heartdisease

January 3, 2024

1 1) Pengumpulan Data

Data didapat dari https://archive.ics.uci.edu/dataset/45/heart+disease File yang digunakan adalah hungarian.data

2 2) Menelaah Data

[224]:
```python
import pandas as pd
import numpy as np
import re
import itertools
```

Load Data

[225]:
```python
direct = '/content/sample_data/hungarian.data'
```

Membuat iterasi untuk membaca dataset

[226]:
```python
with open(direct, encoding='Latin1') as file:
  lines= [line.strip() for line in file]

lines[0:10]
```

[226]:
```
['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 -9 -9 12',
 '20 84 0 -9 -9 -9 -9 -9',
 '-9 -9 -9 -9 -9 1 1 1',
 '1 1 -9. -9. name']
```

Membuat keterangan kolom dan baris dari deskripsi dataset sebelumnya

[227]:
```python
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.from_records(data)

df.head()
```

[227]:

```
     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  1  1  1  1  -9.  -9.
1 1255  0  49  0  1  0  0  -9  3  160  …  -9  -9  1  1  1  1  1  -9.  -9.
2 1256  0  37  1  1  0  0  -9  2  130  …  -9  -9  1  1  1  1  1  -9.  -9.
3 1257  0  48  0  1  1  1  -9  4  138  …   2  -9  1  1  1  1  1  -9.  -9.
4 1258  0  54  1  1  0  1  -9  3  150  …   1  -9  1  1  1  1  1  -9.  -9.

     75
0  name
1  name
2  name
3  name
4  name

[5 rows x 76 columns]
```

Menampilkan informasi dataset

[228]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 76 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 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   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
 11  11      294 non-null    object
 12  12      294 non-null    object
 13  13      294 non-null    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
37  37        294 non-null    object
38  38        294 non-null    object
39  39        294 non-null    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
48  48        294 non-null    object
49  49        294 non-null    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
58  58        294 non-null    object
59  59        294 non-null    object
60  60        294 non-null    object
61  61        294 non-null    object
62  62        294 non-null    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  67      294 non-null    object
 68  68      294 non-null    object
 69  69      294 non-null    object
 70  70      294 non-null    object
 71  71      294 non-null    object
 72  72      294 non-null    object
 73  73      294 non-null    object
 74  74      294 non-null    object
 75  75      294 non-null    object
dtypes: object(76)
memory usage: 174.7+ KB
```

Menghapus kolom ke-0 atau pertama

[229]:
```
df = df.iloc[:,:-1]
df = df.drop(df.columns[0], axis =1)
```

Mengubah type data menjadi float

[230]:
```
df = df.astype(float)
```

[231]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 74 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   1       294 non-null    float64
 1   2       294 non-null    float64
 2   3       294 non-null    float64
 3   4       294 non-null    float64
 4   5       294 non-null    float64
 5   6       294 non-null    float64
 6   7       294 non-null    float64
 7   8       294 non-null    float64
 8   9       294 non-null    float64
 9   10      294 non-null    float64
 10  11      294 non-null    float64
 11  12      294 non-null    float64
 12  13      294 non-null    float64
 13  14      294 non-null    float64
 14  15      294 non-null    float64
 15  16      294 non-null    float64
 16  17      294 non-null    float64
 17  18      294 non-null    float64
```

```
18  19        294 non-null    float64
19  20        294 non-null    float64
20  21        294 non-null    float64
21  22        294 non-null    float64
22  23        294 non-null    float64
23  24        294 non-null    float64
24  25        294 non-null    float64
25  26        294 non-null    float64
26  27        294 non-null    float64
27  28        294 non-null    float64
28  29        294 non-null    float64
29  30        294 non-null    float64
30  31        294 non-null    float64
31  32        294 non-null    float64
32  33        294 non-null    float64
33  34        294 non-null    float64
34  35        294 non-null    float64
35  36        294 non-null    float64
36  37        294 non-null    float64
37  38        294 non-null    float64
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
46  47        294 non-null    float64
47  48        294 non-null    float64
48  49        294 non-null    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
54  55        294 non-null    float64
55  56        294 non-null    float64
56  57        294 non-null    float64
57  58        294 non-null    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  63        294 non-null    float64
63  64        294 non-null    float64
64  65        294 non-null    float64
65  66        294 non-null    float64
```

```
 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
 73  74       294 non-null    float64
dtypes: float64(74)
memory usage: 170.1 KB
```

3 3) Validasi Data

Mengubah value -9.0 pada setiap baris, menjadi null atau NaN

[232]:
```python
df.replace(-9.0, np.nan, inplace=True)
```

Menghitung jumlah nilai null value

[233]:
```python
df.isnull().sum()
```

[233]:
```
1       0
2       0
3       0
4       0
5       0
     …
70      0
71      0
72      0
73    266
74    294
Length: 74, dtype: int64
```

[234]:
```python
df.head()
```

[234]:
```
    1     2    3    4    5    6   7    8      9   10  …  65   66  67   68  \
0  0.0  40.0  1.0  1.0  0.0  0.0 NaN  2.0  140.0  0.0  … NaN  NaN NaN  1.0
1  0.0  49.0  0.0  1.0  0.0  0.0 NaN  3.0  160.0  1.0  … NaN  NaN NaN  1.0
2  0.0  37.0  1.0  1.0  0.0  0.0 NaN  2.0  130.0  0.0  … NaN  NaN NaN  1.0
3  0.0  48.0  0.0  1.0  1.0  1.0 NaN  4.0  138.0  0.0  … NaN  2.0 NaN  1.0
4  0.0  54.0  1.0  1.0  0.0  1.0 NaN  3.0  150.0  0.0  … NaN  1.0 NaN  1.0

    69   70   71   72  73  74
0  1.0  1.0  1.0  1.0 NaN NaN
1  1.0  1.0  1.0  1.0 NaN NaN
2  1.0  1.0  1.0  1.0 NaN NaN
3  1.0  1.0  1.0  1.0 NaN NaN
```

```
4  1.0  1.0  1.0  1.0 NaN NaN

[5 rows x 74 columns]
```

[235]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 74 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   1       294 non-null    float64
 1   2       294 non-null    float64
 2   3       294 non-null    float64
 3   4       294 non-null    float64
 4   5       294 non-null    float64
 5   6       294 non-null    float64
 6   7       0 non-null      float64
 7   8       294 non-null    float64
 8   9       293 non-null    float64
 9   10      293 non-null    float64
 10  11      271 non-null    float64
 11  12      12 non-null     float64
 12  13      1 non-null      float64
 13  14      0 non-null      float64
 14  15      286 non-null    float64
 15  16      21 non-null     float64
 16  17      1 non-null      float64
 17  18      293 non-null    float64
 18  19      294 non-null    float64
 19  20      294 non-null    float64
 20  21      294 non-null    float64
 21  22      293 non-null    float64
 22  23      292 non-null    float64
 23  24      293 non-null    float64
 24  25      293 non-null    float64
 25  26      293 non-null    float64
 26  27      285 non-null    float64
 27  28      292 non-null    float64
 28  29      104 non-null    float64
 29  30      292 non-null    float64
 30  31      293 non-null    float64
 31  32      293 non-null    float64
 32  33      293 non-null    float64
 33  34      293 non-null    float64
 34  35      293 non-null    float64
 35  36      293 non-null    float64
```

```
 36  37      293 non-null    float64
 37  38      292 non-null    float64
 38  39      294 non-null    float64
 39  40      104 non-null    float64
 40  41      293 non-null    float64
 41  42      294 non-null    float64
 42  43      4 non-null      float64
 43  44      0 non-null      float64
 44  45      0 non-null      float64
 45  46      0 non-null      float64
 46  47      3 non-null      float64
 47  48      0 non-null      float64
 48  49      2 non-null      float64
 49  50      28 non-null     float64
 50  51      27 non-null     float64
 51  52      17 non-null     float64
 52  53      0 non-null      float64
 53  54      294 non-null    float64
 54  55      294 non-null    float64
 55  56      294 non-null    float64
 56  57      294 non-null    float64
 57  58      19 non-null     float64
 58  59      58 non-null     float64
 59  60      48 non-null     float64
 60  61      18 non-null     float64
 61  62      59 non-null     float64
 62  63      9 non-null      float64
 63  64      23 non-null     float64
 64  65      5 non-null      float64
 65  66      50 non-null     float64
 66  67      25 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      28 non-null     float64
 73  74      0 non-null      float64
dtypes: float64(74)
memory usage: 170.1 KB
```

4 4) Menentukan Object Data

Mengambil 14 fitur, sesuai instruksi dari file heart-disease.names

[236]:
```
df_selected = df.iloc[:, [1, 2, 7, 8, 10, 14, 17, 30, 36, 38, 39, 42, 49, 56]]
```

[237]:
```
df_selected.head()
```

[237]:
```
      2    3    8      9     11   15   18     31   37   39   40  43  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 NaN  1.0
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 NaN  3.0
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
```

[238]:
```
df_selected.tail()
```

[238]:
```
        2    3    8      9     11   15   18     31   37   39   40  43   50  \
289  48.0  0.0  2.0    NaN  308.0  0.0  1.0    NaN  NaN  2.0  1.0 NaN  NaN
290  36.0  1.0  2.0  120.0  166.0  0.0  0.0  180.0  0.0  0.0  NaN NaN  NaN
291  48.0  1.0  3.0  110.0  211.0  0.0  0.0  138.0  0.0  0.0  NaN NaN  6.0
292  47.0  0.0  2.0  140.0  257.0  0.0  0.0  135.0  0.0  1.0  1.0 NaN  NaN
293  53.0  1.0  4.0  130.0  182.0  0.0  0.0  148.0  0.0  0.0  NaN NaN  NaN

      57
289  0.0
290  0.0
291  0.0
292  0.0
293  0.0
```

[239]:
```
df_selected.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 14 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   2       294 non-null    float64
 1   3       294 non-null    float64
 2   8       294 non-null    float64
 3   9       293 non-null    float64
 4   11      271 non-null    float64
 5   15      286 non-null    float64
 6   18      293 non-null    float64
 7   31      293 non-null    float64
 8   37      293 non-null    float64
 9   39      294 non-null    float64
 10  40      104 non-null    float64
 11  43      4 non-null      float64
 12  50      28 non-null     float64
 13  57      294 non-null    float64
dtypes: float64(14)
```

```
memory usage: 32.3 KB
```

Mengganti 14 nama kolom sesuai instruksi

[240]:
```
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)
```

```
<ipython-input-240-b484e5bfe3ce>:17: 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_guide/indexing.html#returning-a-view-versus-a-copy
  df_selected.rename(columns=column_mapping, inplace=True)
```

[241]:
```
df_selected.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294 entries, 0 to 293
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       294 non-null    float64
 1   sex       294 non-null    float64
 2   cp        294 non-null    float64
 3   trestbps  293 non-null    float64
 4   chol      271 non-null    float64
 5   fbs       286 non-null    float64
 6   restecg   293 non-null    float64
 7   thalach   293 non-null    float64
 8   exang     293 non-null    float64
 9   oldpeak   294 non-null    float64
 10  slope     104 non-null    float64
 11  ca        4 non-null      float64
 12  thal      28 non-null     float64
```

```
 13  target    294 non-null    float64
dtypes: float64(14)
memory usage: 32.3 KB
```

Menghitung jumlah fitur pada dataset

[242]:
```
df_selected.value_counts()
```

[242]:
```
age   sex  cp   trestbps  chol   fbs  restecg  thalach  exang  oldpeak  slope
ca   thal  target
47.0  1.0  4.0  150.0     226.0  0.0  0.0      98.0     1.0    1.5      2.0
0.0  7.0   1.0       1
dtype: int64
```

5 5) Membersihkan Data

Menghitung nilai null pada setiap kolom

[243]:
```
df_selected.isnull().sum()
```

[243]:
```
age           0
sex           0
cp            0
trestbps      1
chol         23
fbs           8
restecg       1
thalach       1
exang         1
oldpeak       0
slope       190
ca          290
thal        266
target        0
dtype: int64
```

Dikarenakan kolom slope, ca, dan thal memiliki banyak nilai null, maka akan didrop atau dihapus

[244]:
```
columns_to_drop = ['ca', 'slope', 'thal']
df_selected = df_selected.drop(columns_to_drop, axis=1)

df_selected.isnull().sum()
```

[244]:
```
age          0
sex          0
cp           0
trestbps     1
chol        23
```

```
fbs           8
restecg       1
thalach       1
exang         1
oldpeak       0
target        0
dtype: int64
```

Pengisian nilai null pada beberapa fitur, dengan mencari nilai mean di setiap kolomnya

[245]:
```
meanTBPS = df_selected['trestbps'].dropna()
meanChol = df_selected['chol'].dropna()
meanfbs = df_selected['fbs'].dropna()
meanRestCG = df_selected['restecg'].dropna()
meanthalach = df_selected['thalach'].dropna()
meanexang = df_selected['exang'].dropna()
```

[246]:
```
meanTBPS = meanTBPS.astype(float)
meanChol = meanChol.astype(float)
meanfbs = meanfbs.astype(float)
meanthalach = meanthalach.astype(float)
meanexang = meanexang.astype(float)
meanRestCG = meanRestCG.astype(float)
```

[247]:
```
meanTBPS = round(meanTBPS.mean())
meanChol = round(meanChol.mean())
meanfbs = round(meanfbs.mean())
meanthalach = round(meanthalach.mean())
meanexang = round(meanexang.mean())
meanRestCG = round(meanRestCG.mean())
```

Mengubah nilai null menjadi nilai mean

[248]:
```
fill_values = {'trestbps': meanTBPS, 'chol': meanChol, 'fbs': meanfbs,
'thalach':meanthalach,'exang':meanexang,'restecg':meanRestCG}
dfClean = df_selected.fillna(value=fill_values)
dfClean.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
 1   sex       294 non-null    float64
 2   cp        294 non-null    float64
 3   trestbps  294 non-null    float64
 4   chol      294 non-null    float64
```

```
 5   fbs       294 non-null    float64
 6   restecg   294 non-null    float64
 7   thalach   294 non-null    float64
 8   exang     294 non-null    float64
 9   oldpeak   294 non-null    float64
 10  target    294 non-null    float64
dtypes: float64(11)
memory usage: 25.4 KB
```

[249]:
```
dfClean.isnull().sum()
```

[249]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
target      0
dtype: int64
```

Pengecekan duplikasi data

[250]:
```
duplicate_rows = dfClean.duplicated()
dfClean[duplicate_rows]
```

[250]:
```
      age  sex   cp  trestbps   chol  fbs  restecg  thalach  exang  oldpeak  \
163  49.0  0.0  2.0     110.0  251.0  0.0      0.0    160.0    0.0      0.0

     target
163     0.0
```

[251]:
```
print("All duplicate rows:")
dfClean[dfClean.duplicated(keep=False)]
```

```
All duplicate rows:
```

[251]:
```
      age  sex   cp  trestbps   chol  fbs  restecg  thalach  exang  oldpeak  \
90   49.0  0.0  2.0     110.0  251.0  0.0      0.0    160.0    0.0      0.0
163  49.0  0.0  2.0     110.0  251.0  0.0      0.0    160.0    0.0      0.0

     target
90      0.0
163     0.0
```

Hapus data yang sama

[252]:
```
dfClean = dfClean.drop_duplicates()
print("All duplicate rows:")
dfClean[dfClean.duplicated(keep=False)]
```

```
All duplicate rows:
```

[252]:
```
Empty DataFrame
Columns: [age, sex, cp, trestbps, chol, fbs, restecg, thalach, exang, oldpeak,
target]
Index: []
```

[253]:
```
dfClean.head()
```

[253]:
```
    age  sex   cp  trestbps   chol  fbs  restecg  thalach  exang  oldpeak  \
0  40.0  1.0  2.0     140.0  289.0  0.0      0.0    172.0    0.0      0.0
1  49.0  0.0  3.0     160.0  180.0  0.0      0.0    156.0    0.0      1.0
2  37.0  1.0  2.0     130.0  283.0  0.0      1.0     98.0    0.0      0.0
3  48.0  0.0  4.0     138.0  214.0  0.0      0.0    108.0    1.0      1.5
4  54.0  1.0  3.0     150.0  251.0  0.0      0.0    122.0    0.0      0.0

   target
0     0.0
1     1.0
2     0.0
3     3.0
4     0.0
```

[254]:
```
dfClean['target'].value_counts()
```

[254]:
```
0.0    187
1.0     37
3.0     28
2.0     26
4.0     15
Name: target, dtype: int64
```

[255]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

Mencari korelasi antar fitur

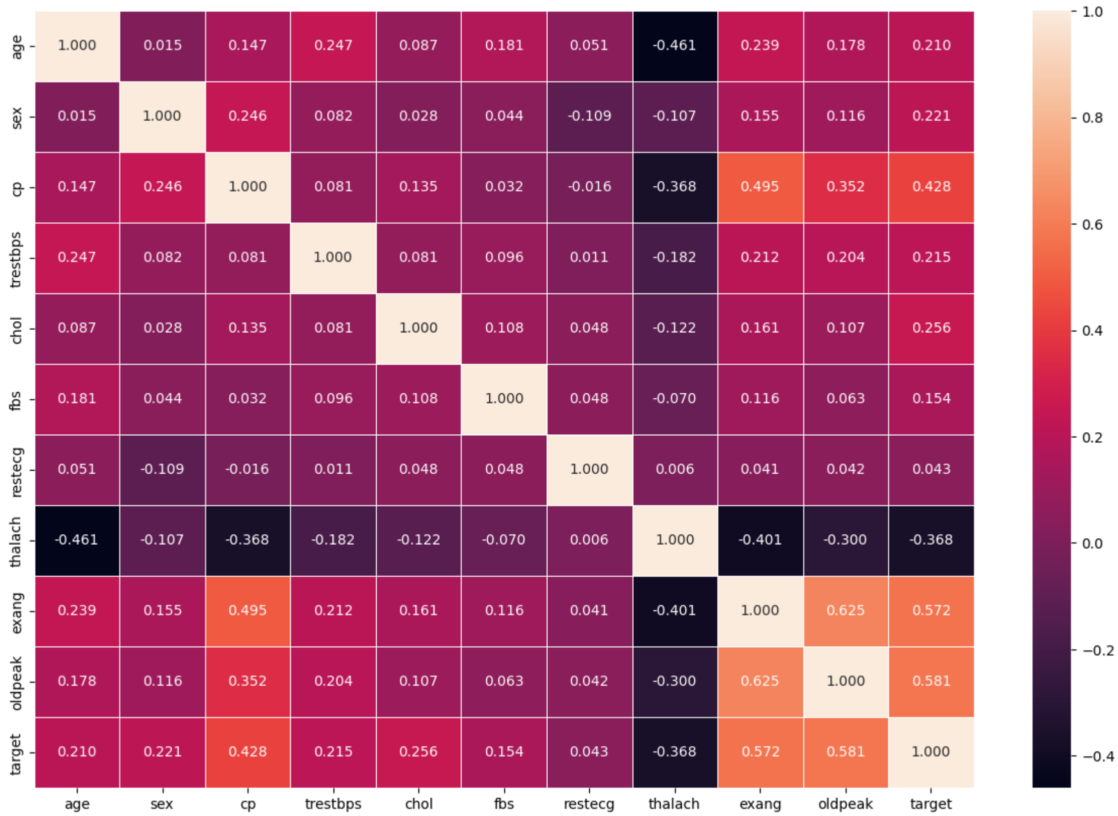
[256]:
```
dfClean.corr()
```

[256]:
```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000  0.014516  0.146616  0.246571  0.087101  0.181130
sex       0.014516  1.000000  0.245769  0.082064  0.027695  0.044372
```

```
cp        0.146616  0.245769  1.000000  0.081293  0.134697  0.031930
trestbps  0.246571  0.082064  0.081293  1.000000  0.080818  0.096222
chol      0.087101  0.027695  0.134697  0.080818  1.000000  0.107686
fbs       0.181130  0.044372  0.031930  0.096222  0.107686  1.000000
restecg   0.050672 -0.108656 -0.016372  0.011256  0.048081  0.047988
thalach  -0.460514 -0.106959 -0.367819 -0.181824 -0.122038 -0.069722
exang     0.239223  0.154925  0.494674  0.211507  0.161055  0.115503
oldpeak   0.178172  0.115959  0.351735  0.204000  0.106743  0.063179
target    0.210429  0.220732  0.427536  0.214898  0.256027  0.154319

           restecg   thalach     exang   oldpeak    target
age       0.050672 -0.460514  0.239223  0.178172  0.210429
sex      -0.108656 -0.106959  0.154925  0.115959  0.220732
cp       -0.016372 -0.367819  0.494674  0.351735  0.427536
trestbps  0.011256 -0.181824  0.211507  0.204000  0.214898
chol      0.048081 -0.122038  0.161055  0.106743  0.256027
fbs       0.047988 -0.069722  0.115503  0.063179  0.154319
restecg   1.000000  0.006084  0.041290  0.042193  0.042643
thalach   0.006084  1.000000 -0.400508 -0.300458 -0.367525
exang     0.041290 -0.400508  1.000000  0.624965  0.571710
oldpeak   0.042193 -0.300458  0.624965  1.000000  0.580732
target    0.042643 -0.367525  0.571710  0.580732  1.000000
```

[257]:
```
cor_mat = dfClean.corr()
fig,ax = plt.subplots(figsize=(15,10))
sns.heatmap(cor_mat, annot=True, linewidths=0.5, fmt=".3f")
```

[257]: <Axes: >



6 6) Konstruksi Data

Dalam tahap ini Konstruksi data salah satu tujuannya yaitu untuk menyesuaikan semua tipe data yang ada di dalam dataset. Namun pada tahap ini dataset sudah memiliki tipe data yang sesuai sehingga tidak perlu dilakukan penyesuaian kembali

[258]:
```
dfClean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 293 entries, 0 to 293
Data columns (total 11 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       293 non-null    float64
 1   sex       293 non-null    float64
 2   cp        293 non-null    float64
 3   trestbps  293 non-null    float64
 4   chol      293 non-null    float64
 5   fbs       293 non-null    float64
 6   restecg   293 non-null    float64
 7   thalach   293 non-null    float64
```

```
 8   exang     293 non-null    float64
 9   oldpeak   293 non-null    float64
 10  target    293 non-null    float64
dtypes: float64(11)
memory usage: 27.5 KB
```

[259]:
```python
dfClean.head(5)
```

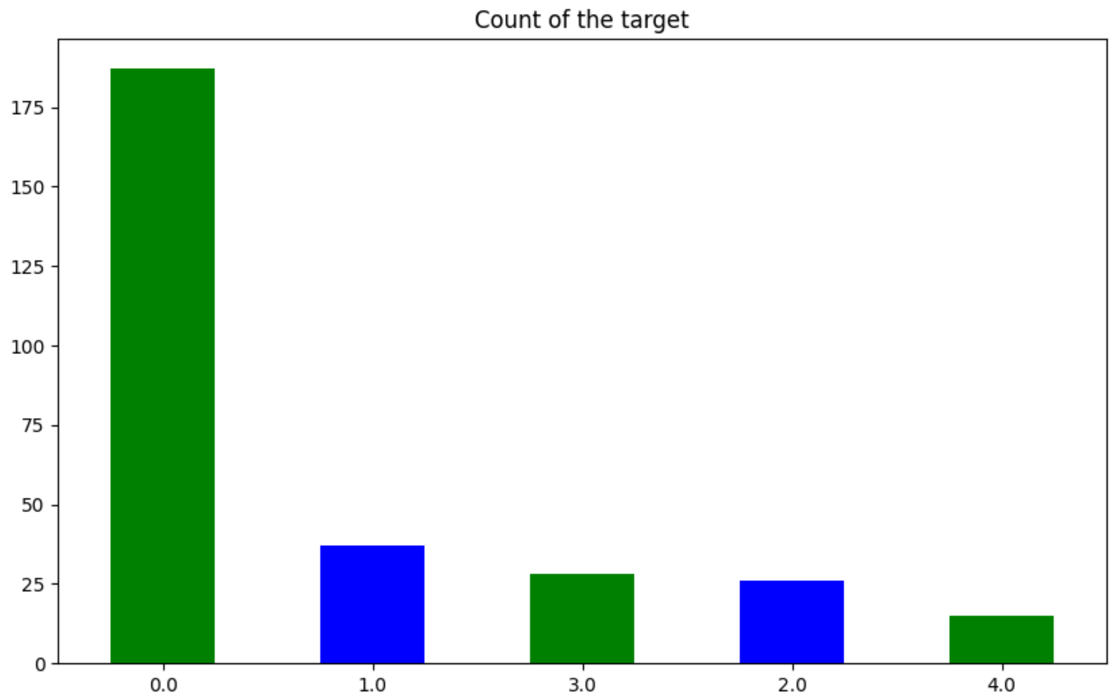
[259]:
```
    age  sex   cp  trestbps   chol  fbs  restecg  thalach  exang  oldpeak  \
0  40.0  1.0  2.0     140.0  289.0  0.0      0.0    172.0    0.0      0.0
1  49.0  0.0  3.0     160.0  180.0  0.0      0.0    156.0    0.0      1.0
2  37.0  1.0  2.0     130.0  283.0  0.0      1.0     98.0    0.0      0.0
3  48.0  0.0  4.0     138.0  214.0  0.0      0.0    108.0    1.0      1.5
4  54.0  1.0  3.0     150.0  251.0  0.0      0.0    122.0    0.0      0.0

   target
0     0.0
1     1.0
2     0.0
3     3.0
4     0.0
```

Memisahkan fitur dan target

[260]:
```python
X = dfClean.drop("target", axis=1).values
y = dfClean.iloc[:, -1]
```

Pengecekan jumlah persebaran target

[261]:
```python
dfClean['target'].value_counts().
 ↪plot(kind='bar',figsize=(10,6),color=['green','blue'])
plt.title("Count of the target")
plt.xticks(rotation=0);
```

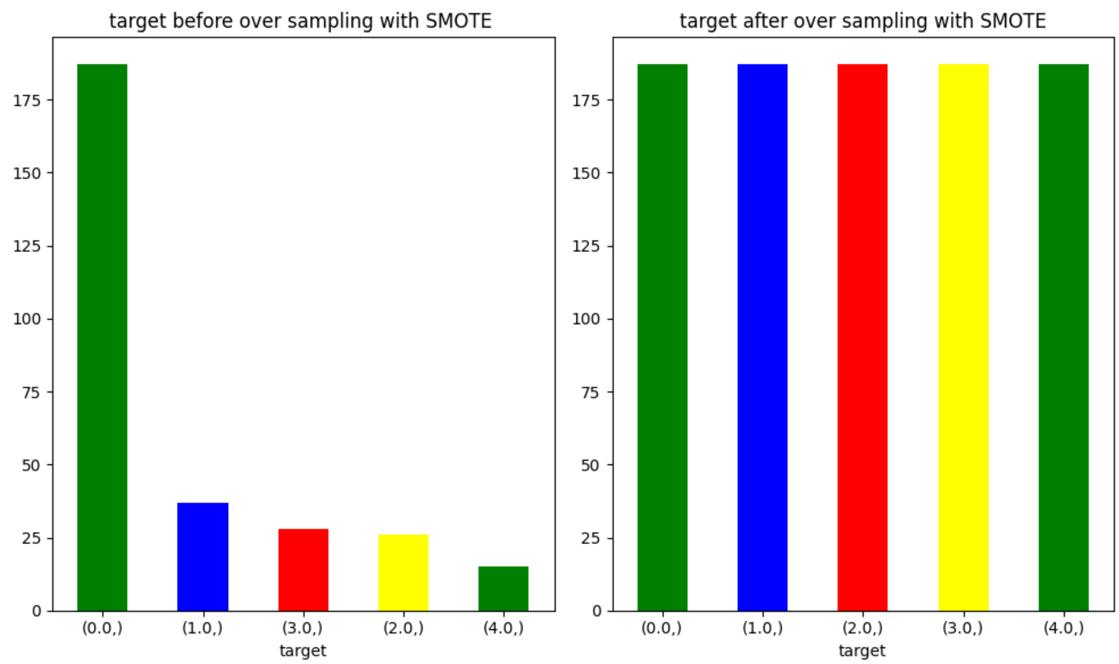


Pada Grafik diatas menunjukan bahwa persebaran jumlah target tidak seimbang oleh karena itu perlu diseimbangkan terlebih dahulu. Menyeimbangkan target ada 2 cara yaitu oversampling dan undersampling. oversampling dilakukan jika jumlah dataset sedikit sedangkan undersampling dilakukan jika jumlah data terlalu banyak. Disini kita akan melakukan oversampling dikarenakan jumlah data kita tidak banyak. Salah satu metode yang Oversampling yang akan kita gunakan adalah SMOTE

[262]:
```python
from imblearn.over_sampling import SMOTE

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

[263]:
```python
plt.subplot(1, 2, 1)

new_df1 = pd.DataFrame(data=y)

plt.subplot(1, 2, 1)
new_df1.value_counts().plot(kind='bar',figsize=(10,6),color=['green', 'blue',␣
 ↪'red', 'yellow'])
plt.title("target before over sampling with SMOTE ")
plt.xticks(rotation=0);

plt.subplot(1, 2, 2)
new_df2 = pd.DataFrame(data=y_smote_resampled)
```

```
new_df2.value_counts().
 ↪plot(kind='bar',figsize=(10,6),color=['green','blue','red','yellow'])
plt.title("target after over sampling with SMOTE")
plt.xticks(rotation=0);

plt.tight_layout()
plt.show()
```



Pada Grafik diatas dapat dilihat ketika target belum di seimbangkan dan sudah diseimbangkan menggunakan oversampling.

[264]:
```
new_df1 = pd.DataFrame(data=y)
new_df1.value_counts()
```

[264]:
```
target
0.0     187
1.0      37
3.0      28
2.0      26
4.0      15
dtype: int64
```

[265]:
```
# oversampling
new_df2 = pd.DataFrame(data=y_smote_resampled)
new_df2.value_counts()
```

[265]:
```
target
0.0    187
1.0    187
2.0    187
3.0    187
4.0    187
dtype: int64
```

Setelah menyeimbangkan persebaran jumlah target kita akan melakukan mengecekan apakah perlu dilakukan normalisasi/standarisasi pada datset kita.

[266]:
```python
dfClean.describe()
```

[266]:

	age	sex	cp	trestbps	chol	fbs
count	293.000000	293.000000	293.000000	293.000000	293.000000	293.000000
mean	47.822526	0.726962	2.986348	132.662116	250.860068	0.068259
std	7.824875	0.446282	0.965049	17.576793	65.059069	0.252622
min	28.000000	0.000000	1.000000	92.000000	85.000000	0.000000
25%	42.000000	0.000000	2.000000	120.000000	211.000000	0.000000
50%	49.000000	1.000000	3.000000	130.000000	248.000000	0.000000
75%	54.000000	1.000000	4.000000	140.000000	277.000000	0.000000
max	66.000000	1.000000	4.000000	200.000000	603.000000	1.000000

	restecg	thalach	exang	oldpeak	target
count	293.000000	293.000000	293.000000	293.000000	293.000000
mean	0.218430	139.058020	0.303754	0.588055	0.795222
std	0.460868	23.558003	0.460665	0.909554	1.238251
min	0.000000	82.000000	0.000000	0.000000	0.000000
25%	0.000000	122.000000	0.000000	0.000000	0.000000
50%	0.000000	140.000000	0.000000	0.000000	0.000000
75%	0.000000	155.000000	1.000000	1.000000	1.000000
max	2.000000	190.000000	1.000000	5.000000	4.000000

Pada deskripsi diatas dapat dilihat bahwa terdapat rentang nilai yang cukup jauh pada standar deviasi setiap fitur dataset yang kita miliki. Oleh karena itu perlu dilakukan normalisasi/standarisasi agar memperkecil rentang antara standar deviasi setiap kolom.

[267]:
```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_smote_resampled_normal = scaler.fit_transform(X_smote_resampled)
```

[268]:
```python
len(X_smote_resampled_normal)
```

[268]: 935

[269]:
```
dfcek1 = pd.DataFrame(X_smote_resampled_normal)
dfcek1.describe()
```

[269]:
```
                0           1           2           3           4           5  \
count  935.000000  935.000000  935.000000  935.000000  935.000000  935.000000
mean     0.563739    0.842507    0.818224    0.403413    0.341027    0.094277
std      0.174873    0.332492    0.274211    0.147493    0.110990    0.252030
min      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%      0.473283    1.000000    0.666667    0.305556    0.267954    0.000000
50%      0.578947    1.000000    1.000000    0.387952    0.330240    0.000000
75%      0.683363    1.000000    1.000000    0.487481    0.393811    0.000000
max      1.000000    1.000000    1.000000    1.000000    1.000000    1.000000

                6           7           8           9
count  935.000000  935.000000  935.000000  935.000000
mean     0.117938    0.453354    0.598398    0.227015
std      0.199527    0.197232    0.450288    0.201293
min      0.000000    0.000000    0.000000    0.000000
25%      0.000000    0.312720    0.000000    0.000000
50%      0.000000    0.440606    0.962447    0.200000
75%      0.201473    0.593629    1.000000    0.386166
max      1.000000    1.000000    1.000000    1.000000
```

Setelah dilakukan normalisasi pada fitur, selanjutnya kita perlu membagi fitur dan target menjadi data train dan test.

[270]:
```
from sklearn.model_selection import train_test_split
```

[271]:
```
# membagi fitur dan target menjadi data train dan test (untuk yang oversample␣
↪saja)
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)
```

[272]:
```
# membagi fitur dan target menjadi data train dan test (untuk yang oversample +␣
↪normalization)
X_train_normal, X_test_normal, y_train_normal, y_test_normal =␣
↪train_test_split(X_smote_resampled_normal, y_smote_resampled, test_size=0.2,␣
↪random_state=42,stratify = y_smote_resampled)
```

7 7) Model

Pada tahap ini kita akan memulai untuk membangun sebuah model.

Dibawah ini merupakan sebuah fungsi untuk menampilkan hasil akurasi dan rata - rata dari recall , f1 dan precision score setiap model. Fungsi ini nantinya akan dipanggil di setiap model. Membuat Fungsi ini bersifat opsional.

[273]:
```
from sklearn.metrics import␣
↪accuracy_score,recall_score,f1_score,precision_score,roc_auc_score,confusion_matrix,precisi

def evaluation(Y_test,Y_pred):
  acc = accuracy_score(Y_test,Y_pred)
  rcl = recall_score(Y_test,Y_pred,average = 'weighted')
  f1 = f1_score(Y_test,Y_pred,average = 'weighted')
  ps = precision_score(Y_test,Y_pred,average = 'weighted')
  metric_dict={'accuracy': round(acc,3),
    'recall': round(rcl,3),
    'F1 score': round(f1,3),
    'Precision score': round(ps,3)
  }
  return print(metric_dict)
```

8 KNN

Pada tahap ini kita akan akan memulai membangun model dengan algoritma KNN dengan nilai neighbors yaitu 3.

[274]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report

knn_model = KNeighborsClassifier(n_neighbors = 3)
knn_model.fit(X_train, y_train)
```

[274]:
```
KNeighborsClassifier(n_neighbors=3)
```

Berikut adalah kode program untuk menampilkan hasil akurasi dengan algoritma KNN

[275]:
```
y_pred_knn = knn_model.predict(X_test)

# Evaluate the KNN model
print("K-Nearest Neighbors (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))
```

```
K-Nearest Neighbors (KNN) Model:
Accuracy: 0.754
Classification Report:
              precision    recall  f1-score   support

         0.0       0.65      0.39      0.49        38
```

```
         1.0       0.73      0.81      0.77        37
         2.0       0.80      0.86      0.83        37
         3.0       0.77      0.87      0.81        38
         4.0       0.78      0.84      0.81        37

    accuracy                           0.75       187
   macro avg       0.75      0.76      0.74       187
weighted avg       0.74      0.75      0.74       187
```

[276]:

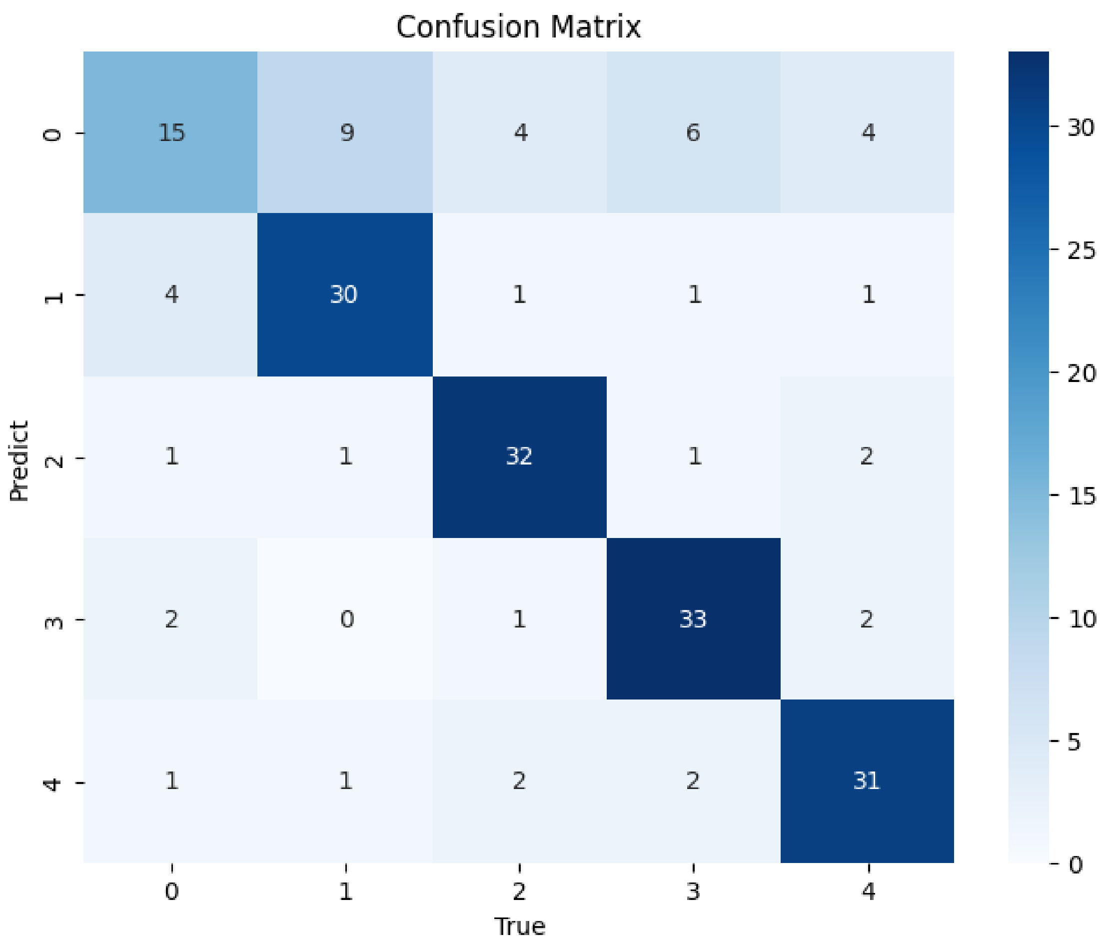
```python
evaluation(y_test,y_pred_knn)
```

```
{'accuracy': 0.754, 'recall': 0.754, 'F1 score': 0.741, 'Precision score':
0.745}
```

Pada visualisasi ini ditampilkan visualisasi confusion matrix untuk membandingkan hasil prediksi model dengan nilai sebenarnya.

[277]:

```python
cm = confusion_matrix(y_test, y_pred_knn)

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



9 Random Forest

Selanjutnya kita akan membangun model dengan algoritma random forest dengan n_estimators yaitu 100, n_estimators sendiri berguna mengatur jumlah pohon keputusan yang akan dibangun

[278]:
```python
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

[278]:
```
RandomForestClassifier(random_state=42)
```

[279]:
```python
y_pred_rf = rf_model.predict(X_test)

# Evaluate the Random Forest model
print("\nRandom Forest Model:")
accuracy_rf_smote = round(accuracy_score(y_test, y_pred_rf),3)
print("Accuracy:",accuracy_rf_smote)
print("Classification Report:")
```

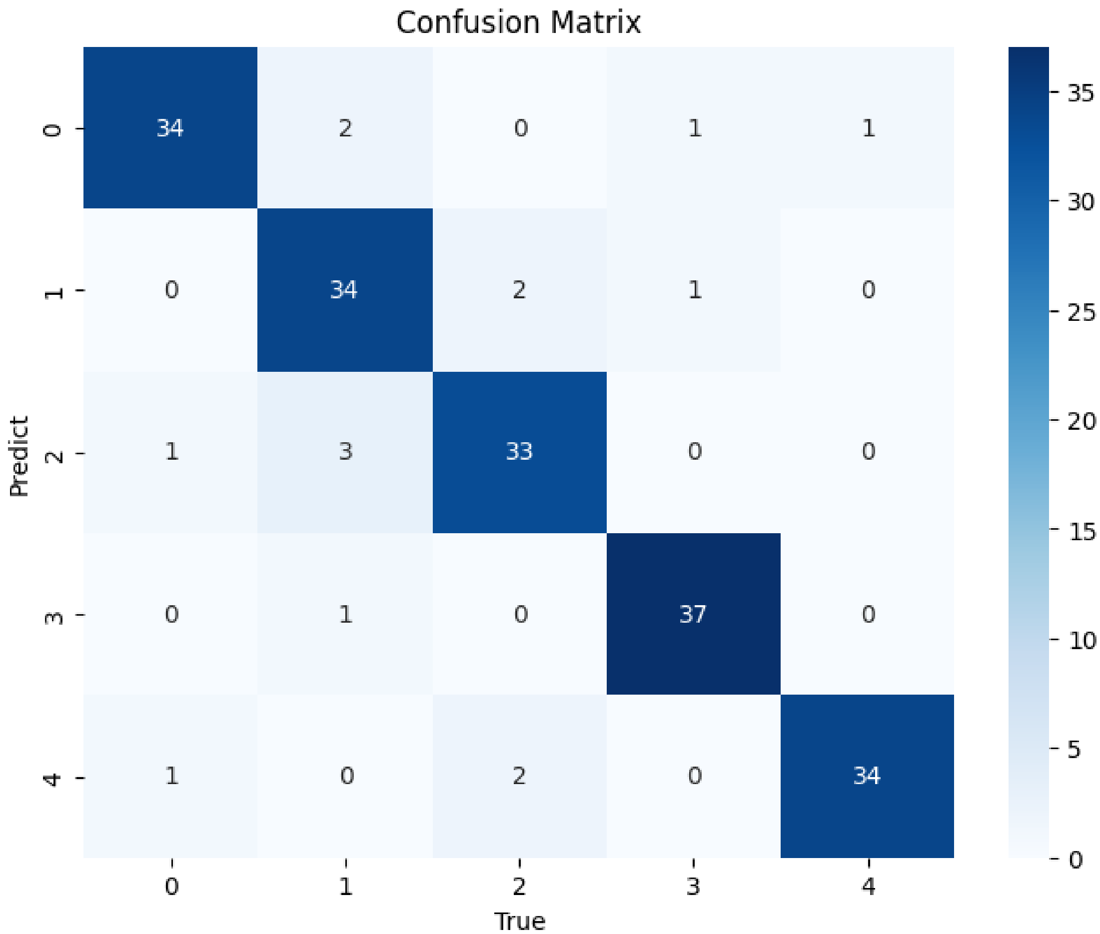
```
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Model:
Accuracy: 0.92
Classification Report:
              precision    recall  f1-score   support

         0.0       0.94      0.89      0.92        38
         1.0       0.85      0.92      0.88        37
         2.0       0.89      0.89      0.89        37
         3.0       0.95      0.97      0.96        38
         4.0       0.97      0.92      0.94        37

    accuracy                           0.92       187
   macro avg       0.92      0.92      0.92       187
weighted avg       0.92      0.92      0.92       187
```

[280]:
```
evaluation(y_test,y_pred_rf)
```

```
{'accuracy': 0.92, 'recall': 0.92, 'F1 score': 0.92, 'Precision score': 0.922}
```

[281]:
```
cm = confusion_matrix(y_test, y_pred_rf)

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



10 XGBoost

Pada tahap ini dalam membangun model, kita akan menggunakan algoritma XGBoost dengan learning rate yaitu 0.1. learning rate berguna untuk mengontrol seberapa besar kita menyesuaikan bobot model.

[282]:
```
xgb_model = XGBClassifier(learning_rate=0.1, n_estimators=100, random_state=42)
xgb_model.fit(X_train, y_train)
```

[282]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              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,
              max_delta_step=None, max_depth=None, max_leaves=None,
```

```
                min_child_weight=None, missing=nan, monotone_constraints=None,
                multi_strategy=None, n_estimators=100, n_jobs=None,
                num_parallel_tree=None, objective='multi:softprob', …)
```

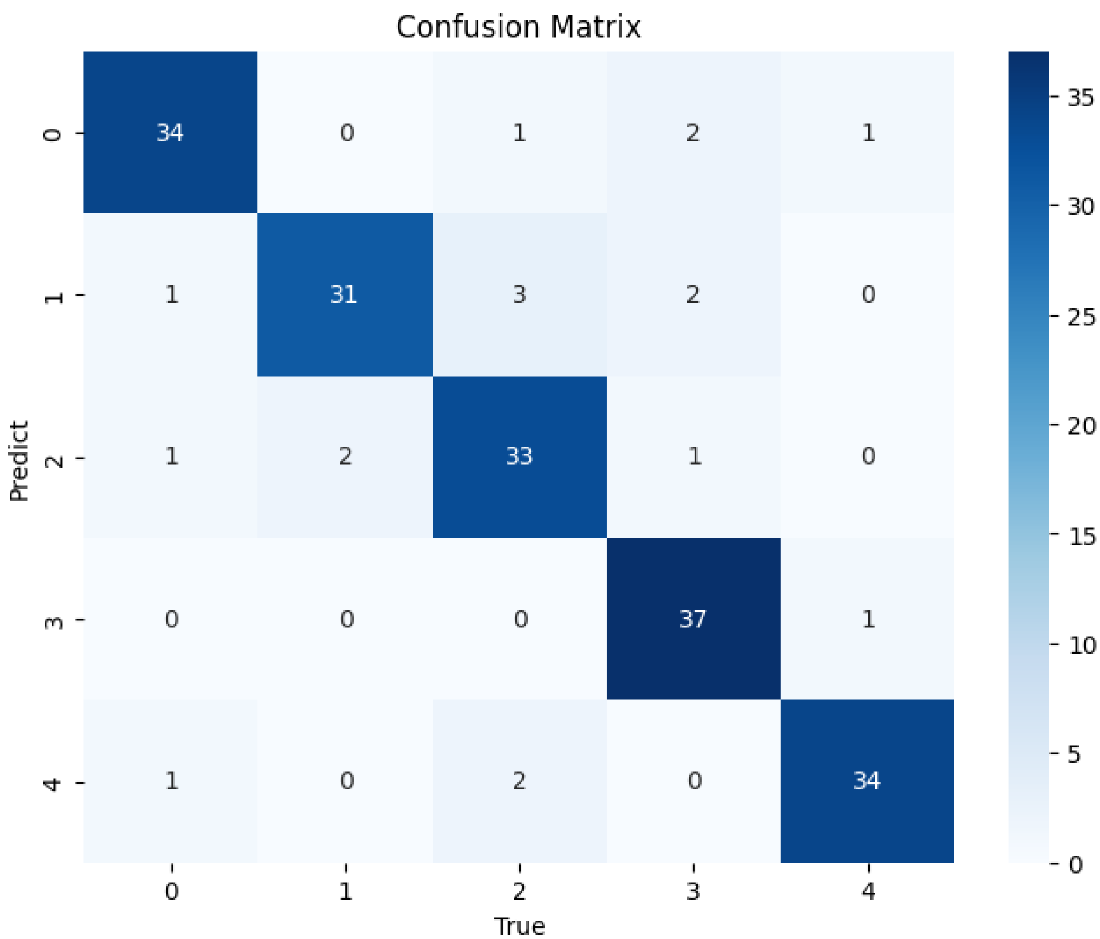
[283]:
```
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate the XGBoost model
print("\nXGBoost 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  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

    accuracy                           0.90       187
   macro avg       0.91      0.90      0.90       187
weighted avg       0.91      0.90      0.90       187
```

[284]:
```
evaluation(y_test,y_pred_xgb)
```

```
{'accuracy': 0.904, 'recall': 0.904, 'F1 score': 0.904, 'Precision score':
0.906}
```

[285]:
```
cm = confusion_matrix(y_test, y_pred_xgb)

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



11 Oversample + Normalisasi

Pada bagian ini kita akan membuat sebuah model yang dimana data yang dipakai kali ini yang sudah dilakukan oversample dan normalisasi. Algoritma yang digunakan sama seperti sebelumnya yaitu KNN, Random Forest, dan XGBoost. Sekaligus dibuat visualisasi hasil evaluasi pada masing-masing model.

12 KNN

[286]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report

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

[286]: KNeighborsClassifier(n_neighbors=3)

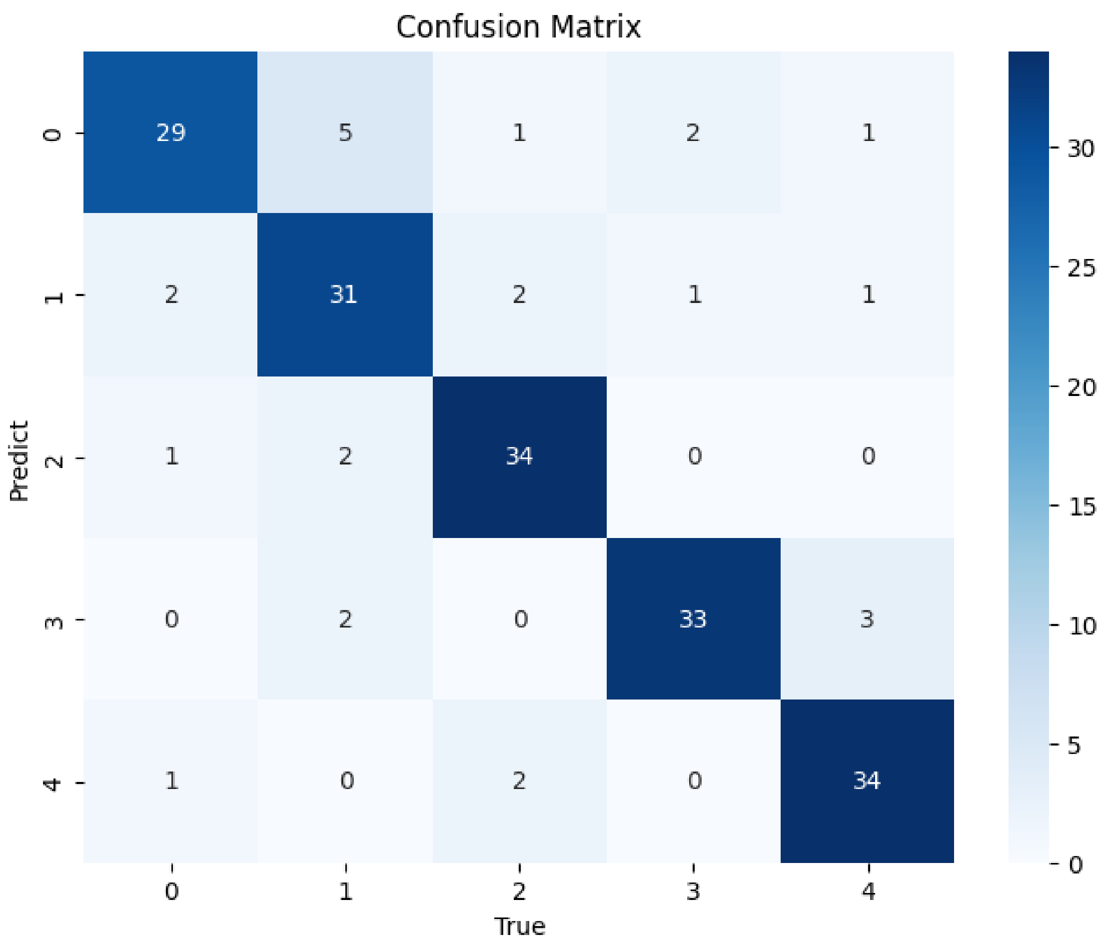
[287]:
```python
y_pred_knn = knn_model.predict(X_test_normal)

# Evaluate the KNN model
print("K-Nearest Neighbors (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))
```

```
K-Nearest Neighbors (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

    accuracy                           0.86       187
   macro avg       0.86      0.86      0.86       187
weighted avg       0.86      0.86      0.86       187
```

[288]:
```python
evaluation(y_test_normal,y_pred_knn)
```

```
{'accuracy': 0.861, 'recall': 0.861, 'F1 score': 0.861, 'Precision score':
0.863}
```

[289]:
```python
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('Confusion Matrix')
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



13 Random Forest

[290]:
```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_normal, y_train_normal)
```

[290]: RandomForestClassifier(random_state=42)

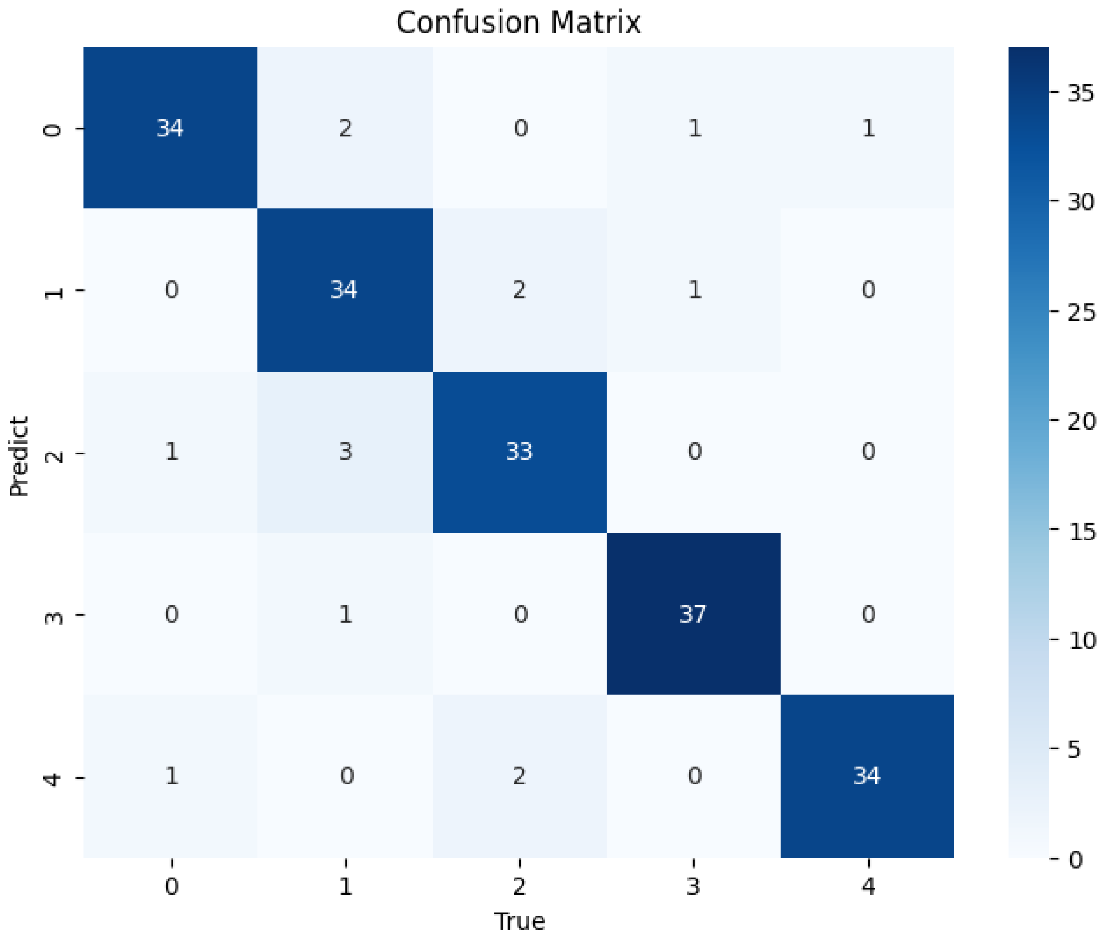
[291]:
```
y_pred_rf = rf_model.predict(X_test_normal)

# Evaluate the Random Forest model
print("\nRandom 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))
```

```
Random Forest Model:
Accuracy: 0.92
Classification Report:
              precision    recall  f1-score   support

         0.0       0.94      0.89      0.92        38
         1.0       0.85      0.92      0.88        37
         2.0       0.89      0.89      0.89        37
         3.0       0.95      0.97      0.96        38
         4.0       0.97      0.92      0.94        37

    accuracy                           0.92       187
   macro avg       0.92      0.92      0.92       187
weighted avg       0.92      0.92      0.92       187
```

[292]:
```
evaluation(y_test_normal,y_pred_rf)
```

```
{'accuracy': 0.92, 'recall': 0.92, 'F1 score': 0.92, 'Precision score': 0.922}
```

[293]:
```
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('Confusion Matrix')
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



14 XGBoost

[294]:
```
xgb_model = XGBClassifier(learning_rate=0.1, n_estimators=100, random_state=42)
xgb_model.fit(X_train_normal, y_train_normal)
```

[294]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              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,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=100, n_jobs=None,
              num_parallel_tree=None, objective='multi:softprob', …)
```

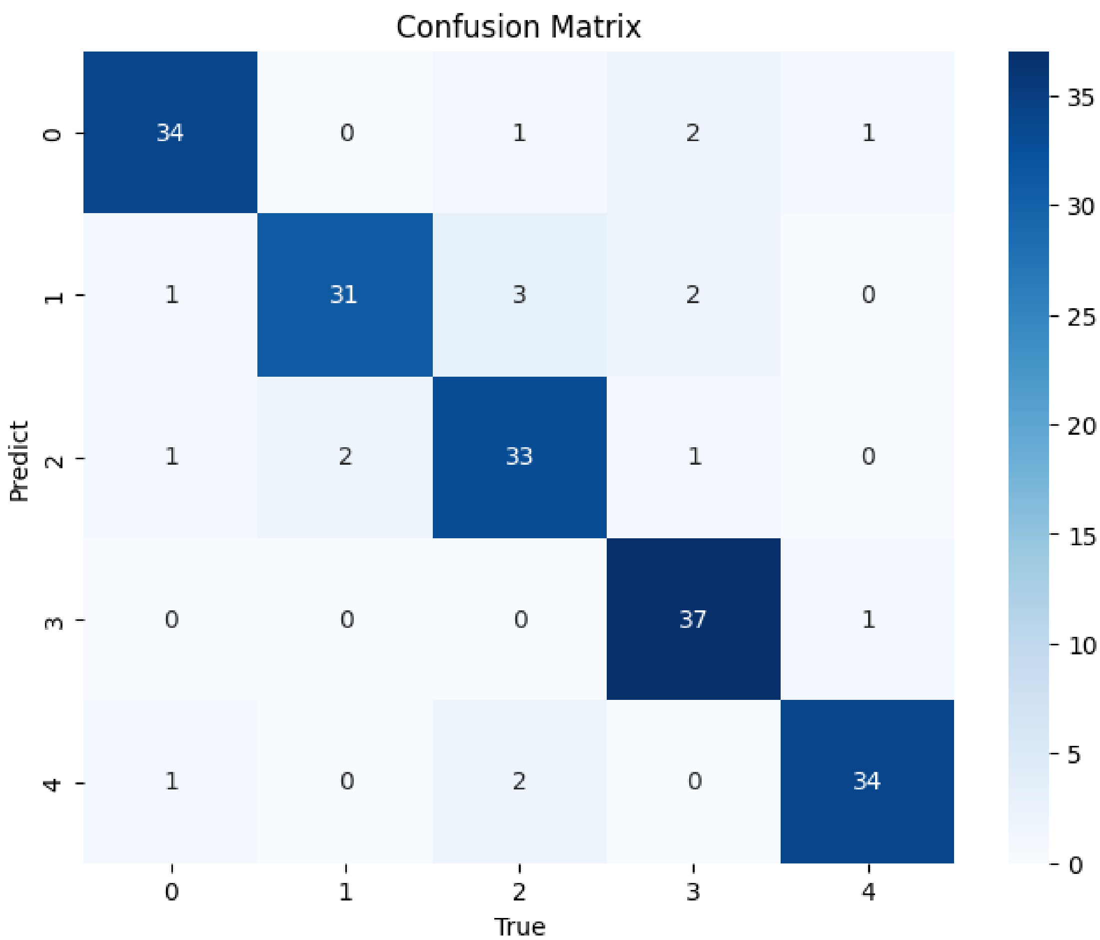
[295]:
```
y_pred_xgb = xgb_model.predict(X_test_normal)

# Evaluate the XGBoost model
print("\nXGBoost 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_normal, y_pred_xgb))
```

```
XGBoost Model:
Accuracy: 0.904
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

    accuracy                           0.90       187
   macro avg       0.91      0.90      0.90       187
weighted avg       0.91      0.90      0.90       187
```

[296]:
```
evaluation(y_test_normal,y_pred_xgb)
```

```
{'accuracy': 0.904, 'recall': 0.904, 'F1 score': 0.904, 'Precision score':
0.906}
```

[297]:
```
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('Confusion Matrix')
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



15 Tunning + Normalisasi + Oversample

Pada pembuatan model kali ini masih menggunakan algoritma yang sama (KNN, Random Forest, dan XGBoost), namun data yang digunakan adalah data yang sudah dilakukan TunNIng Parameter, Normalisasi, dan Oversample.

16 KNN

[298]:
```
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
```

Setiap parameter tunnning tidak selalu sama karena bergantung pada algoritma yang digunakan.

[299]:
```
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_iter=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_size': 45, 'algorithm': 'ball_tree'}
```

[300]:
```
y_pred_knn = knn_model.predict(X_test_normal)

# Evaluate the KNN model
print("K-Nearest Neighbors (KNN) Model:")
accuracy_knn_smote_normal_Tun =␣
 ↪round(accuracy_score(y_test_normal,y_pred_knn),3)
print("Accuracy:", accuracy_knn_smote_normal_Tun)
print("Classification Report:")
print(classification_report(y_test_normal, y_pred_knn))
```

```
K-Nearest Neighbors (KNN) Model:
Accuracy: 0.93
Classification Report:
              precision    recall  f1-score   support

         0.0       0.94      0.89      0.92        38
         1.0       0.86      0.86      0.86        37
         2.0       0.92      0.92      0.92        37
         3.0       0.97      0.97      0.97        38
         4.0       0.95      1.00      0.97        37

    accuracy                           0.93       187
   macro avg       0.93      0.93      0.93       187
weighted avg       0.93      0.93      0.93       187
```

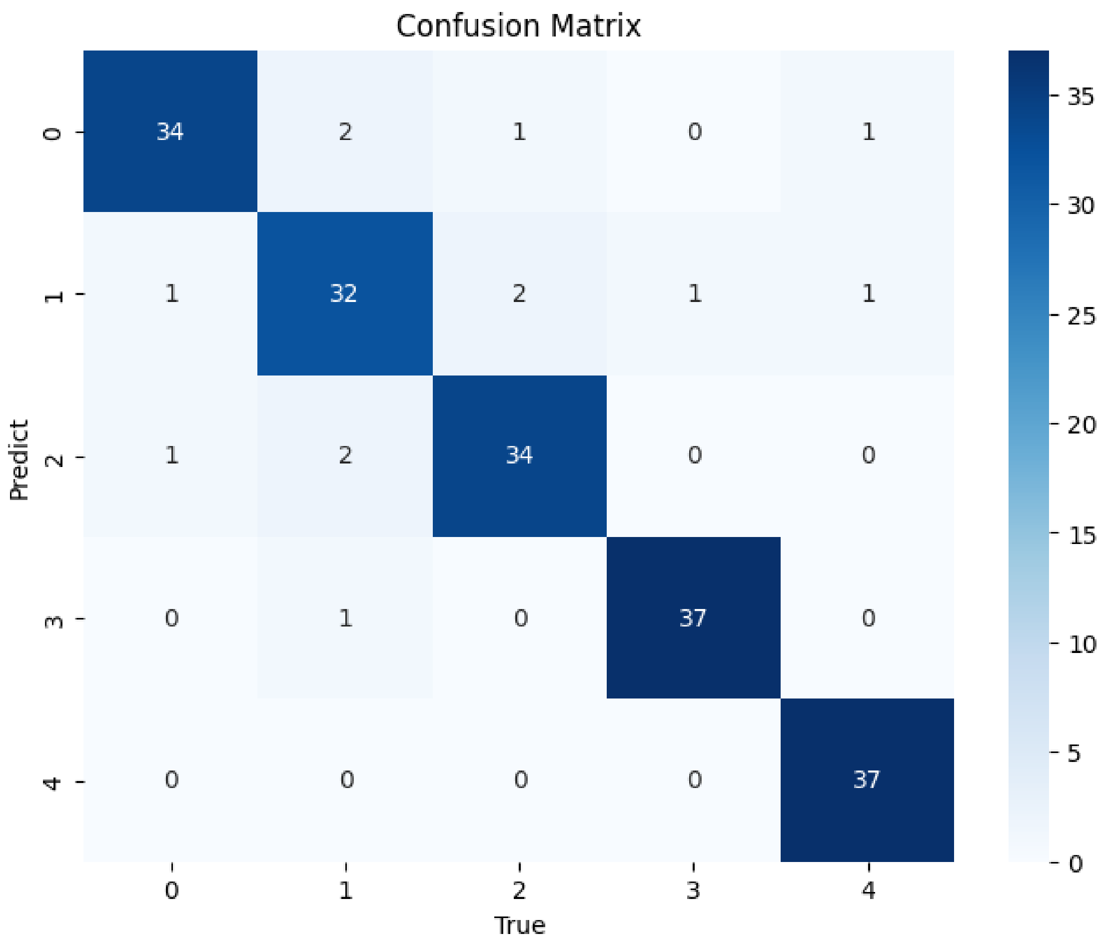
[301]:

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

```
{'accuracy': 0.93, 'recall': 0.93, 'F1 score': 0.93, 'Precision score': 0.93}
```

[302]:

```
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('Confusion Matrix')
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



17 Random Forest

[329]:
```
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"],
  # "random_state": [42, 100, 200]
}

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:
UserWarning: The total space of parameters 32 is smaller than n_iter=100.
Running 32 iterations. For exhaustive searches, use GridSearchCV.
  warnings.warn(
```

```
Best parameters: {'n_estimators': 200, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2', 'max_depth': 15}
```

[330]:
```
y_pred_rf = rf_model.predict(X_test_normal)

# Evaluate the Random Forest model
print("\nRandom Forest Model:")
accuracy_rf_smote_normal_Tun = round(accuracy_score(y_test_normal, y_pred_rf),3)
print("Accuracy:",accuracy_rf_smote_normal_Tun)
print("Classification Report:")
print(classification_report(y_test_normal, y_pred_rf))
```

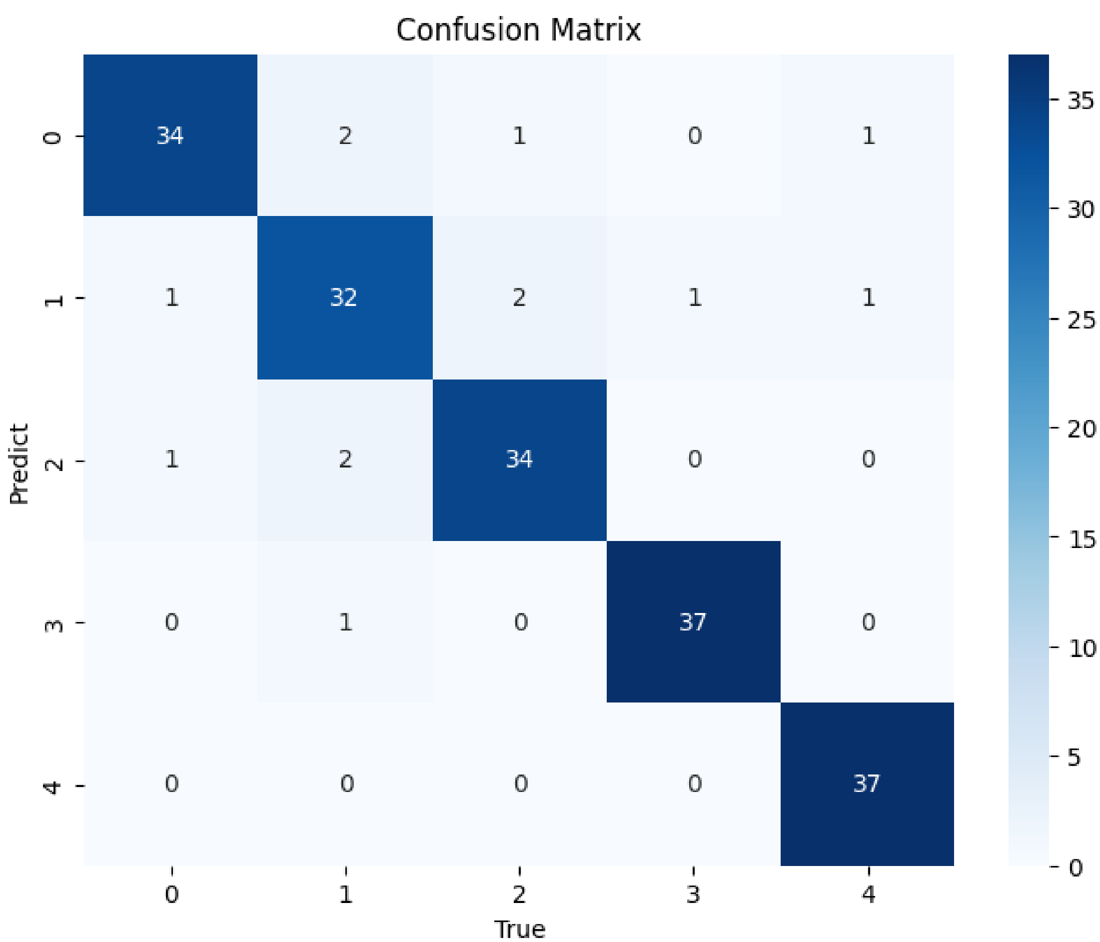
```

Random Forest Model:
Accuracy: 0.909
Classification Report:
              precision    recall  f1-score   support

         0.0       0.95      0.92      0.93        38
         1.0       0.86      0.86      0.86        37
         2.0       0.84      0.86      0.85        37
         3.0       0.93      0.97      0.95        38
         4.0       0.97      0.92      0.94        37
```

```
    accuracy                           0.91       187
   macro avg       0.91      0.91      0.91       187
weighted avg       0.91      0.91      0.91       187
```

[331]:
```
evaluation(y_test_normal,y_pred_rf)
```

```
{'accuracy': 0.909, 'recall': 0.909, 'F1 score': 0.909, 'Precision score': 0.91}
```

[332]:
```
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('Confusion Matrix')
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



18 XGBoost

[345]:
```
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}
```

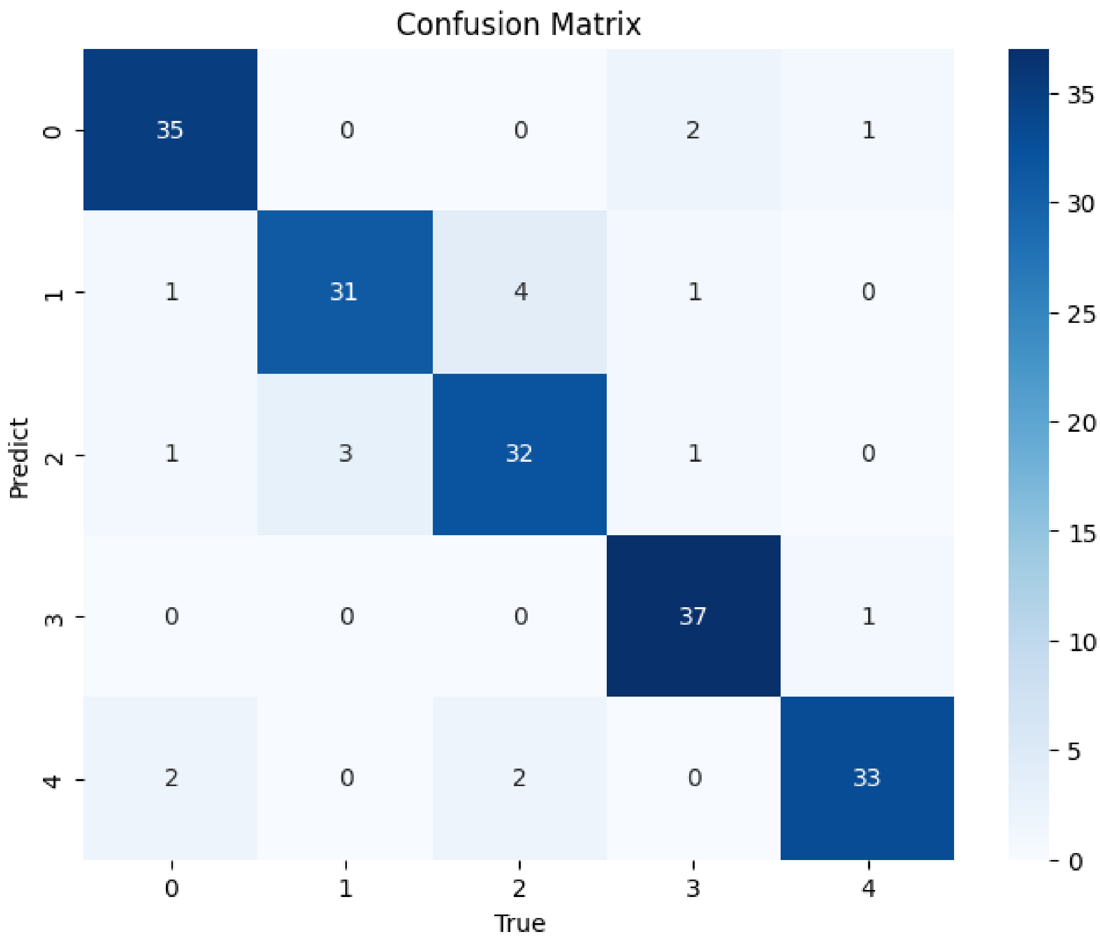
[346]:
```
y_pred_xgb = xgb_model.predict(X_test_normal)

# Evaluate the XGBoost model
print("\nXGBoost Model:")
accuracy_xgb_smote_normal_Tun = round(accuracy_score(y_test_normal,␣
 ↪y_pred_xgb),3)
print("Accuracy:",accuracy_xgb_smote_normal_Tun)
print("Classification Report:")
print(classification_report(y_test_normal, y_pred_xgb))
```

```
XGBoost Model:
Accuracy: 0.92
Classification Report:
              precision    recall  f1-score   support

         0.0       0.90      0.95      0.92        38
         1.0       0.91      0.86      0.89        37
         2.0       0.89      0.86      0.88        37
         3.0       0.93      1.00      0.96        38
         4.0       0.97      0.92      0.94        37

    accuracy                           0.92       187
   macro avg       0.92      0.92      0.92       187
weighted avg       0.92      0.92      0.92       187
```

[335]:
```
evaluation(y_test_normal,y_pred_xgb)
```

```
{'accuracy': 0.898, 'recall': 0.898, 'F1 score': 0.898, 'Precision score':
0.899}
```

[336]:
```
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('Confusion Matrix')
plt.xlabel('True')
plt.ylabel('Predict')
plt.show()
```



19 8) Evaluasi

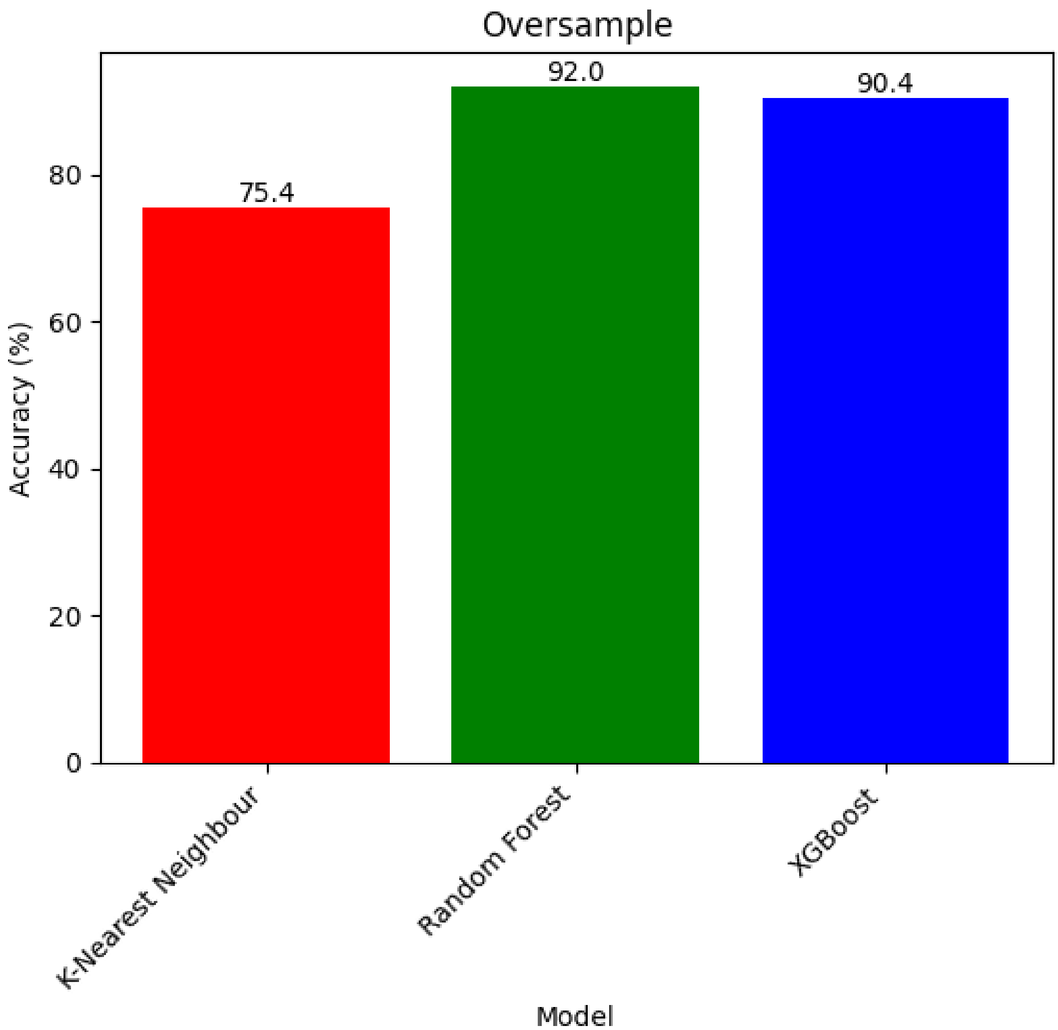
Selanjutnya kita akan melakukan evaluasi data sekaligus membandingkan antar algoritma guna dengan tujuan mengetahui jenis model algoritma yang menghasilkan hasil akurasi terbaik.

[337]:
```
import matplotlib.pyplot as plt

model_comp1 = pd.DataFrame({'Model': ['K-Nearest Neighbour','Random Forest',
                                      'XGBoost'], 'Accuracy':␣
 ↪[accuracy_knn_smote*100,
                                                                             ␣
 ↪accuracy_rf_smote*100,accuracy_xgb_smote*100]})

model_comp1.head()
```

[337]:

	Model	Accuracy
0	K-Nearest Neighbour	75.4
1	Random Forest	92.0
2	XGBoost	90.4

[338]:
```
# Membuat bar plot dengan keterangan jumlah
fig, ax = plt.subplots()
bars = plt.bar(model_comp1['Model'], model_comp1['Accuracy'], color=['red',␣
 ↪'green', 'blue'])
plt.xlabel('Model')
plt.ylabel('Accuracy (%)')
plt.title('Oversample')
plt.xticks(rotation=45, ha='right') # Untuk memutar label sumbu x agar lebih␣
 ↪mudah dibaca

# Menambahkan keterangan jumlah di atas setiap bar
for bar in bars:
  yval = bar.get_height()
  plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2), ha='center',␣
 ↪va='bottom')

plt.show()
```



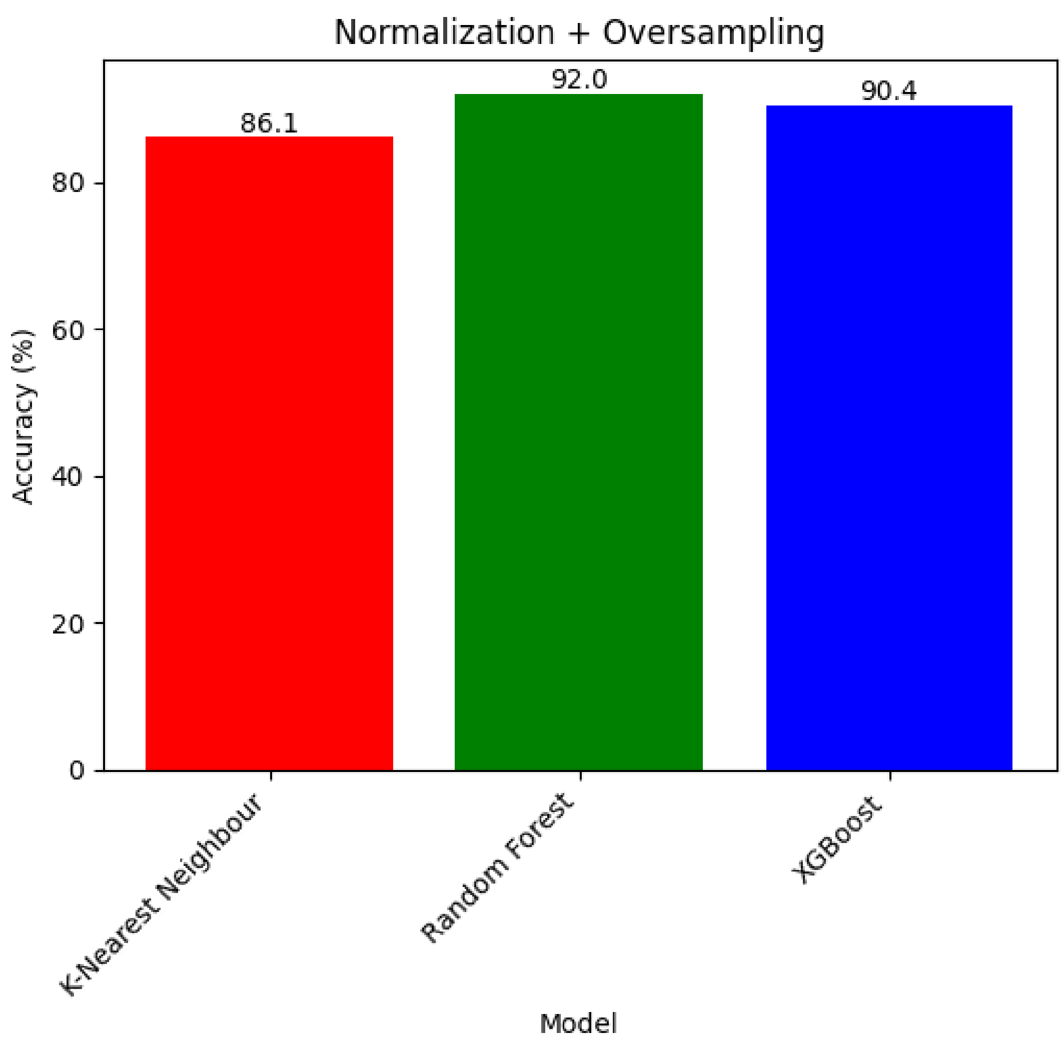
[339]:

```
model_comp2 = pd.DataFrame({'Model': ['K-Nearest Neighbour','Random Forest',
                                      'XGBoost'], 'Accuracy':␣
 ↪[accuracy_knn_smote_normal*100,
                                                                         ␣
 ↪accuracy_rf_smote_normal*100,accuracy_xgb_smote_normal*100]})

model_comp2.head()
```

[339]:

	Model	Accuracy
0	K-Nearest Neighbour	86.1
1	Random Forest	92.0
2	XGBoost	90.4

[340]:
```
# Membuat bar plot dengan keterangan jumlah
fig, ax = plt.subplots()
bars = plt.bar(model_comp2['Model'], model_comp2['Accuracy'], color=['red',␣
↪'green', 'blue'])
plt.xlabel('Model')
plt.ylabel('Accuracy (%)')
plt.title('Normalization + Oversampling')
plt.xticks(rotation=45, ha='right') # Untuk memutar label sumbu x agar lebih␣
↪mudah dibaca

# Menambahkan keterangan jumlah di atas setiap bar
for bar in bars:
  yval = bar.get_height()
  plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2), ha='center',␣
↪va='bottom')

plt.show()
```



[347]:

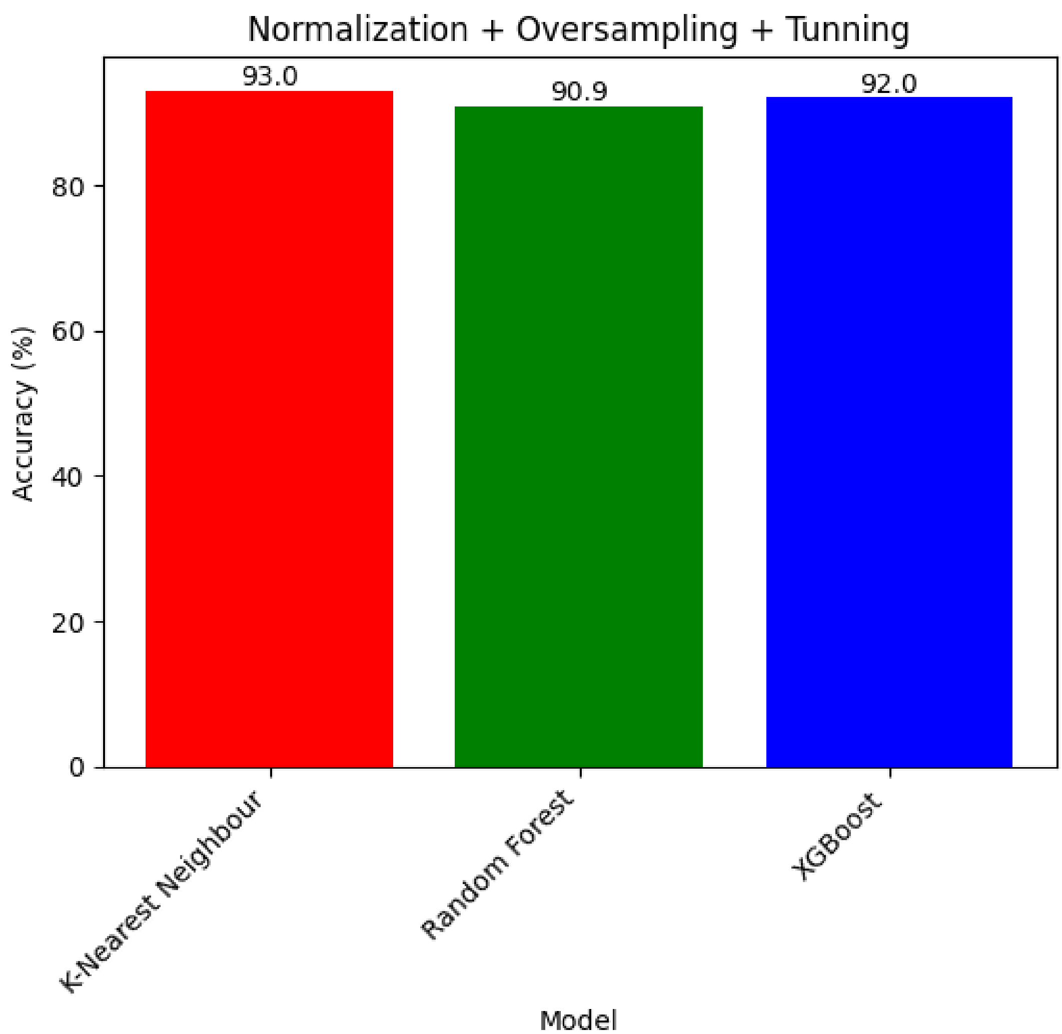
```python
model_comp3 = pd.DataFrame({'Model': ['K-Nearest Neighbour','Random Forest',
                                     'XGBoost'], 'Accuracy':␣
 ↪[accuracy_knn_smote_normal_Tun*100,
                                                                           ␣
 ↪accuracy_rf_smote_normal_Tun*100,accuracy_xgb_smote_normal_Tun*100]})

model_comp3.head()
```

[347]:

	Model	Accuracy
0	K-Nearest Neighbour	93.0
1	Random Forest	90.9
2	XGBoost	92.0

[348]:

```python
# Membuat bar plot dengan keterangan jumlah
fig, ax = plt.subplots()
bars = plt.bar(model_comp3['Model'], model_comp3['Accuracy'], color=['red',␣
 ↪'green', 'blue'])
plt.xlabel('Model')
plt.ylabel('Accuracy (%)')
plt.title('Normalization + Oversampling + Tunning')
plt.xticks(rotation=45, ha='right') # Untuk memutar label sumbu x agar lebih␣
 ↪mudah dibaca

# Menambahkan keterangan jumlah di atas setiap bar
for bar in bars:
  yval = bar.get_height()
  plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2), ha='center',␣
 ↪va='bottom')

plt.show()
```



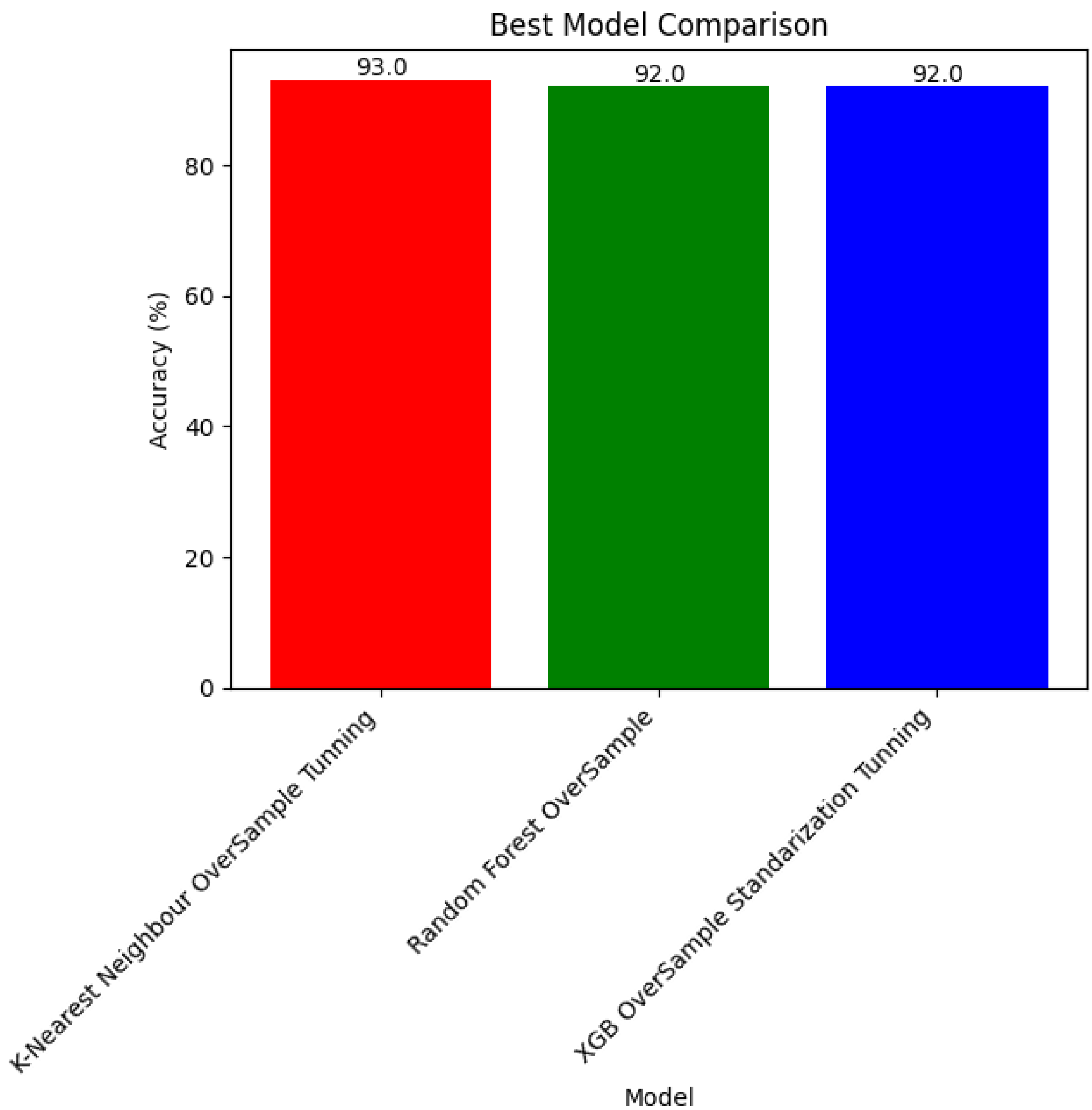
[349]:

```
# Data frame
model_compBest = pd.DataFrame({
    'Model': ['K-Nearest Neighbour OverSample Tunning', 'Random Forest␣
 ↪OverSample',
              'XGB OverSample Standarization Tunning'],
    'Accuracy': [accuracy_knn_smote_normal_Tun*100,␣
 ↪accuracy_rf_smote_normal*100,
                 accuracy_xgb_smote_normal_Tun*100]
})
```

[350]:

```
# Membuat bar plot dengan keterangan jumlah
fig, ax = plt.subplots()
bars = plt.bar(model_compBest['Model'], model_compBest['Accuracy'],␣
 ↪color=['red', 'green', 'blue'])
```

```python
plt.xlabel('Model')
plt.ylabel('Accuracy (%)')
plt.title('Best Model Comparison')
plt.xticks(rotation=45, ha='right') # Untuk memutar label sumbu x agar lebih␣
 ↪mudah dibaca

# Menambahkan keterangan jumlah di atas setiap bar
for bar in bars:
  yval = bar.get_height()
  plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2), ha='center',␣
 ↪va='bottom')
plt.show()
```



20 9) Streamlit

21 10) Kesimpulan

Dari penelitian diatas setelah melakukan pemodelan dengan algoritma KNN, Random Forest, dan XGBoost dengan berbagai penanganan data antara lain menggunakan random over sampling SMOTE untuk penanganan imbalance data, RandomSearchCV untuk tunning, dan Normalisasi data. Dapat disimpulkan bahwa klasifikasi menggunakan Random Over Sampling SMOTE pada model KNN menghasilkan akurasi 75.4 %, model Random Forest dengan akurasi yang dihasilkan yaitu 92%, dan model XGBoots menghasilkan akurasi 90.4%. Disamping itu bila klasifikasi menggunakan data yang sudah dilakukan normalisasi dan Random Over Sampling SMOTE pada model KNN menghasilkan akurasi 86.1%, model Random Forest menghasilkan akurasi 92%, dan model XGBoots menghasilkan akurasi 90.4%. Dan pada klasifikasi menggunakan data yang telah dilakukan tunning RandomSearchCV, normalisasi, dan Random Over Sampling SMOTE dalam model KNN menghasilkan akurasi 93%, pada model Random Forest menghasilkan akurasi 87.7%. dan model XGBoots menghasilkan akurasi 92%. Oleh karena itu, dalam penanganan data yang optimal untuk mengatasi ketidakseimbangan data adalah dengan menggunakan metode random Oversampling SMOTE sekaligus yang dilengkapi dengan tuning menggunakan RandomSearchCV dan normalisasi data, memberikan hasil yang signifikan dalam meningkatkan akurasi model klasifikasi khususnya pada model KNN dan XGBoots, namun hal itu tidak terjadi pada model Random Forest yang

mengalami penurunan akurasi yang signifikan. Secara keseluruhan, penanganan dalam ketidakseimbangan data dengan menggunakan tunning parameter, normalisasi, dan oversampling dapat memberikan dampak signifikan terhadap performa model klasifikasi. Pemilihan model terbaik dan parameter optimal dapat meningkatkan akurasi dan kinerja model secara keseluruhan.