plot



Modele name : GaussianNB Scaler name : MinMaxScaler

10 K-Fold Average Accuracy\_score : 89.33 %

Accuracy\_score: 84.0 %

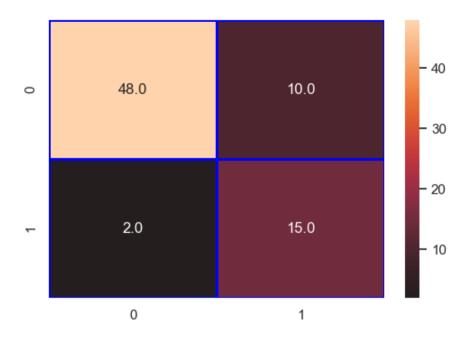
Loss: 16.0 %

Cohen\_kappa\_score: 60.87 %
Classification\_report:

	precision	recall	f1-score	support
6	0.96	0.83	0.89	58
1	0.60	0.88	0.71	17
accuracy	,		0.84	75
macro avg	0.78	0.85	0.80	75
weighted avg	0.88	0.84	0.85	75

confusion\_matrix:

[[48 10] [ 2 15]]



Modele name : GaussianNB Scaler name : StandardScaler

10 K-Fold Average Accuracy\_score : 89.33 %

Accuracy\_score: 84.0 %

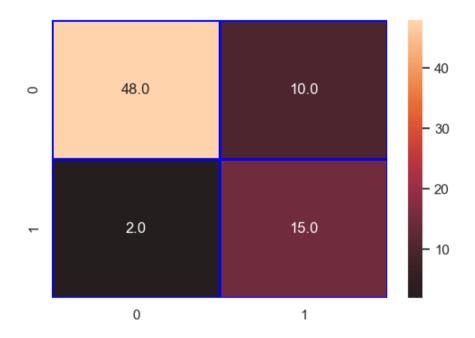
Loss: 16.0 %

Cohen\_kappa\_score: 60.87 %
Classification report:

	precision	recall	f1-score	support
0	0.96	0.83	0.89	58
1	0.60	0.88	0.71	17
accuracy			0.84	75
macro avg	0.78	0.85	0.80	75
weighted avg	0.88	0.84	0.85	75

confusion\_matrix:

[[48 10]



Modele name : GaussianNB Scaler name : MaxAbsScaler

10 K-Fold Average Accuracy\_score : 89.33 %

Accuracy\_score: 84.0 %

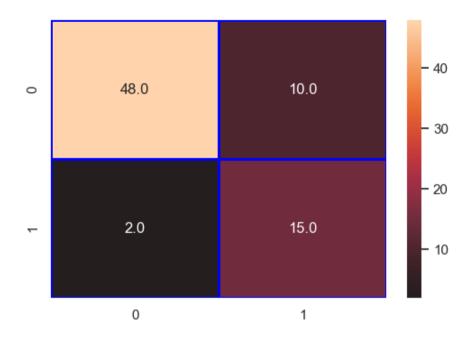
Loss: 16.0 %

Cohen\_kappa\_score: 60.87 %
Classification\_report:

	precision	recall	f1-score	support
0	0.96	0.83	0.89	58
1	0.60	0.88	0.71	17
accuracy			0.84	75
macro avg	0.78	0.85	0.80	75
weighted avg	0.88	0.84	0.85	75

confusion\_matrix:

[[48 10]



Modele name : GaussianNB Scaler name : RobustScaler

10 K-Fold Average Accuracy\_score : 89.33 %

Accuracy\_score: 84.0 %

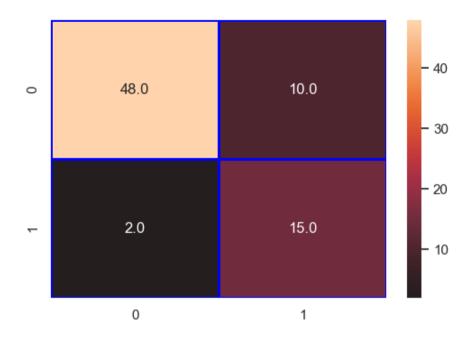
Loss: 16.0 %

Cohen\_kappa\_score: 60.87 %
Classification report:

	precision	recall	f1-score	support
0	0.96	0.83	0.89	58
1	0.60	0.88	0.71	17
accuracy			0.84	75
macro avg	0.78	0.85	0.80	75
weighted avg	0.88	0.84	0.85	75

confusion\_matrix:

[[48 10]



Modele name : GaussianNB

Scaler name : QuantileTransformer

10 K-Fold Average Accuracy\_score : 88.67 %

Accuracy\_score: 88.0 %

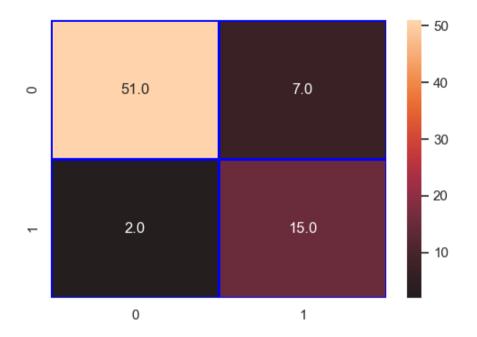
Loss: 12.0 %

Cohen\_kappa\_score: 68.99 %
Classification report:

	precision	recall	f1-score	support
0	0.96	0.88	0.92	58
1	0.68	0.88	0.77	17
accuracy			0.88	75
macro avg	0.82	0.88	0.84	75
weighted avg	0.90	0.88	0.88	75

confusion\_matrix:

[[51 7]



Modele name : GaussianNB

Scaler name : PowerTransformer

10 K-Fold Average Accuracy\_score : 89.0 %

Accuracy\_score: 88.0 %

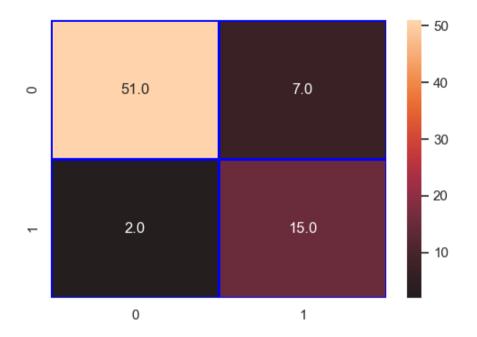
Loss: 12.0 %

Cohen\_kappa\_score: 68.99 %
Classification report:

precision recall f1-score support 0.96 0.88 0.92 0 58 0.68 0.77 1 0.88 17 accuracy 0.88 75 macro avg 0.82 0.84 75 0.88 weighted avg 0.90 0.88 0.88 75

confusion\_matrix:

[[51 7]



Modele name : GaussianNB Scaler name : Normalizer

10 K-Fold Average Accuracy\_score : 87.67 %

Accuracy\_score: 85.33 %

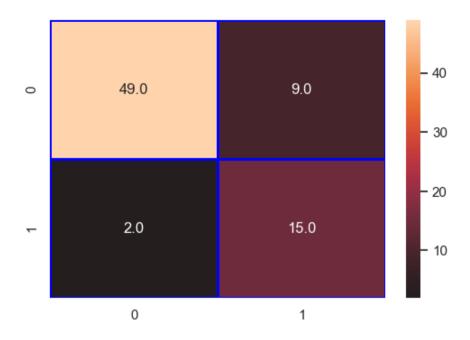
Loss: 14.67 %

Cohen\_kappa\_score: 63.48 %
Classification\_report:

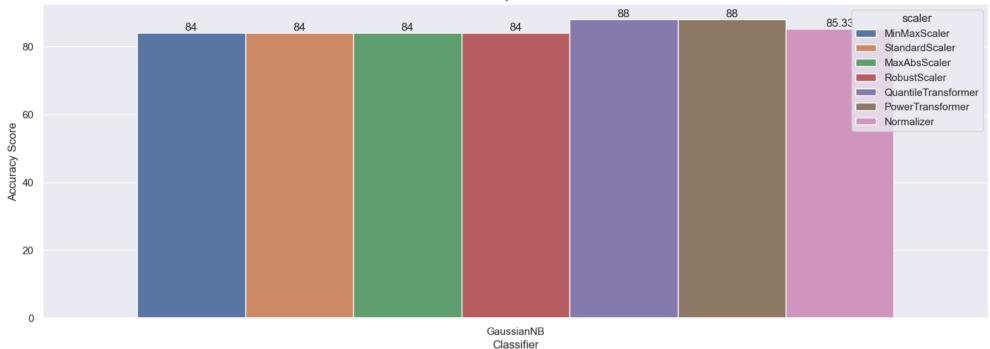
	precision	recall	f1-score	support
0	0.96	0.84	0.90	58
1	0.62	0.88	0.73	17
accuracy			0.85	75
macro avg	0.79	0.86	0.82	75
weighted avg	0.88	0.85	0.86	75

confusion\_matrix:

[[49 9]



## Accuracy Score Plot



Modele name : DecisionTreeClassifier

Scaler name : MinMaxScaler

10 K-Fold Accuracy\_score : [0.9667 0.9 0.9667 0.9 0.8667 1. 0.9 0.9 0.9333 0.9 ]

10 K-Fold Average Accuracy\_score : 92.33 %

Accuracy\_score: 92.0 %

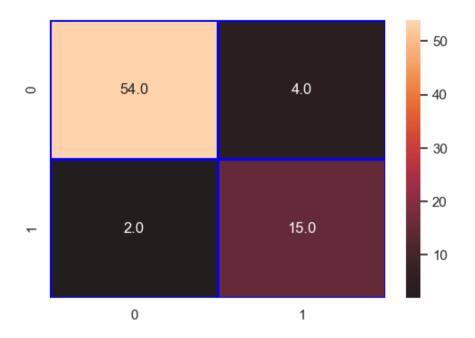
Loss: 8.0 %

Cohen\_kappa\_score: 78.09 %
Classification report:

		precision	recall	f1-score	support
	0	0.96	0.93	0.95	58
	1	0.79	0.88	0.83	17
accur	racy			0.92	75
macro	avg	0.88	0.91	0.89	75
weighted	avg	0.92	0.92	0.92	75

confusion\_matrix:

[[54 4] [ 2 15]]



Modele name : DecisionTreeClassifier

Scaler name : StandardScaler

10 K-Fold Accuracy\_score : [0.9333 0.9 0.9667 0.9 0.8667 0.9667 0.9 0.9667 0.9 ]

10 K-Fold Average Accuracy\_score : 92.0 %

Accuracy\_score: 94.67 %

Loss: 5.33 %

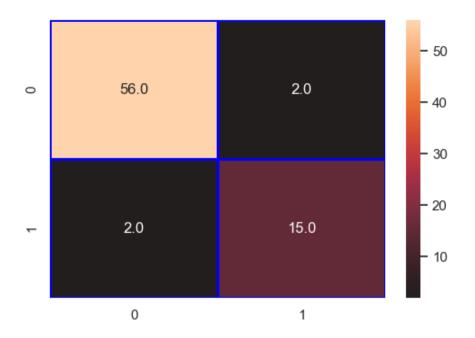
Cohen\_kappa\_score: 84.79 %
Classification report:

	precision	recall	f1-score	support
0	0.97	0.97	0.97	58
1	0.88	0.88	0.88	17
accuracy			0.95	75
macro avg	0.92	0.92	0.92	75
weighted avg	0.95	0.95	0.95	75

confusion\_matrix:

[[56 2]

[ 2 15]]



Modele name : DecisionTreeClassifier

Scaler name : MaxAbsScaler

10 K-Fold Accuracy\_score : [0.9333 0.9 0.9667 0.9 0.9 0.9333 0.9 0.8667 0.9333 0.9 ]

10 K-Fold Average Accuracy\_score : 91.33 %

Accuracy\_score: 93.33 %

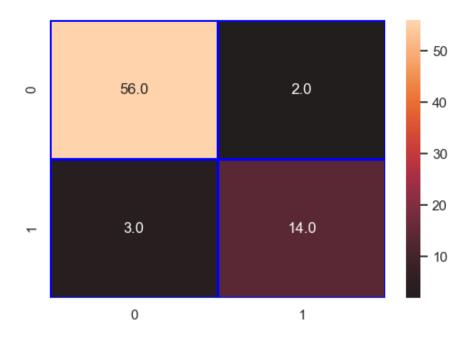
Loss: 6.67 %

Cohen\_kappa\_score: 80.58 %
Classification report:

precision recall f1-score support 0.95 0.97 0.96 0 58 0.88 0.85 1 0.82 17 accuracy 0.93 75 macro avg 0.91 0.90 75 0.89 weighted avg 0.93 0.93 75 0.93

confusion\_matrix:

[[56 2]



Modele name : DecisionTreeClassifier

Scaler name : RobustScaler

10 K-Fold Accuracy\_score : [0.9333 0.9 0.9667 0.9 0.9 0.9333 0.9 0.9 0.9 ]

10 K-Fold Average Accuracy\_score : 91.33 %

Accuracy\_score: 90.67 %

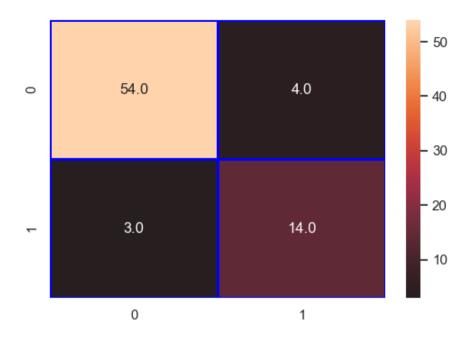
Loss: 9.33 %

Cohen\_kappa\_score: 73.92 %
Classification report:

		precision	recall	f1-score	support
	0	0.95	0.93	0.94	58
	1	0.78	0.82	0.80	17
accur	racy			0.91	75
macro	avg	0.86	0.88	0.87	75
weighted	avg	0.91	0.91	0.91	75

confusion\_matrix:

[[54 4]



Modele name : DecisionTreeClassifier Scaler name : QuantileTransformer

10 K-Fold Accuracy\_score : [0.9667 0.8667 0.9667 0.9 0.8333 1. 0.9 0.9 0.9667 0.9 ]

10 K-Fold Average Accuracy\_score : 92.0 %

Accuracy\_score: 92.0 %

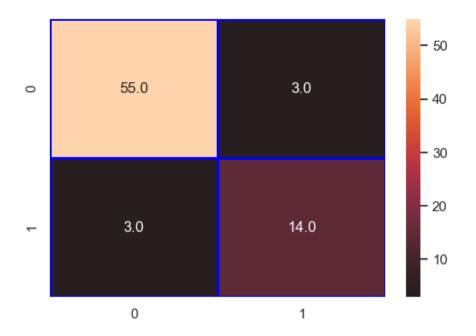
Loss: 8.0 %

Cohen\_kappa\_score: 77.18 %
Classification report:

	precision	recall	f1-score	support
0	0.95	0.95	0.95	58
1	0.82	0.82	0.82	17
accuracy			0.92	75
macro avg	0.89	0.89	0.89	75
weighted avg	0.92	0.92	0.92	75

confusion\_matrix:

[[55 3]



 ${\tt Modele\ name\ :\ DecisionTreeClassifier}$ 

Scaler name : PowerTransformer

10 K-Fold Accuracy\_score : [0.9667 0.9333 0.9667 0.9 0.9 0.9333 0.9 0.9 0.9333 0.9 ]

10 K-Fold Average Accuracy\_score : 92.33 %

Accuracy\_score: 92.0 %

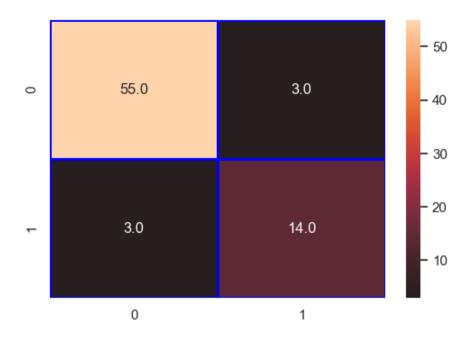
Loss: 8.0 %

Cohen\_kappa\_score: 77.18 %
Classification report:

	precision	recall	f1-score	support
0	0.95	0.95	0.95	58
1	0.82	0.82	0.82	17
accuracy			0.92	75
macro avg	0.89	0.89	0.89	75
weighted avg	0.92	0.92	0.92	75

confusion\_matrix:

[[55 3]



Modele name : DecisionTreeClassifier

Scaler name : Normalizer

10 K-Fold Average Accuracy\_score : 93.67 %

Accuracy\_score: 97.33 %

Loss: 2.67 %

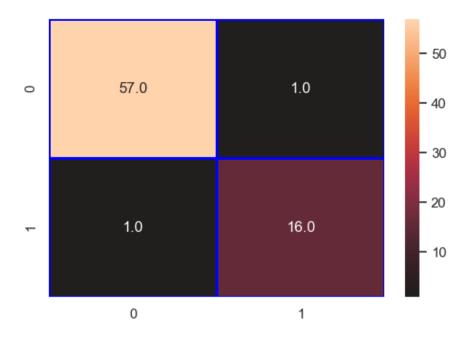
Cohen\_kappa\_score: 92.39 %
Classification report:

	precision	recall	f1-score	support
0	0.98	0.98	0.98	58
1	0.94	0.94	0.94	17
accuracy			0.97	75
macro avg	0.96	0.96	0.96	75
weighted avg	0.97	0.97	0.97	75

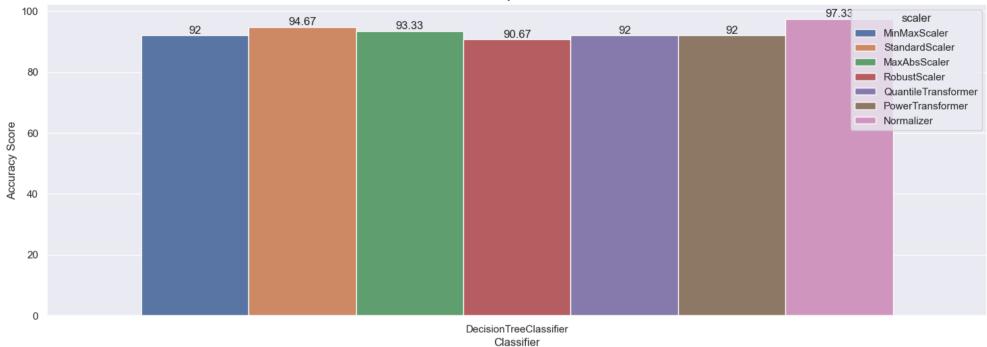
confusion\_matrix:

[[57 1]

[ 1 16]]



## Accuracy Score Plot



Modele name : RandomForestClassifier

Scaler name : MinMaxScaler

10 K-Fold Accuracy\_score : [1. 0.9 0.9667 0.8667 0.9 0.9667 0.9333 1. 0.9667 0.9333]

10 K-Fold Average Accuracy\_score : 94.33 %

Accuracy\_score: 93.33 %

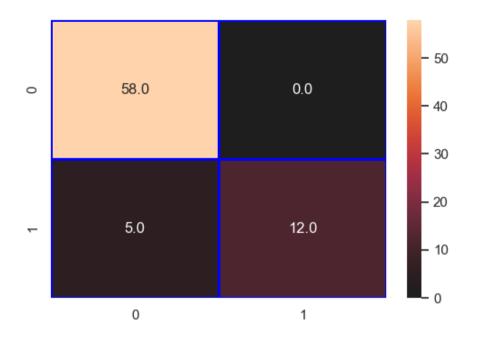
Loss: 6.67 %

Cohen\_kappa\_score: 78.78 %
Classification report:

		precision	recall	f1-score	support
		p. cc1310		. 1 300. 0	suppor c
	0	0.92	1.00	0.96	58
	1	1.00	0.71	0.83	17
				0.02	75
accur	acy			0.93	75
macro	avg	0.96	0.85	0.89	75
weighted	avg	0.94	0.93	0.93	75

confusion\_matrix:

[[58 0] [ 5 12]]



Modele name : RandomForestClassifier

Scaler name : StandardScaler

10 K-Fold Average Accuracy\_score : 94.33 %

Accuracy\_score: 93.33 %

Loss: 6.67 %

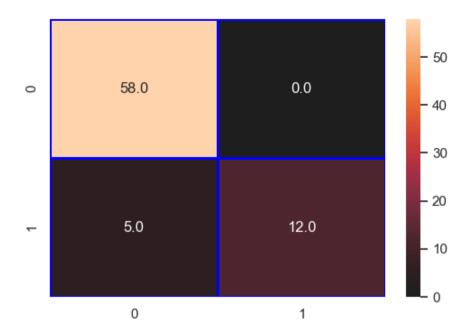
Cohen\_kappa\_score: 78.78 %
Classification report:

	precision	recall	f1-score	support
0	0.92	1.00	0.96	58
1	1.00	0.71	0.83	17
accuracy			0.93	75
macro avg	0.96	0.85	0.89	75
weighted avg	0.94	0.93	0.93	75

confusion\_matrix:

[[58 0]

[ 5 12]]



Modele name : RandomForestClassifier

Scaler name : MaxAbsScaler

10 K-Fold Average Accuracy\_score : 94.33 %

Accuracy\_score: 94.67 %

Loss: 5.33 %

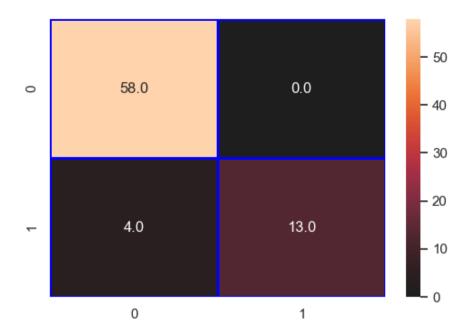
Cohen\_kappa\_score: 83.41 %
Classification report:

	precision	recall	f1-score	support
0	0.94	1.00	0.97	58
1	1.00	0.76	0.87	17
accuracy			0.95	75
macro avg	0.97	0.88	0.92	75
weighted avg	0.95	0.95	0.94	75

confusion\_matrix:

[[58 0]

[ 4 13]]



Modele name : RandomForestClassifier

Scaler name : RobustScaler

10 K-Fold Accuracy\_score : [0.9667 0.9667 0.9667 0.9667 0.9 0.9667 0.9 0.9667 1. 0.9333]

10 K-Fold Average Accuracy\_score : 94.33 %

Accuracy\_score: 93.33 %

Loss: 6.67 %

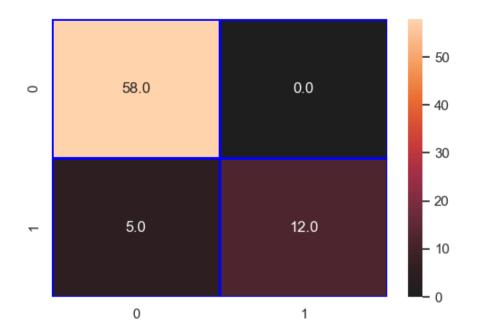
Cohen\_kappa\_score: 78.78 %
Classification report:

	precision	recall	f1-score	support
0	0.92	1.00	0.96	58
1	1.00	0.71	0.83	17
accuracy			0.93	75
macro avg	0.96	0.85	0.89	75
weighted avg	0.94	0.93	0.93	75

confusion\_matrix:

[[58 0]

[ 5 12]]



Modele name : RandomForestClassifier Scaler name : QuantileTransformer

10 K-Fold Accuracy\_score : [0.9667 0.9333 0.9667 0.8667 0.9 0.9667 0.9 0.9667 1. 0.9333]

10 K-Fold Average Accuracy\_score : 94.0 %

Accuracy\_score: 96.0 %

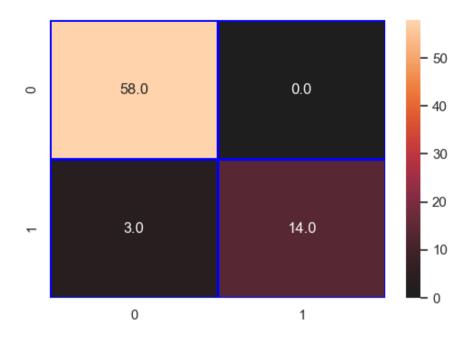
Loss: 4.0 %

Cohen\_kappa\_score: 87.83 %
Classification\_report:

	precision	recall	f1-score	support
0	0.95	1.00	0.97	58
1	1.00	0.82	0.90	17
accuracy			0.96	75
macro avg	0.98	0.91	0.94	75
weighted avg	0.96	0.96	0.96	75

confusion\_matrix:

[[58 0]



 ${\tt Modele\ name\ :\ Random Forest Classifier}$ 

Scaler name : PowerTransformer

10 K-Fold Average Accuracy\_score : 94.0 %

Accuracy\_score: 94.67 %

Loss: 5.33 %

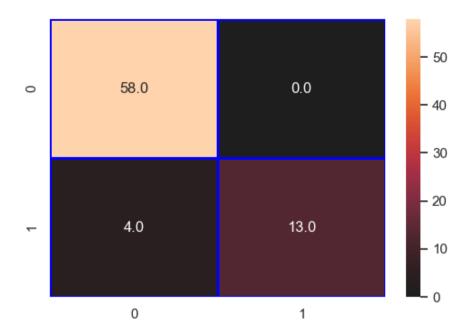
Cohen\_kappa\_score: 83.41 %
Classification\_report:

	precision	recall	f1-score	support
0	0.94	1.00	0.97	58
1	1.00	0.76	0.87	17
accuracy			0.95	75
macro avg	0.97	0.88	0.92	75
weighted avg	0.95	0.95	0.94	75

confusion\_matrix:

[[58 0]

[ 4 13]]



Modele name : RandomForestClassifier

Scaler name : Normalizer

10 K-Fold Accuracy\_score : [0.9667 0.9333 0.9667 0.8667 0.9333 0.9667 0.9 0.9333 1. 0.9333]

10 K-Fold Average Accuracy\_score : 94.0 %

Accuracy\_score: 94.67 %

Loss: 5.33 %

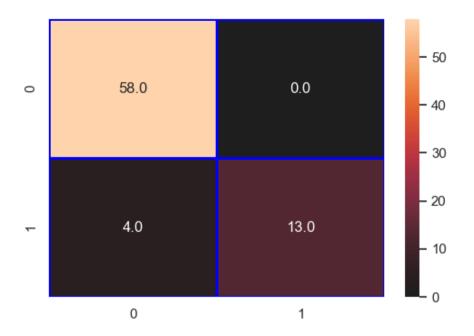
Cohen\_kappa\_score: 83.41 %
Classification report:

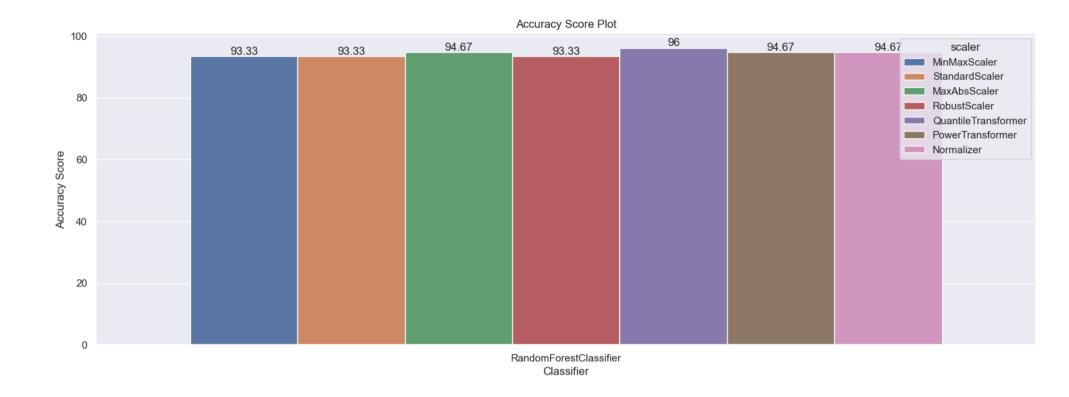
	precision	recall	f1-score	support
0	0.94	1.00	0.97	58
1	1.00	0.76	0.87	17
accuracy			0.95	75
macro avg	0.97	0.88	0.92	75
weighted avg	0.95	0.95	0.94	75

confusion\_matrix:

[[58 0]

[ 4 13]]





Done...

In [ ]: