```
In [ ]:
import pandas as pd
import re
import numpy as np
import itertools
In [ ]:
from google.colab import drive
drive.mount('/content/drive')
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount
("/content/drive", force remount=True).
In [ ]:
file path = '/content/drive/MyDrive/bk/processed.hungarian.data'
In [ ]:
with open(file path, encoding='Latin1') as file:
    lines = [line.strip() for line in file]
In [ ]:
lines[0:10]
Out[]:
['1254 0 40 1 1 0 0',
 '-9 2 140 0 289 -9 -9 -9',
 '0 -9 -9 0 12 16 84 0',
 '0 0 0 0 150 18 -9 7',
 '172 86 200 110 140 86 0 0',
 '0 -9 26 20 -9 -9 -9',
 '-9 -9 -9 -9 -9 -9 12',
 '20 84 0 -9 -9 -9 -9 -9',
 '-9 -9 -9 -9 1 1 1',
 '1 1 -9. -9. name']
In [ ]:
data = itertools.takewhile(
    lambda x: len(x) == 76,
    (' '.join(lines[i:(i+10)]).split() for i in range(0, len(lines), 10))
df = pd.DataFrame(data)
df.head(10)
Out[]:
     0 1 2 3 4 5 6 7 8 9 ... 66 67 68 69 70 71 72 73 74
0 1254 0 40 1 1 0 0 -9 2 140 ... -9 -9
                                                  1 -9. -9. name
1 1255 0 49 0 1 0 0 -9 3 160 ... -9 -9
                                      1
                                         1
                                            1
                                               1
                                                  1 -9. -9. name
2 1256 0 37 1 1 0 0 -9 2 130 ... -9 -9
                                                  1 -9. -9. name
3 1257 0 48 0 1 1 1 -9 4 138 ... 2 -9
                                      1
                                         1
                                            1
                                               1
                                                  1 -9. -9. name
4 1258 0 54 1 1 0 1 -9 3 150 ... 1 -9
                                      1
                                         1
                                                  1 -9. -9. name
```

5 1259 0 39 1 1 0 1 -9 3 120 ... -9 -9

6 1260 0 45 0 0 1 0 -9 2 130 ... -9 -9

7 1261 0 54 1 1 0 0 -9 2 110 ... -9 -9

8 1262 0 37 1 1 1 1 -9 4 140 ... -9 -9 1 1

1 1

1 1 1

1 1

1 -9. -9. name

1 -9. -9. name

1 1 1 -9. -9. name

9 1263 0 48 0 1 5 6 5 2 129 ... 66 67 68 69 70 71 72 73 74 name

10 rows × 76 columns

In []:

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 294 entries, 0 to 293 Data columns (total 76 columns): Dtype Column Non-Null Count 0 0 294 non-null object 1 1 294 non-null object 2 2 294 non-null object 3 3 294 non-null object 4 4 294 non-null object 5 5 294 non-null object 6 294 non-null object 7 7 294 non-null object 8 8 294 non-null object 9 9 294 non-null object 10 10 294 non-null object 294 non-null 11 11 object 294 non-null 12 12 object 13 294 non-null 13 object 14 14 294 non-null object 15 15 294 non-null object 16 16 294 non-null object 17 17 294 non-null object 18 18 294 non-null object 19 19 294 non-null object 20 20 294 non-null object 21 21 294 non-null object 22 22 294 non-null object 23 23 294 non-null object 24 24 294 non-null object 25 25 294 non-null object 26 26 294 non-null object 27 27 294 non-null object 28 28 294 non-null object 29 29 294 non-null object 30 30 294 non-null object 31 31 294 non-null object 32 32 294 non-null object 33 33 294 non-null object 34 34 294 non-null object 35 35 294 non-null object 36 36 294 non-null object 294 non-null 37 37 object 38 294 non-null 38 object 294 non-null 39 39 object 40 40 294 non-null object 41 41 294 non-null object 42 42 294 non-null object 43 43 294 non-null object 44 44 294 non-null object 45 45 294 non-null object 46 46 294 non-null object 47 47 294 non-null object 294 non-null 48 48 object 49 294 non-null 49 object 50 50 294 non-null object 51 51 294 non-null object 52 52 294 non-null object 53 53 294 non-null object 54 54 294 non-null object 55 55 294 non-null object 56 56 294 non-null object 57 57 294 non-null object

```
object
   58
 58
            294 non-null
59 59
            294 non-null
                          object
 60 60
           294 non-null
                         object
 61 61
           294 non-null
                         object
           294 non-null
 62
   62
                         object
63 63
           294 non-null
                         object
64
   64
           294 non-null
                         object
65
   65
           294 non-null
                         object
66
   66
           294 non-null
                         object
67
           294 non-null
    67
                          object
           294 non-null
68
   68
                           object
 69
    69
           294 non-null
                           object
                         object
70
    70
           294 non-null
                         object
 71
    71
            294 non-null
                         object
72
    72
            294 non-null
73
    73
            294 non-null
                         object
            294 non-null
74 74
                         object
         294 non-null
75 75
                         object
dtypes: object(76)
memory usage: 174.7+ KB
In [ ]:
df = df.iloc[:,:-1]
df = df.drop(df.columns[0], axis=1)
df = df.astype(float)
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 74 columns):
# Column Non-Null Count Dtype
0
            294 non-null float64
    1
1
    2
           294 non-null float64
```

294 non-null float64

294 non-null float64 294 non-null float64

294 non-null float64

294 non-null float64

294 non-null float64 294 non-null float64

294 non-null float64

294 non-null float64

294 non-null 294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

294 non-null

float64

float64 float64

float64

float64

float64 float64

2 3

3 4

4 5 5 6

6 7

7 8

8 9

9 10

10 11

11 12

12 13

13 14

14 15

16

17

18

19

19 20

20 21

21 22

22 23

23 24

24 25

25 26

26 27

28 29

28

30

30 31

32

33

34

35

36

37

38

27

29

31

32

33

34

35

36

37

15

16

17

18

```
38
     39
              294 non-null
                                float64
 39
     40
              294 non-null
                                float64
 40
    41
              294 non-null
                                float64
 41
     42
              294 non-null
                                float64
 42
     43
              294 non-null
                                float64
 43
     44
              294 non-null
                                float64
 44
     45
              294 non-null
                                float64
 45
     46
              294 non-null
                                float64
     47
              294 non-null
 46
                                float64
 47
     48
              294 non-null
                                float64
              294 non-null
 48
     49
                                float64
 49
     50
              294 non-null
                                float64
 50
     51
              294 non-null
                                float64
 51
     52
              294 non-null
                                float64
 52
     53
              294 non-null
                                float64
 53
     54
              294 non-null
                                float64
     55
 54
              294 non-null
                                float64
 55
     56
              294 non-null
                                float64
 56
    57
              294 non-null
                                float64
 57
              294 non-null
     58
                                float64
 58
    59
              294 non-null
                                float64
 59
     60
              294 non-null
                                float64
 60
    61
              294 non-null
                                float64
 61
     62
              294 non-null
                                float64
 62
              294 non-null
     63
                                float64
              294 non-null
 63
                                float64
     64
              294 non-null
 64
     65
                                float64
                                float64
 65
              294 non-null
     66
 66
     67
              294 non-null
                                float64
 67
     68
              294 non-null
                                float64
 68
     69
              294 non-null
                                float64
 69
     70
              294 non-null
                                float64
 70
     71
              294 non-null
                                float64
 71
     72
              294 non-null
                                float64
 72
     73
              294 non-null
                                float64
              294 non-null
 73
     74
                                float64
dtypes: float64(74)
memory usage: 170.1 KB
In [ ]:
df.replace(-9.0, np.nan, inplace=True)
In [ ]:
df_selected = df.iloc[:, [1, 2, 7, 8, 10, 14, 17, 30, 36, 38, 39, 42, 49, 56]]
df selected.head()
Out[]:
                                     37
                                                  43
     2
        3
            8
                 9
                      11
                        15
                            18
                                  31
                                        39
                                              40
                                                       50
                                                          57
0 40.0 1.0 2.0 140.0 289.0 0.0 0.0 172.0 0.0 0.0 NaN NaN
                                                     NaN 0.0
1 49.0 0.0 3.0 160.0 180.0 0.0 0.0 156.0 0.0 1.0
                                             2.0
                                                NaN
2 37.0 1.0 2.0 130.0 283.0 0.0 1.0
                                98.0 0.0 0.0 NaN
                                                 NaN
                                                      NaN 0.0
3 48.0 0.0 4.0 138.0 214.0 0.0 0.0 108.0 1.0 1.5
                                             2.0
                                                 NaN
4 54.0 1.0 3.0 150.0 NaN 0.0 0.0 122.0 0.0 0.0 NaN NaN
                                                     NaN 0.0
In [ ]:
column mapping = {
```

2: 'age',
3: 'sex',
8: 'cp',

9: 'trestbps', 11: 'chol', 15: 'fbs', 18: 'restecg',

```
31: 'thalach',
    37: 'exang',
    39: 'oldpeak',
    40: 'slope',
    43: 'ca',
    50: 'thal',
    57: 'target'
df selected.rename(columns=column mapping, inplace=True)
df selected.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 14 columns):
  Column Non-Null Count Dtype
___
              294 non-null
0
   age
                            float64
1
   sex
              294 non-null
                            float64
   ср
              294 non-null
                            float64
3
   trestbps 293 non-null float64
   chol
                            float64
              271 non-null
 4
5
   fbs
                            float64
              286 non-null
                            float64
 6
   restecg
             293 non-null
7
              293 non-null
                             float64
    thalach
8
    exang
              293 non-null
                             float64
9
    oldpeak
              294 non-null
                             float64
                            float64
10 slope
              104 non-null
                            float64
11 ca
              4 non-null
12 thal
              28 non-null
                            float64
             294 non-null
                            float64
13 target
dtypes: float64(14)
memory usage: 32.3 KB
<ipython-input-385-b35476392aaf>:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
 df selected.rename(columns=column mapping, inplace=True)
In [ ]:
df selected.value counts()
Out[]:
age
              trestbps chol
                                   restecg thalach exang oldpeak
     sex cp
                                fbs
                                                                     slope
                                                                                 thal
target
                         226.0 0.0 0.0
                                             98.0
                                                                      2.0
                                                                            0.0 7.0
47.0 1.0 4.0
              150.0
                                                      1.0
                                                             1.5
1.0
         1
dtype: int64
In [ ]:
df selected.isnull().sum()
Out[]:
             0
age
             0
sex
             0
ср
trestbps
             1
            23
chol
             8
fbs
restecg
             1
thalach
             1
exang
            1
oldpeak
            0
           190
slope
           290
са
           266
thal
             0
target
```

```
dtype: int64
In [ ]:
columns to drop = ['ca', 'slope', 'thal']
df selected = df selected.drop(columns to drop, axis=1)
In [ ]:
df selected.isnull().sum()
Out[]:
            0
age
ср
trestbps
            1
           23
chol
fbs
            1
restecg
thalach
exang
            0
oldpeak
target
dtype: int64
In [ ]:
meanTBPS = round(df selected['trestbps'].dropna().astype(float).mean())
meanChol = round(df selected['chol'].dropna().astype(float).mean())
meanFbs = round(df selected['fbs'].dropna().astype(float).mean())
meanRestEcg = round(df selected['restecg'].dropna().astype(float).mean())
meanThalach = round(df selected['thalach'].dropna().astype(float).mean())
meanExang = round(df selected['exang'].dropna().astype(float).mean())
fill values = {
    'trestbps': meanTBPS,
    'chol': meanChol,
    'fbs': meanFbs,
    'thalach': meanThalach,
    'exang': meanExang,
    'restecg': meanRestEcg
df clean = df selected.fillna(value=fill values)
df clean.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 11 columns):
 # Column Non-Null Count Dtype
___
              -----
0 age
             294 non-null float64
             294 non-null float64
1 sex
             294 non-null float64
 2 cp
 3 trestbps 294 non-null float64
 4 chol
             294 non-null float64
              294 non-null float64
   fbs
 5
             294 non-null float64
   restecg
             294 non-null float64
 7
    thalach
                            float64
 8
              294 non-null
    exang
                            float64
 9
    oldpeak
              294 non-null
             294 non-null
                             float64
10 target
dtypes: float64(11)
memory usage: 25.4 KB
In [ ]:
df clean.isnull().sum()
Out[]:
age
           0
COV
           \cap
```

```
cp 0
trestbps 0
chol 0
fbs 0
restecg 0
thalach 0
exang 0
oldpeak 0
target 0
dtype: int64
```

```
duplicate_rows = df_clean.duplicated()
df_clean[duplicate_rows]
```

Out[]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	target
163	49.0	0.0	2.0	110.0	251.0	0.0	0.0	160.0	0.0	0.0	0.0

In []:

```
df_clean = df_clean.drop_duplicates()
df_clean[df_clean.duplicated(keep=False)]
```

Out[]:

age sex cp trestbps chol fbs restecg thalach exang oldpeak target

In []:

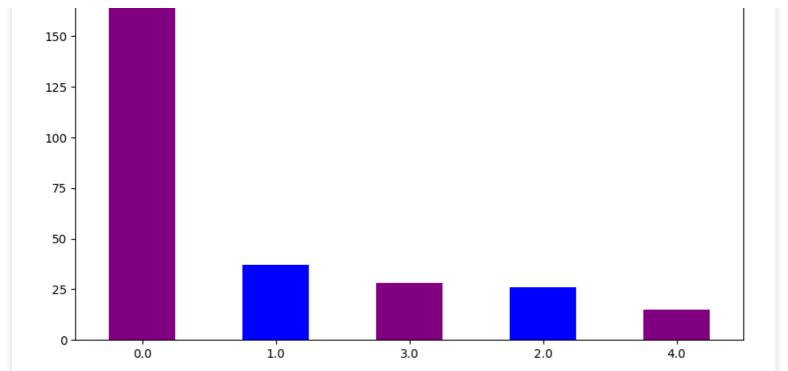
```
df_clean.corr()
```

Out[]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	target
age	1.000000	0.014516	0.146616	0.246571	0.087101	0.181130	0.050672	- 0.460514	0.239223	0.178172	0.210429
sex	0.014516	1.000000	0.245769	0.082064	0.027695	0.044372	- 0.108656	- 0.106959	0.154925	0.115959	0.220732
ср	0.146616	0.245769	1.000000	0.081293	0.134697	0.031930	0.016372	0.367819	0.494674	0.351735	0.427536
trestbps	0.246571	0.082064	0.081293	1.000000	0.080818	0.096222	0.011256	- 0.181824	0.211507	0.204000	0.214898
chol	0.087101	0.027695	0.134697	0.080818	1.000000	0.107686	0.048081	0.122038	0.161055	0.106743	0.256027
fbs	0.181130	0.044372	0.031930	0.096222	0.107686	1.000000	0.047988	0.069722	0.115503	0.063179	0.154319
restecg	0.050672	- 0.108656	0.016372	0.011256	0.048081	0.047988	1.000000	0.006084	0.041290	0.042193	0.042643
thalach	- 0.460514	- 0.106959	0.367819	- 0.181824	- 0.122038	0.069722	0.006084	1.000000	0.400508	- 0.300458	0.367525
exang	0.239223	0.154925	0.494674	0.211507	0.161055	0.115503	0.041290	0.400508	1.000000	0.624965	0.571710
oldpeak	0.178172	0.115959	0.351735	0.204000	0.106743	0.063179	0.042193	0.300458	0.624965	1.000000	0.580732
target	0.210429	0.220732	0.427536	0.214898	0.256027	0.154319	0.042643	0.367525	0.571710	0.580732	1.000000

```
import seaborn as sns
import matplotlib.pyplot as plt
corr_mat = df_clean.corr()
fig, ax = plt.subplots(figsize=(15, 10))
sns.heatmap(corr_mat, annot=True, linewidths=0.5, fmt=".3f")
Out[]:
<Axes: >
                                                                                                                    - 1.0
      1.000
               0.015
                                           0.087
                                                    0.181
                                                             0.051
                                                                       -0.461
                                                                                                   0.210
               1.000
                        0.246
                                  0.082
                                           0.028
                                                    0.044
                                                             -0.109
                                                                       -0.107
 sex
                                                                                                   0.221
                                                                                                                    - 0.8
      0.147
               0.246
                        1.000
                                  0.081
                                                    0.032
                                                             -0.016
                                                                       -0.368
                                                                                                                    - 0.6
      0.247
               0.082
                        0.081
                                  1.000
                                           0.081
                                                    0.096
                                                             0.011
                                                                       -0.182
                                                                                         0.204
 chol
               0.028
                        0.135
                                  0.081
                                           1.000
                                                    0.108
                                                             0.048
                                                                      -0.122
                                                                                         0.107
      0.087
                                                                                0.161
                                                                                                   0.256
                                                                                                                    - 0.4
                                           0.108
                                                    1.000
                                                             0.048
 fbs
      0.181
               0.044
                        0.032
                                  0.096
                                                                       -0.070
                                                                                         0.063
                                                                                                   0.154
                                                                                                                    - 0.2
 restecg
      0.051
                                                    0.048
                                                              1.000
               -0.109
                        -0.016
                                           0.048
                                                                       0.006
                                                                                0.041
                                                                                         0.042
                                                                                                   0.043
thalach
     -0.461
                                                                       1.000
                                                                                -0.401
               -0.107
                        -0.368
                                 -0.182
                                           -0.122
                                                    -0.070
                                                             0.006
                                                                                         -0.300
                                                                                                   -0.368
                                                                                                                    - 0.0
 exang
                                                             0.041
                                                                       -0.401
                                                                                1.000
               0.155
                                           0.161
                                                                                                                    - -0.2
 oldpeak
      0.178
               0.116
                                  0.204
                                           0.107
                                                    0.063
                                                             0.042
                                                                      -0.300
                                                                                         1.000
               0.221
                                  0.215
                                           0.256
                                                    0.154
                                                             0.043
                                                                       -0.368
                                                                                                   1.000
                                                                                                                     -0.4
                sex
                                 trestbps
                                            chol
                                                     fbs
                                                             restecg
                                                                      thalach
                                                                                         oldpeak
       age
                          ср
                                                                                exang
                                                                                                  target
In [ ]:
X = df clean.drop("target", axis=1).values
y = df_{clean.iloc[:, -1]}
In [ ]:
df clean['target'].value counts().plot(kind='bar', figsize=(10,6), color=['purple', 'blu
plt.title("Count target")
plt.xticks(rotation=0)
Out[]:
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, '0.0'),
  Text(1, 0, '1.0'),
  Text(2, 0, '3.0'),
  Text(3, 0, '2.0'),
  Text(4, 0, '4.0')])
```

Count target



```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
X_smote_resampled, y_smote_resampled = smote.fit_resample(X, y)

new_df1 = pd.DataFrame(data=y)
new_df2 = pd.DataFrame(data=y_smote_resampled)
```

In []:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_smote_resampled_normal = scaler.fit_transform(X_smote_resampled)
```

In []:

```
df_check1 = pd.DataFrame(X_smote_resampled_normal)
df_check1.describe()
```

Out[]:

	0	1	2	3	4	5	6	7	8	
count	935.000000	935.000000	935.000000	935.000000	935.000000	935.000000	935.000000	935.000000	935.000000	935.0000
mean	0.563739	0.842507	0.818224	0.403413	0.341027	0.094277	0.117938	0.453354	0.598398	0.2270
std	0.174873	0.332492	0.274211	0.147493	0.110990	0.252030	0.199527	0.197232	0.450288	0.2012
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	0.473283	1.000000	0.666667	0.305556	0.267954	0.000000	0.000000	0.312720	0.000000	0.0000
50%	0.578947	1.000000	1.000000	0.387952	0.330240	0.000000	0.000000	0.440606	0.962447	0.2000
75%	0.683363	1.000000	1.000000	0.487481	0.393811	0.000000	0.201473	0.593629	1.000000	0.3861
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.0000
1										

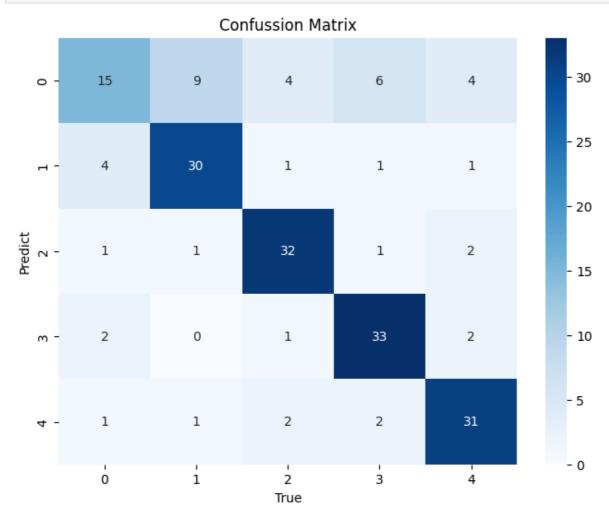
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_smote_resampled, y_smote_resampled)
```

```
, test_size=0.2, random_state=42, stratify=y_smote_resampled)
X_train_normal, X_test_normal, y_train_normal, y_test_normal = train_test_split(X_smote_r
esampled normal, y smote resampled, test size=0.2, random state=42, stratify=y smote res
ampled)
In [ ]:
from sklearn.metrics import accuracy score, recall score, f1 score, precision score, roc
auc score, confusion matrix, precision score
def evaluation(y test, y pred):
    return print({
        'accuracy': round(accuracy score(y test, y pred), 3),
        'recall': round(recall_score(y_test, y_pred, average='weighted'), 3),
        'f1 score': round(f1_score(y_test, y_pred, average='weighted'), 3),
        'precision score': round(precision score(y test, y pred, average='weighted'), 3)
    })
In [ ]:
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy score, classification report
In [ ]:
knn model = KNeighborsClassifier(n neighbors=3)
knn model.fit(X train, y train)
Out[]:
        KNeighborsClassifier
KNeighborsClassifier(n neighbors=3)
In [ ]:
y pred knn = knn model.predict(X test)
In [ ]:
print("KNN Model:")
accuracy knn smote = round(accuracy score(y test, y pred knn), 3)
print("Accuracy: ", accuracy knn smote)
print("Classification Report: ")
print(classification report(y test, y pred knn))
KNN Model:
Accuracy: 0.754
Classification Report:
              precision
                          recall f1-score
                                              support
         0.0
                   0.65
                             0.39
                                       0.49
                                                    38
                             0.81
                                       0.77
         1.0
                   0.73
                                                    37
                                       0.83
         2.0
                   0.80
                             0.86
                                                    37
         3.0
                   0.77
                             0.87
                                       0.81
                                                   38
         4.0
                   0.78
                             0.84
                                       0.81
                                                   37
                                       0.75
                                                  187
   accuracy
                   0.75
                             0.76
                                       0.74
                                                   187
   macro avg
                                       0.74
weighted avg
                   0.74
                             0.75
                                                   187
In [ ]:
evaluation(y_test, y_pred_knn)
{'accuracy': 0.754, 'recall': 0.754, 'f1 score': 0.741, 'precision score': 0.745}
```

```
cm = confusion_matrix(y_test, y_pred_knn)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



```
In [ ]:
```

```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In []:

```
y_pred_rf = rf_model.predict(X_test)
```

In []:

```
print("Random Forest Model:")
accuracy_rf_smote = round(accuracy_score(y_test, y_pred_rf), 3)
print("Accuracy: ", accuracy_rf_smote)
print("Classification Report: ")
print(classification_report(y_test, y_pred_rf))
```

```
υ.υ
                     0.94
                                0.89
                                           0.92
                                                         38
          1.0
                     0.85
                                0.92
                                           0.88
                                                         37
                     0.89
                                0.89
                                           0.89
                                                         37
          2.0
                                0.97
                                           0.96
          3.0
                     0.95
                                                         38
          4.0
                     0.97
                                0.92
                                           0.94
                                                         37
                                           0.92
                                                       187
    accuracy
                                           0.92
   macro avg
                     0.92
                                0.92
                                                       187
                                           0.92
weighted avg
                     0.92
                                0.92
                                                       187
```

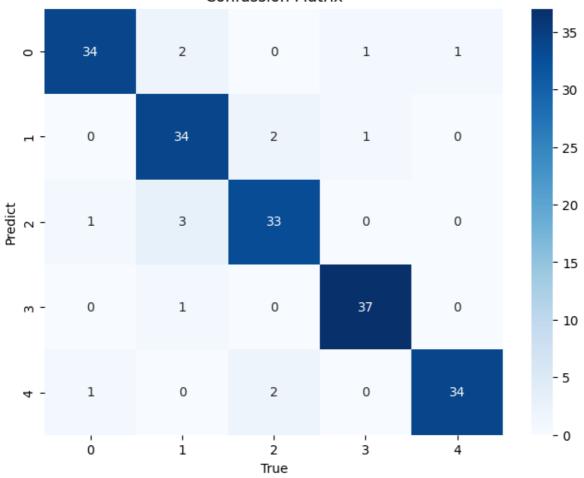
```
evaluation(y_test, y_pred_rf)
{'accuracy': 0.92, 'recall': 0.92, 'f1_score': 0.92, 'precision_score': 0.92}
```

In []:

```
cm = confusion_matrix(y_test, y_pred_rf)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```





In []:

```
xgb_model = XGBClassifier(learning_rate=0.1, n_estimators=100, random_state=42)
xgb_model.fit(X_train, y_train)
```

Out[]:

```
colsample_bytree=None, device=None, early_stopping_rounds=None,

e,

enable_categorical=False, eval_metric=None, feature_types=None,

gamma=None, grow_policy=None, importance_type=None,
 interaction_constraints=None, learning_rate=0.1, max_bin=None

,

max_cat_threshold=None, max_cat_to_onehot=None,
```

```
y_pred_xgb = xgb_model.predict(X_test)
```

In []:

```
print("XGBoost Model:")
accuracy_xgb_smote = round(accuracy_score(y_test, y_pred_xgb), 3)
print("Accuracy: ", accuracy_xgb_smote)
print("Classification Report: ")
print(classification_report(y_test, y_pred_xgb))
```

XGBoost Model: Accuracy: 0.904

 ${\tt Classification\ Report:}$

		precision	recall	f1-score	support
	0.0	0.92	0.89	0.91	38
	1.0	0.94	0.84	0.89	37
	2.0	0.85	0.89	0.87	37
	3.0	0.88	0.97	0.93	38
	4.0	0.94	0.92	0.93	37
accur	racy			0.90	187
macro	avg	0.91	0.90	0.90	187
weighted	avg	0.91	0.90	0.90	187

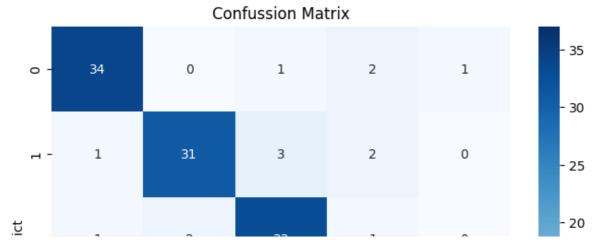
In []:

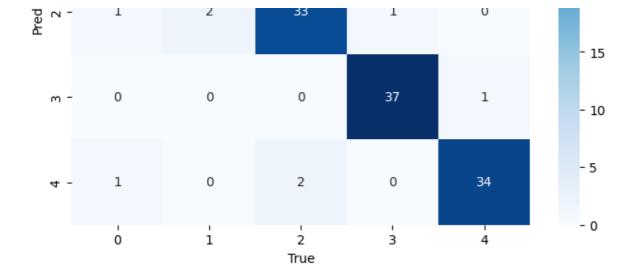
```
evaluation(y_test, y_pred_xgb)
```

{'accuracy': 0.904, 'recall': 0.904, 'f1 score': 0.904, 'precision score': 0.906}

```
cm = confusion_matrix(y_test, y_pred_xgb)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```





```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report
```

In []:

```
knn_model = KNeighborsClassifier(n_neighbors=3)
knn_model.fit(X_train_normal, y_train_normal)
```

Out[]:

```
KNeighborsClassifier
KNeighborsClassifier(n neighbors=3)
```

In []:

```
y_pred_knn = knn_model.predict(X_test_normal)
```

In []:

```
print("KNN Model:")
accuracy_knn_smote_normal = round(accuracy_score(y_test_normal, y_pred_knn), 3)
print("Accuracy: ", accuracy_knn_smote_normal)
print("Classification Report: ")
print(classification_report(y_test_normal, y_pred_knn))
```

KNN Model:

Accuracy: 0.861 Classification Report:

precision recall f1-score support

	-				
	0.0	0.88	0.76	0.82	38
	1.0	0.78	0.84	0.81	37
:	2.0	0.87	0.92	0.89	37
	3.0	0.92	0.87	0.89	38
	4.0	0.87	0.92	0.89	37
accur	acy			0.86	187
macro a	avg	0.86	0.86	0.86	187
weighted a	avg	0.86	0.86	0.86	187

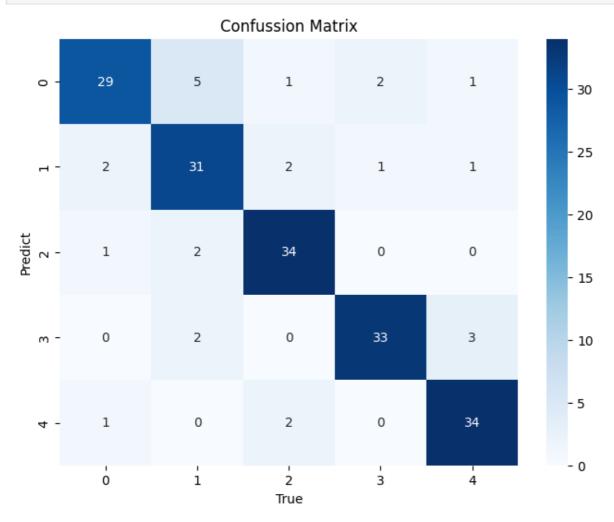
In []:

```
evaluation(y_test_normal, y_pred_knn)
```

{'accuracy': 0.861, 'recall': 0.861, 'f1_score': 0.861, 'precision_score': 0.863}

```
cm = confusion_matrix(y_test_normal, y_pred_knn)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

Out[]:

```
▼ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In []:

```
y_pred_rf = rf_model.predict(X_test)
```

In []:

```
print("Random Forest Model:")
accuracy_rf_smote = round(accuracy_score(y_test, y_pred_rf), 3)
print("Accuracy: ", accuracy_rf_smote)
print("Classification Report: ")
print(classification_report(y_test, y_pred_rf))
```

```
υ.υ
                     0.94
                                0.89
                                           0.92
                                                         38
          1.0
                     0.85
                                0.92
                                           0.88
                                                         37
                     0.89
                                0.89
                                           0.89
                                                         37
          2.0
                                0.97
                                           0.96
          3.0
                     0.95
                                                         38
          4.0
                     0.97
                                0.92
                                           0.94
                                                         37
                                           0.92
                                                       187
    accuracy
                                           0.92
   macro avg
                     0.92
                                0.92
                                                       187
                                           0.92
weighted avg
                     0.92
                                0.92
                                                       187
```

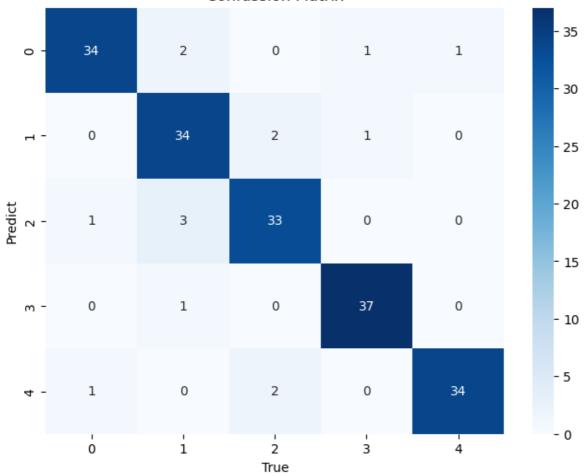
```
evaluation(y_test, y_pred_rf)
{'accuracy': 0.92, 'recall': 0.92, 'f1_score': 0.92, 'precision_score': 0.922}
```

In []:

```
cm = confusion_matrix(y_test, y_pred_rf)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```





In []:

```
xgb_model = XGBClassifier(learning_rate=0.1, n_estimators=100, random_state=42)
xgb_model.fit(X_train, y_train)
```

Out[]:

```
colsample_bytree=None, device=None, early_stopping_rounds=None,

e,

enable_categorical=False, eval_metric=None, feature_types=None,

gamma=None, grow_policy=None, importance_type=None,
 interaction_constraints=None, learning_rate=0.1, max_bin=None

,

max_cat_threshold=None, max_cat_to_onehot=None,
```

```
y_pred_xgb = xgb_model.predict(X_test)
```

In []:

```
print("XGBoost Model:")
accuracy_xgb_smote = round(accuracy_score(y_test, y_pred_xgb), 3)
print("Accuracy: ", accuracy_xgb_smote)
print("Classification Report: ")
print(classification_report(y_test, y_pred_xgb))
```

XGBoost Model: Accuracy: 0.904

Classification Report:

	precision	recall	il-score	support
0.0	0.92	0.89	0.91	38
1.0	0.94	0.84	0.89	37
2.0	0.85	0.89	0.87	37
3.0	0.88	0.97	0.93	38
4.0	0.94	0.92	0.93	37
accuracy			0.90	187
macro avg	0.91	0.90	0.90	187
weighted avg	0.91	0.90	0.90	187

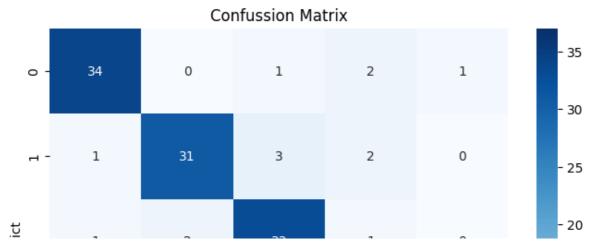
In []:

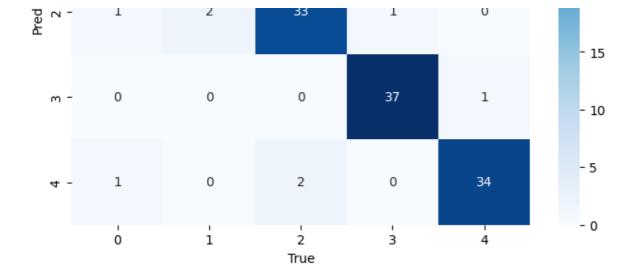
```
evaluation(y_test, y_pred_xgb)
```

{'accuracy': 0.904, 'recall': 0.904, 'f1_score': 0.904, 'precision_score': 0.906}

```
cm = confusion_matrix(y_test, y_pred_xgb)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```





```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report
```

In []:

```
knn_model = KNeighborsClassifier(n_neighbors=3)
knn_model.fit(X_train_normal, y_train_normal)
```

Out[]:

```
KNeighborsClassifier
KNeighborsClassifier(n neighbors=3)
```

In []:

```
y_pred_knn = knn_model.predict(X_test_normal)
```

In []:

```
print("KNN Model:")
accuracy_knn_smote_normal = round(accuracy_score(y_test_normal, y_pred_knn), 3)
print("Accuracy: ", accuracy_knn_smote_normal)
print("Classification Report: ")
print(classification_report(y_test_normal, y_pred_knn))
```

KNN Model:

Accuracy: 0.861 Classification Report:

precision recall f1-score support

	-				
	0.0	0.88	0.76	0.82	38
	1.0	0.78	0.84	0.81	37
:	2.0	0.87	0.92	0.89	37
	3.0	0.92	0.87	0.89	38
	4.0	0.87	0.92	0.89	37
accur	acy			0.86	187
macro a	avg	0.86	0.86	0.86	187
weighted a	avg	0.86	0.86	0.86	187

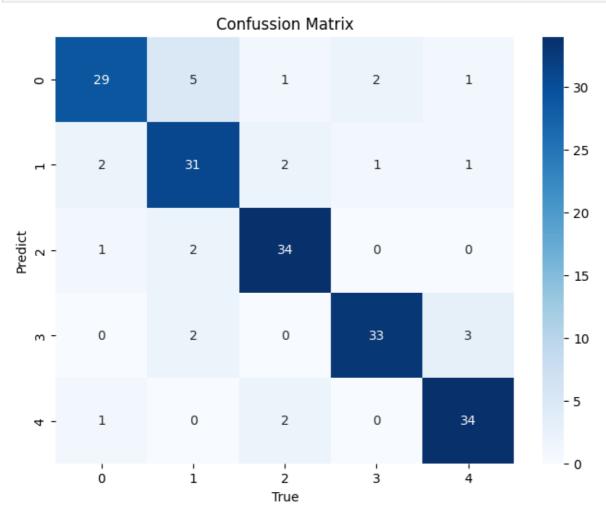
In []:

```
evaluation(y_test_normal, y_pred_knn)
```

{'accuracy': 0.861, 'recall': 0.861, 'f1_score': 0.861, 'precision_score': 0.863}

```
cm = confusion_matrix(y_test_normal, y_pred_knn)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_normal, y_train_normal)
```

Out[]:

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In []:

```
y_pred_rf = rf_model.predict(X_test_normal)
```

```
print("Random Forest Model:")
accuracy_rf_smote_normal = round(accuracy_score(y_test_normal, y_pred_rf), 3)
print("Accuracy: ", accuracy_rf_smote_normal)
print("Classification Report: ")
print(classification_report(y_test_normal, y_pred_rf))
```

```
υ.υ
                     0.94
                                0.89
                                           0.92
                                                         38
          1.0
                     0.85
                                0.92
                                           0.88
                                                         37
                                0.89
                                           0.89
                                                         37
          2.0
                     0.89
                                           0.96
          3.0
                     0.95
                                0.97
                                                         38
          4.0
                     0.97
                                0.92
                                           0.94
                                                         37
                                           0.92
                                                       187
    accuracy
                                           0.92
   macro avg
                     0.92
                                0.92
                                                       187
                                           0.92
weighted avg
                     0.92
                                0.92
                                                       187
```

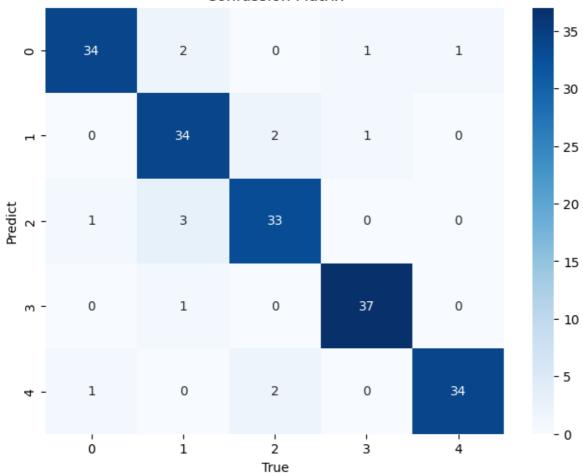
```
evaluation(y_test_normal, y_pred_rf)
{'accuracy': 0.92, 'recall': 0.92, 'f1 score': 0.92, 'precision score': 0.92}
```

In []:

```
cm = confusion_matrix(y_test_normal, y_pred_rf)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```





In []:

```
xgb_model = XGBClassifier(learning_rate=0.1, n_estimators=100, random_state=42)
xgb_model.fit(X_train_normal, y_train_normal)
```

Out[]:

```
colsample_bytree=None, device=None, early_stopping_rounds=None,

e,

enable_categorical=False, eval_metric=None, feature_types=None,

gamma=None, grow_policy=None, importance_type=None,
 interaction_constraints=None, learning_rate=0.1, max_bin=None

,

max_cat_threshold=None, max_cat_to_onehot=None,
```

```
y_pred_xgb = xgb_model.predict(X_test_normal)
```

In []:

```
print("XGBoost Model:")
accuracy_xgb_smote_normal = round(accuracy_score(y_test_normal, y_pred_xgb), 3)
print("Accuracy: ", accuracy_xgb_smote_normal)
print("Classification Report: ")
print(classification_report(y_test, y_pred_xgb))
```

XGBoost Model: Accuracy: 0.904

Classification Report:

	precision	recall	fl-score	support
0.0	0.92	0.89	0.91	38
1.0	0.94	0.84	0.89	37
2.0	0.85	0.89	0.87	37
3.0	0.88	0.97	0.93	38
4.0	0.94	0.92	0.93	37
accuracy			0.90	187
macro avg	0.91	0.90	0.90	187
weighted avg	0.91	0.90	0.90	187

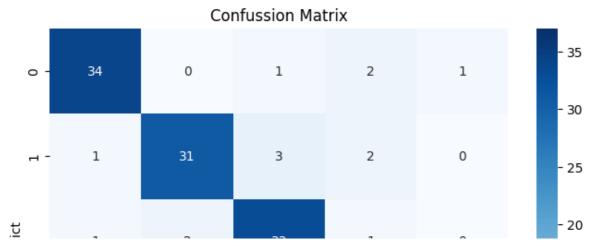
In []:

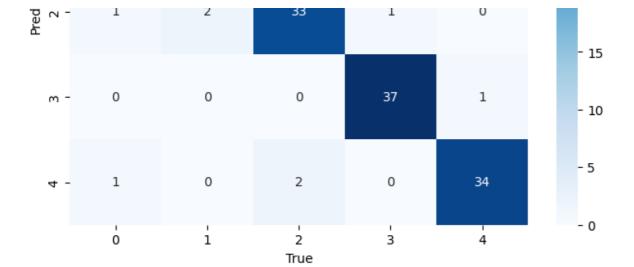
```
evaluation(y_test_normal, y_pred_xgb)
```

{'accuracy': 0.904, 'recall': 0.904, 'f1 score': 0.904, 'precision score': 0.906}

```
cm = confusion_matrix(y_test_normal, y_pred_xgb)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```





```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import RandomizedSearchCV
```

In []:

```
knn_model = KNeighborsClassifier()

param_grid = {
    "n_neighbors": range(3, 21),
    "metric": ["euclidean", "manhattan", "chebyshev"],
    "weights": ["uniform", "distance"],
    "algorithm": ["auto", "ball_tree", "kd_tree"],
    "leaf_size": range(10, 61),
}

knn_model = RandomizedSearchCV(estimator=knn_model, param_distributions=param_grid, n_ite
    r=100, scoring="accuracy", cv=5)
knn_model.fit(X_train_normal, y_train_normal)
best_params = knn_model.best_params_
    print(f"Best_Parameters: {best_params}")
```

Best Parameters: {'weights': 'distance', 'n_neighbors': 4, 'metric': 'manhattan', 'leaf_s
ize': 52, 'algorithm': 'auto'}

In []:

```
y_pred_knn = knn_model.predict(X_test_normal)
```

In []:

```
print("KNN Model:")
accuracy_knn_smote_normal_tunning = round(accuracy_score(y_test_normal, y_pred_knn), 3)
print("Accuracy: ", accuracy_knn_smote_normal_tunning)
print("Classification Report: ")
print(classification_report(y_test_normal, y_pred_knn))
```

KNN Model:

Accuracy: 0.93

Classification Report:

support	f1-score	recall	precision	
38	0.92	0.89	0.94	0.0
37	0.86	0.86	0.86	1.0
37	0.92	0.92	0.92	2.0
38	0.97	0.97	0.97	3.0
37	0.97	1.00	0.95	4.0

```
      accuracy
      0.93
      187

      macro avg
      0.93
      0.93
      0.93

      weighted avg
      0.93
      0.93
      0.93
```

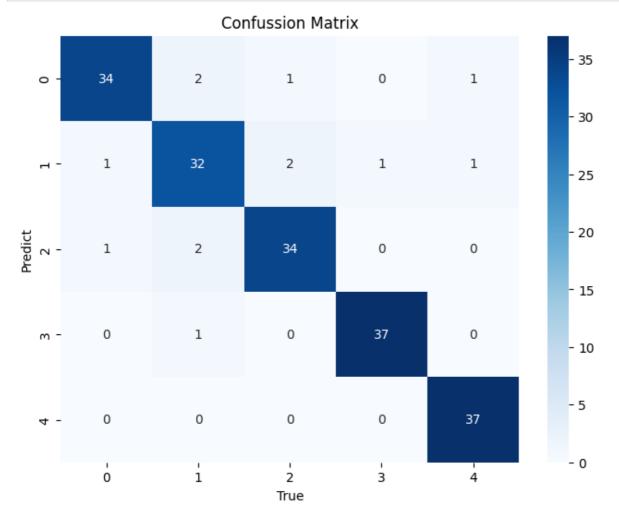
```
evaluation(y_test_normal, y_pred_knn)
```

{'accuracy': 0.93, 'recall': 0.93, 'f1_score': 0.93, 'precision_score': 0.93}

In []:

```
cm = confusion_matrix(y_test_normal, y_pred_knn)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



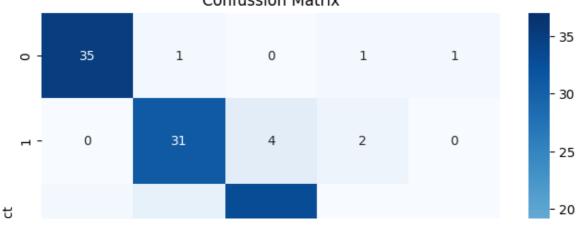
```
rf_model = RandomForestClassifier()

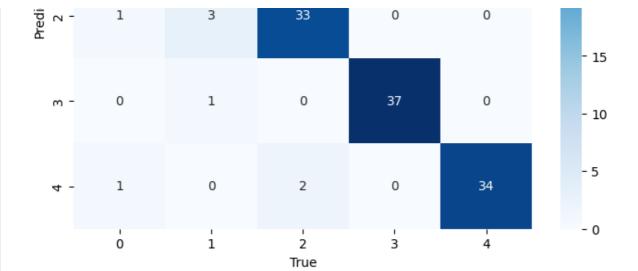
param_grid = {
    "n_estimators": [100, 200],
    "max_depth": [10, 15],
    "min_samples_leaf": [1, 2],
    "min_samples_split": [2, 5],
    "max_features": ["sqrt", "log2"],
}

rf_model = RandomizedSearchCV(rf_model, param_grid, n_iter=100, cv=5, n_jobs=-1)

rf_model.fit(X_train_normal, y_train_normal)
```

```
best params = rf model.best params
print(f"Best Parameters: {best params})")
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:305: UserWarni
ng: The total space of parameters 32 is smaller than n iter=100. Running 32 iterations. F
or exhaustive searches, use GridSearchCV.
 warnings.warn(
Best Parameters: {'n_estimators': 200, 'min_samples_split': 2, 'min_samples_leaf': 1, 'ma
x features': 'sqrt', 'max depth': 15})
In [ ]:
y pred rf = rf model.predict(X test normal)
In [ ]:
print("Random Forest Model:")
accuracy_rf_smote_normal_tunning = round(accuracy_score(y_test_normal, y_pred_rf), 3)
print("Accuracy: ", accuracy rf smote normal tunning)
print("Classification Report: ")
print(classification_report(y_test_normal, y_pred_rf))
Random Forest Model:
Accuracy: 0.909
Classification Report:
              precision
                          recall f1-score
                                               support
         0.0
                   0.95
                             0.92
                                       0.93
                                                    38
                                                    37
                             0.84
                                       0.85
         1.0
                   0.86
                                       0.87
                                                    37
         2.0
                   0.85
                             0.89
         3.0
                   0.93
                             0.97
                                       0.95
                                                    38
         4.0
                   0.97
                             0.92
                                       0.94
                                                    37
                                       0.91
                                                   187
   accuracy
                             0.91
                                       0.91
                   0.91
                                                   187
   macro avq
                   0.91
                             0.91
                                       0.91
                                                   187
weighted avg
In [ ]:
evaluation(y test normal, y pred rf)
{'accuracy': 0.909, 'recall': 0.909, 'f1 score': 0.909, 'precision score': 0.91}
In [ ]:
cm = confusion matrix(y test normal, y pred rf)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
                          Confussion Matrix
```





```
xgb_model = XGBClassifier()

param_grid = {
    "max_depth": [3, 5, 7],
    "learning_rate": [0.01, 0.1],
    "n_estimators": [100, 200],
    "gamma": [0, 0.1],
    "colsample_bytree": [0.7, 0.8],
}

xgb_model = RandomizedSearchCV(xgb_model, param_grid, n_iter=10, cv=5, n_jobs=-1)

xgb_model.fit(X_train_normal, y_train_normal)

best_params = xgb_model.best_params_
print(f"Best_Parameters: {best_params})")
```

Best Parameters: {'n_estimators': 100, 'max_depth': 7, 'learning_rate': 0.1, 'gamma': 0,
'colsample bytree': 0.7})

In []:

```
y_pred_xgb = xgb_model.predict(X_test_normal)
```

In []:

```
print("XGBoost Model:")
accuracy_xgb_smote_normal_tunning = round(accuracy_score(y_test_normal, y_pred_xgb), 3)
print("Accuracy: ", accuracy_xgb_smote_normal_tunning)
print("Classification Report: ")
print(classification_report(y_test, y_pred_xgb))
```

XGBoost Model:

Accuracy: 0.92

Classification Report:

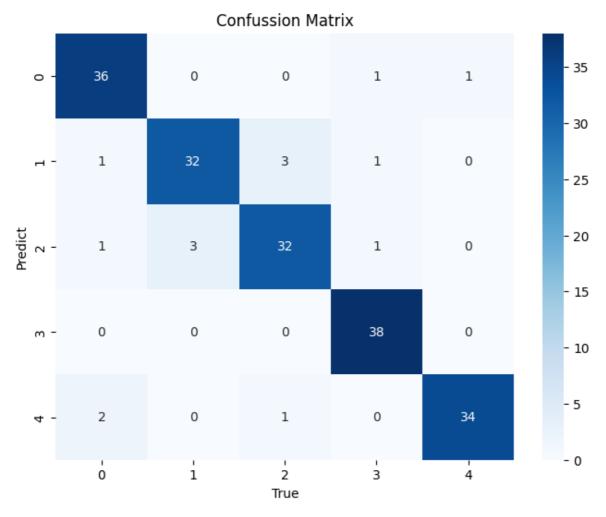
support	f1-score	recall	precision	
38	0.92	0.95	0.90	0.0
37	0.89	0.86	0.91	1.0
37	0.88	0.86	0.89	2.0
38	0.96	1.00	0.93	3.0
37	0.94	0.92	0.97	4.0
187	0.92			accuracy
187	0.92	0.92	0.92	macro avg
187	0.92	0.92	0.92	weighted avg

```
evaluation(y_test_normal, y_pred_xgb)
```

```
{'accuracy': 0.92, 'recall': 0.92, 'f1_score': 0.919, 'precision_score': 0.92}
```

```
cm = confusion_matrix(y_test_normal, y_pred_xgb)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confussion Matrix")
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



In []:

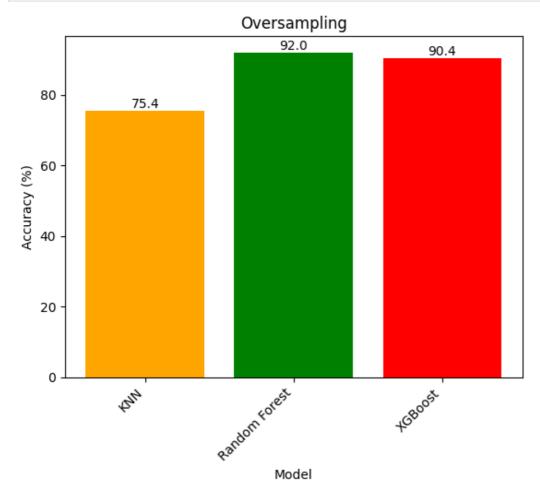
```
import matplotlib.pyplot as plt
```

In []:

```
model_comp1 = pd.DataFrame({
    'Model': [
        'KNN',
        'Random Forest',
        'XGBoost'
],
    'Accuracy': [
        accuracy_knn_smote*100,
        accuracy_rf_smote*100,
        accuracy_rf_smote*100
]
})
model_comp1.head()
```

Out[]:

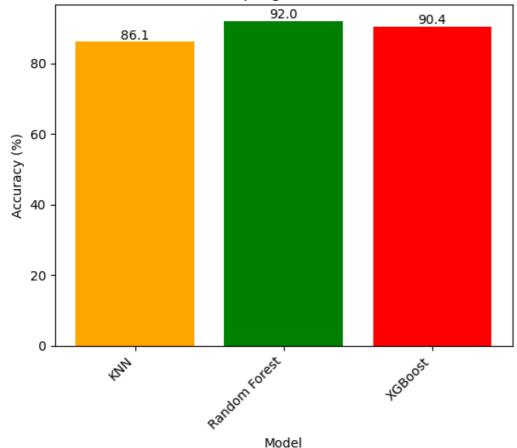
```
Model Accuracy 75.4
Random Forest 92.0
XGBoost 90.4
```



	Model	Accuracy
0	KNN	86.1
1	Random Forest	92.0
2	XGBoost	90.4

In []:

Oversampling + Normalisasi



```
model_comp3 = pd.DataFrame({
    'Model': [
        'KNN',
        'Random Forest',
        'XGBoost'
],
    'Accuracy': [
        accuracy_knn_smote_normal_tunning*100,
        accuracy_rf_smote_normal_tunning*100,
```

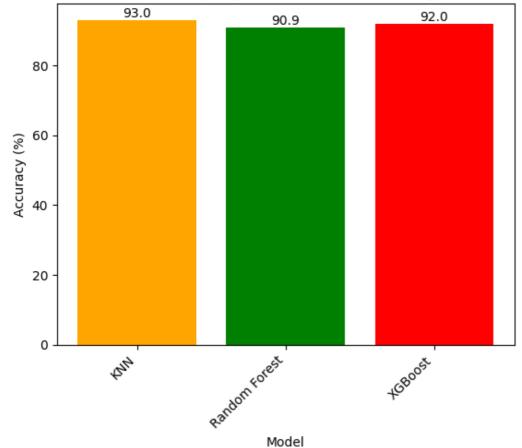
```
accuracy_xgb_smote_normal_tunning*100

]
})
model_comp3.head()
```

	Model	Accuracy
0	KNN	93.0
1	Random Forest	90.9
2	XGBoost	92.0

In []:

Oversampling + Normalisasi + Tunning



```
model_comp_best = pd.DataFrame({
    'Model': [
          'KNN (Oversampling + Normalisasi + Tunning)',
          'Random Forest (Oversampling)',
```

```
'XGBoost (Oversampling + Normalisasi)'
],
    'Accuracy': [
        accuracy_knn_smote_normal_tunning*100,
        accuracy_rf_smote*100,
        accuracy_xgb_smote_normal*100
]
})
model_comp_best.head()
```

	Model	Accuracy
0	KNN (Oversampling + Normalisasi + Tunning)	93.0
1	Random Forest (Oversampling)	92.0
2	XGBoost (Oversampling + Normalisasi)	90.4

93.0

In []:

```
fig, ax = plt.subplots()
bars = plt.bar(model_comp_best['Model'], model_comp_best['Accuracy'], color=['orange', '
green', 'red'])
plt.title("Best Model Comparison")
plt.xlabel('Model')
plt.ylabel('Accuracy (%)')
plt.xticks(rotation=45, ha='right')

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2), ha='center', va='bot
tom')
plt.show()
```



Best Model Comparison

92.0

90.4

O Random Forest (Oversamping) Random Forest (Oversamping & Normalisasi)

4HH Oversai

+G8003

Model

```
In []:
import joblib
joblib.dump(knn_model, 'knn.joblib')
Out[]:
['knn.joblib']
In []:
In []:
```