Project Bimbingan Karir Data Science

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1) Pengumpulan Data

Dataset yang digunakan adalah dataset yang bersumber dari link berikut : https://archive.ics.uci.edu/dataset/45/heart+disease

Dataset yang dipakai adalah dataset dengan nama file "Hungarian.data" diharapkan sebelum memakai dataset tersebut anda dapat membaca deskripsi dataset yang ada di dalam file "heart-disease.names"

2) Menelaah Data

pilih dan masukan library yang anda butuhkan untuk menelaah data

```
import pandas as pd
import re
import numpy as np
import itertools
```

Load Data

masukkan dataset yang dibutuhkan dengan alamat penyimpanan yang tepat dan simpan kedalam sebuah variabel

```
dir =  'hungarian.data'
```

buatlah iterasi untuk membaca dataset

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

```
lines[0:10]
```

```
['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']
```

setelah membaca file dataset lakukan iterasi sesuai jumlah kolom dan baris yang ada pada dataset. Untuk keterangan kolom dan baris dapat dilihat melalui deskripsi dataset yang sudah dijelaskan sebelumnya

```
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()
```

	0	1	2	3	4	5	6	7	8	9	...	66	67	68	69	70	71	72	73	74	75
0	1254	0	40	1	1	0	0	-9	2	140	...	-9	-9	1	1	1	1	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	1	1	1	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	1	1	-9.	-9.	name

5 rows × 76 columns

menampilan informasi dari file dataset yang sudah dimasukkan kedalam dataframe

```
df.info()
```

```
 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
```

Pada kondisi dataset yang kita miliki terdapat kondisi khusus yang dimana sebelum memasuki tahap validasi data untuk tipe data object atau string perlu dilakukan penghapusan fitur dikarenakan pada dataset ini nilai null disimbolkan dengan angka -9.0

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

mengubah tipe data file dataset menjadi tipe data float sesuai dengan nilai null yaitu -9.0

```
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   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
```

3) Validasi Data

Pada tahap ini bertujuan untuk mengetahui dan memahami isi dari dataset agar dapat dilakukan penanganan sesuai dengan kondisinya mengubah nilai -9.0 menjadi nilai null value sesuai dengan deskripsi dataset

```
df.replace(-9.0, np.nan, inplace=True)
```

menghitung jumlah nilai null value

```
df.isnull().sum()
```

```
1       0
2       0
3       0
4       0
5       0
     ...
70      0
71      0
72      0
73    266
74    294
Length: 74, dtype: int64
```

```
df.head()
```

	1	2	3	4	5	6	7	8	9	10	...	65	66	67	68	69	70	71	72	73	74
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	1.0	1.0	1.0	NaN	NaN
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	1.0	1.0	1.0	1.0	NaN	NaN
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	1.0	1.0	1.0	1.0	NaN	NaN
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	1.0	1.0	1.0	1.0	NaN	NaN
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	1.0	1.0	1.0	1.0	NaN	NaN

5 rows × 74 columns

```
df.info()
```

```
 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)
```

4) Menentukan Object Data

Memilih 14 fitur yang akan digunakan sesuai dengan deskripsi dataset

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

```
df_selected.head()
```

	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

```
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 nama kolom sesuai dengan 14 nama kolom yang ada pada deskripsi dataset

```
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-16-edcc9cd19c95>: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_guide/indexing.html#returning-a-view-versus-a-copy
  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  
---  ------    --------------  -----  
 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

```
df_selected.value_counts()
```

```
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) Membersihkan Data

Sebelum melakukan pemodelan dilakukan pembersihan data agar model yang dihasilkan lebih akurat

menghitung jumlah null values yang ada diddalam dataset

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

```
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
```

Berdasarkan output kode program diatas ada beberapa fitur yang hampir 90% datanya memiliki nilai null sehingga perlu dilakukan penghapusan fitur menggunakan fungsi drop

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

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

```
age          0
sex          0
cp           0
trestbps     1
chol        23
fbs          8
restecg      1
thalach      1
exang        1
oldpeak      0
target       0
dtype: int64
```

Dikarenakan masih ada nilai null dibeberapa kolom fitur maka akan dilakukan pengisian nilai null menggunakan nilai mean di setiap kolomnya

```
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()
```

```
meanTBPS = meanTBPS.astype(float)
meanChol = meanChol.astype(float)
meanfbs = meanfbs.astype(float)
meanthalach = meanthalach.astype(float)
meanexang = meanexang.astype(float)
meanRestCG = meanRestCG.astype(float)
```

```
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 yang sudah ditentukan sebelumnya

```
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
```

```
dfClean.isnull().sum()
```

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

melalukan pengecekan terhadap duplikaksi data

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

	age	sex	cp	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

```
print("All Duplicate Rows:")
dfClean[dfClean.duplicated(keep=False)]
```

All Duplicate Rows:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	target
90	49.0	0.0	2.0	110.0	251.0	0.0	0.0	160.0	0.0	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	0.0

Menghapus data yang memiliki duplikat

```
dfClean = dfClean.drop_duplicates()
print("All Duplicate Rows:")
dfClean[dfClean.duplicated(keep=False)]
```

```
All Duplicate Rows:
  age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  target
```

```
dfClean.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	target
0	40.0	1.0	2.0	140.0	289.0	0.0	0.0	172.0	0.0	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	1.0
2	37.0	1.0	2.0	130.0	283.0	0.0	1.0	98.0	0.0	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	3.0
4	54.0	1.0	3.0	150.0	251.0	0.0	0.0	122.0	0.0	0.0	0.0

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

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

```
import seaborn as sns
import matplotlib.pyplot as plt
```

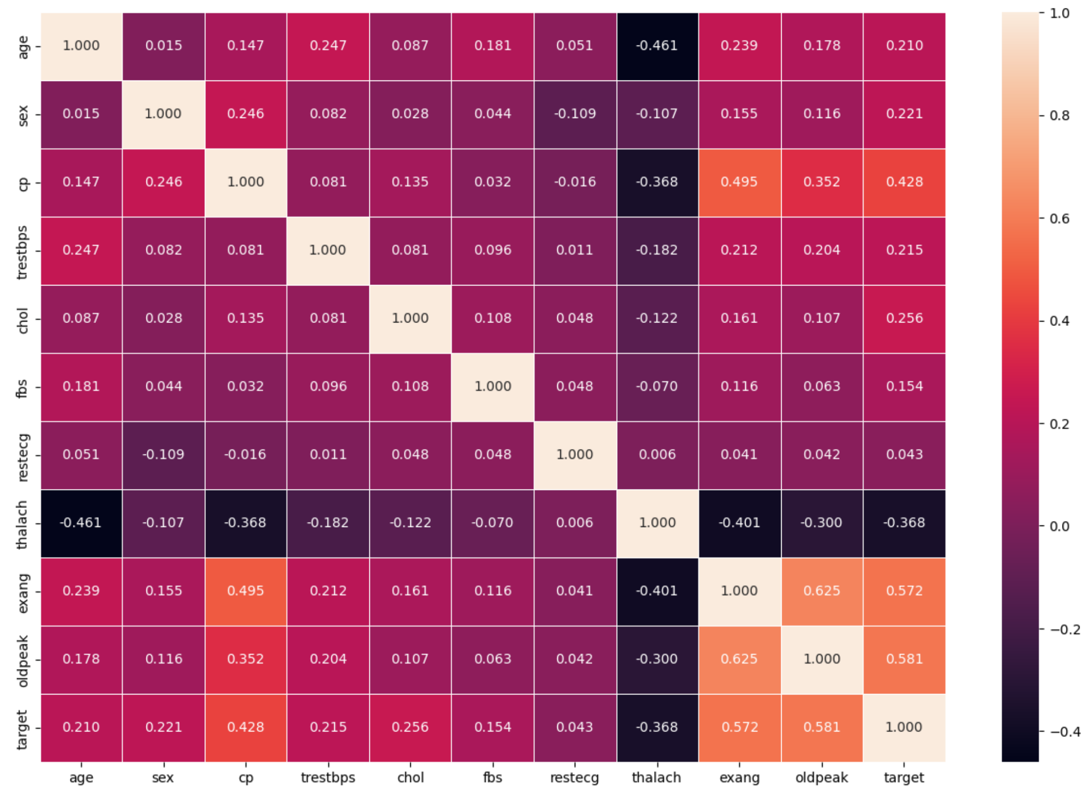
Mencari korelasi antar fitur

```
dfClean.corr()
```

	age	sex	cp	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
cp	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

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

```
<Axes: >
```



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

```
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
```

```
dfClean.head(5)
```

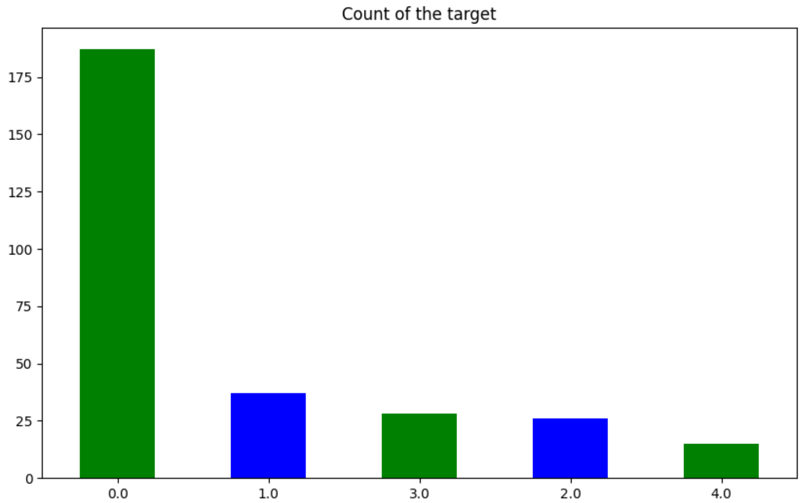
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	target
0	40.0	1.0	2.0	140.0	289.0	0.0	0.0	172.0	0.0	0.0	0.0
1	49.0	0.0	3.0	160.0	180.0	0.0	0.0	156.0	0.0	1.0	1.0
2	37.0	1.0	2.0	130.0	283.0	0.0	1.0	98.0	0.0	0.0	0.0
3	48.0	0.0	4.0	138.0	214.0	0.0	0.0	108.0	1.0	1.5	3.0
4	54.0	1.0	3.0	150.0	251.0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

Setelah Menyesuaikan tipe dataset kita , kita harus memisahkan antara fitur dan target lalu simpan kedalam variabel.

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

Setelah kita memisahkan antara fitur dan target , sebaiknya kita melakukan pengecekan terlebih dahulu terhadap persebaran jumlah target terlebih dahulu.

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

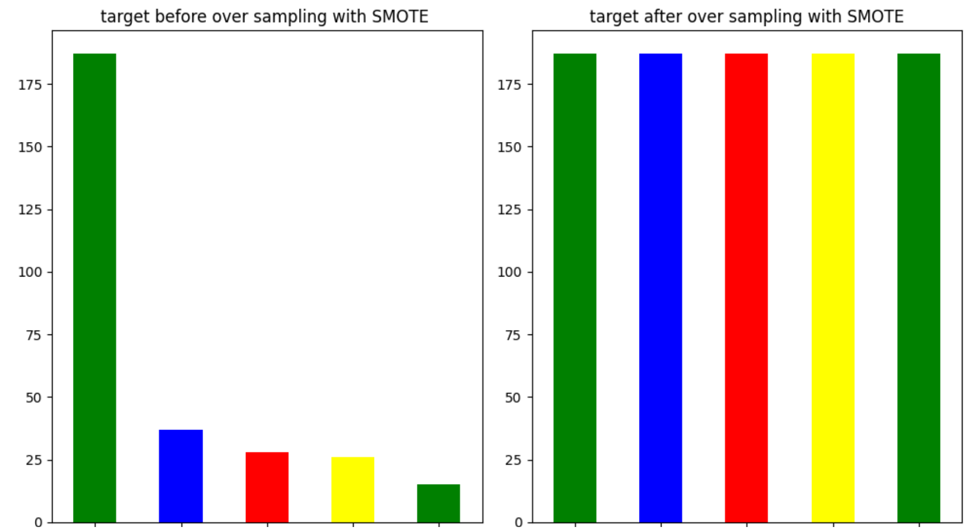


Pada Grafik diatas menunjukan bahwa persebaran jumlah target tidak seimbang oleh karena itu perlu diseimbangkan terlebih dahulu. Menyeimbangkan target ada 2 cara yaitu oversampling dan undersampling. oversampling dilakukan jika jumlah dataset sedikit sedangkan undersampling dilakukan jika jumlah data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

```
from imblearn.over_sampling import SMOTE
```

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

```
plt.figure(figsize=(12, 4))

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.

```
new_df1 = pd.DataFrame(data=y)
new_df1.value_counts()
```

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

```
# over
new_df2 = pd.DataFrame(data=y_smote_resampled)
new_df2.value_counts()
```

```
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.

```
dfClean.describe()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	target
count	293.000000	293.000000	293.000000	293.000000	293.000000	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	0.218430	139.058020	0.303754	0.588055	0.795222
std	7.824875	0.446282	0.965049	17.576793	65.059069	0.252622	0.460868	23.558003	0.460665	0.909554	1.238251
min	28.000000	0.000000	1.000000	92.000000	85.000000	0.000000	0.000000	82.000000	0.000000	0.000000	0.000000
25%	42.000000	0.000000	2.000000	120.000000	211.000000	0.000000	0.000000	122.000000	0.000000	0.000000	0.000000
50%	49.000000	1.000000	3.000000	130.000000	248.000000	0.000000	0.000000	140.000000	0.000000	0.000000	0.000000
75%	54.000000	1.000000	4.000000	140.000000	277.000000	0.000000	0.000000	155.000000	1.000000	1.000000	1.000000
max	66.000000	1.000000	4.000000	200.000000	603.000000	1.000000	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.

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_smote_resampled_normal = scaler.fit_transform(X_smote_resampled)
```

```
len(X_smote_resampled_normal)
```

```
935
```

```
dfcek1 = pd.DataFrame(X_smote_resampled_normal)
dfcek1.describe()
```

	0	1	2	3	4	5	6	7	8	9
count	935.000000	935.000000	935.000000	935.000000	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	0.117938	0.453354	0.598398	0.227015
std	0.174873	0.332492	0.274211	0.147493	0.110990	0.252030	0.199527	0.197232	0.450288	0.201293
min	0.000000	0.000000	0.000000	0.000000	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	0.000000	0.312720	0.000000	0.000000
50%	0.578947	1.000000	1.000000	0.387952	0.330240	0.000000	0.000000	0.440606	0.962447	0.200000
75%	0.683363	1.000000	1.000000	0.487481	0.393811	0.000000	0.201473	0.593629	1.000000	0.386166
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	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.

```
from sklearn.model_selection import train_test_split


# 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)


# 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) 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.

```
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):
    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)
```

Oversample

KNN

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

```
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)
```

```
▾       KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

Berikut adalah kode program untuk menampilkan hasil akurasi dengan algoritma KNN

```
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))
```

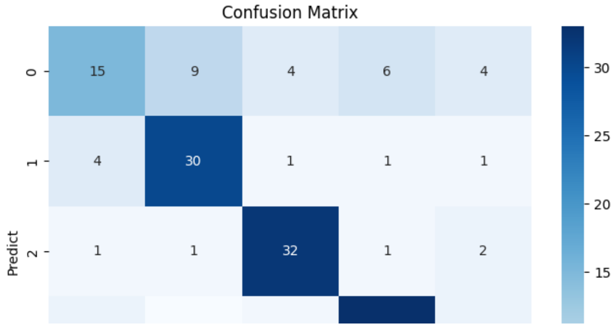
```
K-Nearest Neighbors (KNN) Model:
Accuracy: 0.754
Classification Report:
              precision    recall  f1-score   support

         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
```

```
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.

```
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()
```



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

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

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

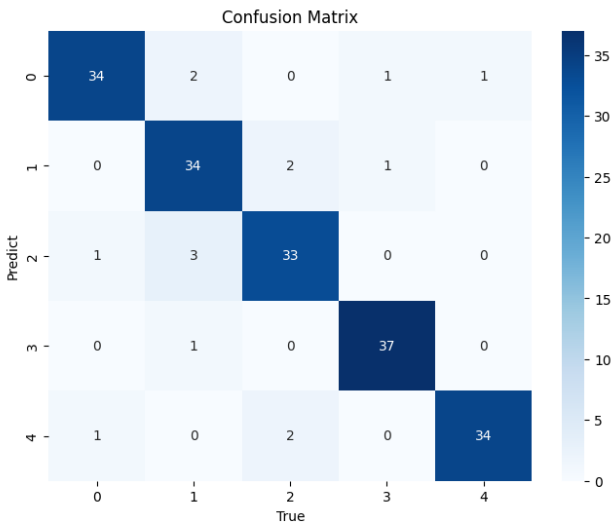
```
y_pred_rf = rf_model.predict(X_test)

# 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
```

```
evaluation(y_test,y_pred_rf)
```

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

```
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()
```



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.

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

```
▾                              XGBClassifier
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,
```

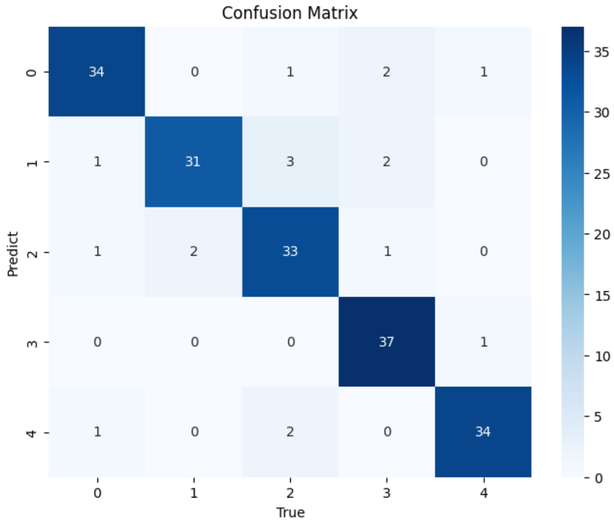
```
y_pred_xgb = xgb_model.predict(X_test)

# 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
```

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



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.

KNN

```
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)
```

```
▾       KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

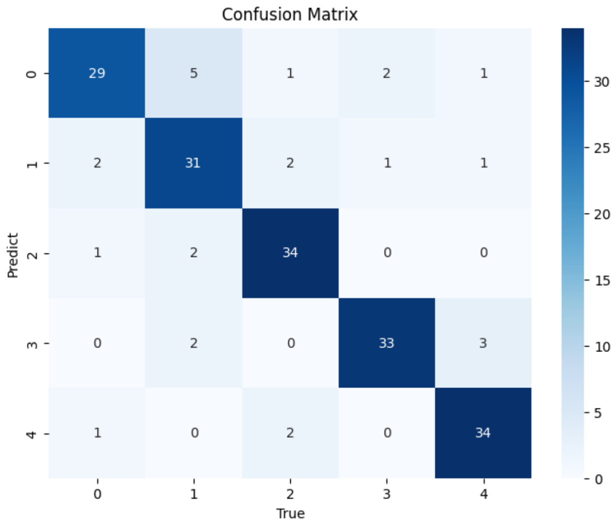
```
y_pred_knn = knn_model.predict(X_test_normal)

# 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
```

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



Random Forest

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

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

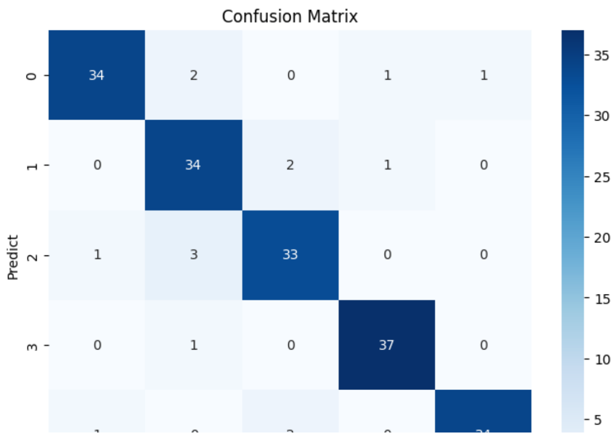
```
y_pred_rf = rf_model.predict(X_test_normal)

# 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
```

```
evaluation(y_test_normal,y_pred_rf)
```

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

```
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()
```



XGBOOST

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

```
XGBClassifier
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', ...)
```

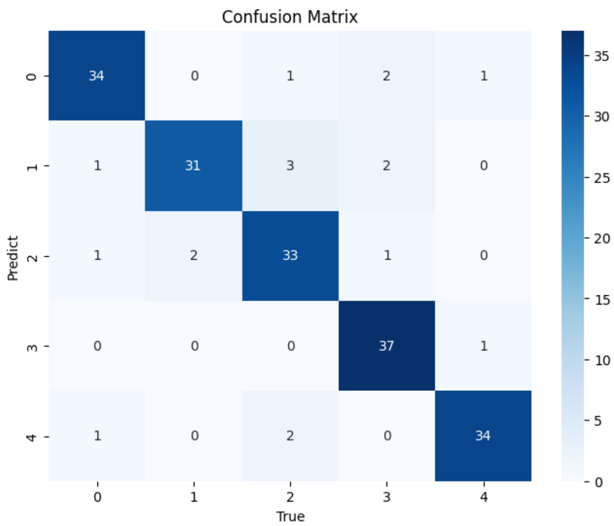
```
y_pred_xgb = xgb_model.predict(X_test_normal)

# 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
```

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



Tunning + Normalization + 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.

KNN

```
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.

```
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': 30, 'algorithm': 'ball_tree'}
```

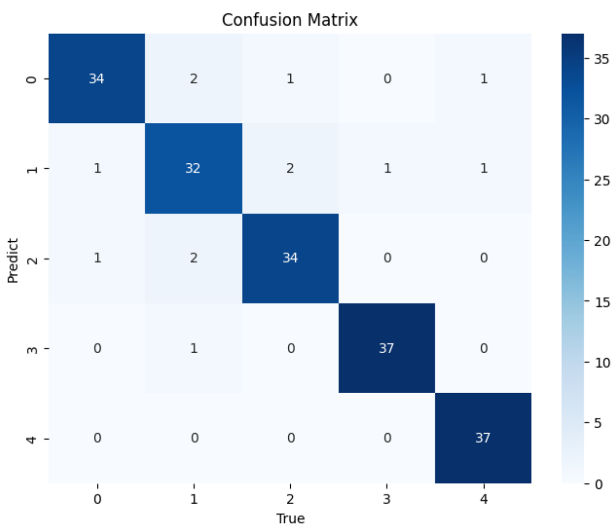
```
y_pred_knn = knn_model.predict(X_test_normal)

# 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
```

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

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

```
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()
```



RandomForest

```
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, u
  warnings.warn(
Best parameters: {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'sqrt', 'max_depth': 15}
```

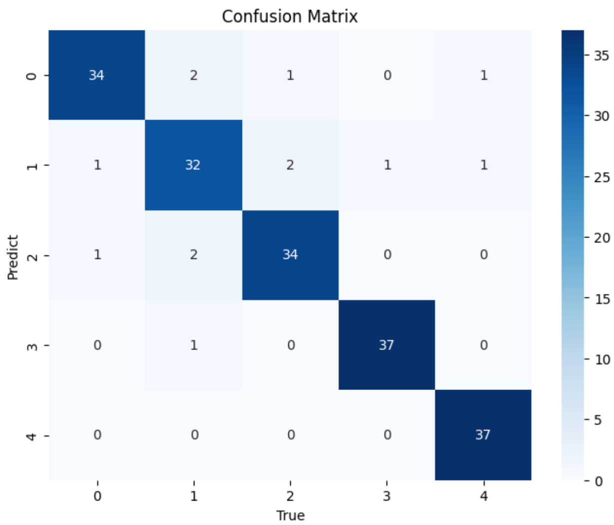
```
y_pred_rf = rf_model.predict(X_test_normal)

# 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: 0.904
Classification Report:
              precision    recall  f1-score   support

         0.0       0.94      0.89      0.92        38
         1.0       0.85      0.89      0.87        37
         2.0       0.86      0.86      0.86        37
         3.0       0.90      0.95      0.92        38
         4.0       0.97      0.92      0.94        37

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

```
evaluation(y_test_normal,y_pred_rf)
```

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

```
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()
```



XGBOOST

```
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}
```

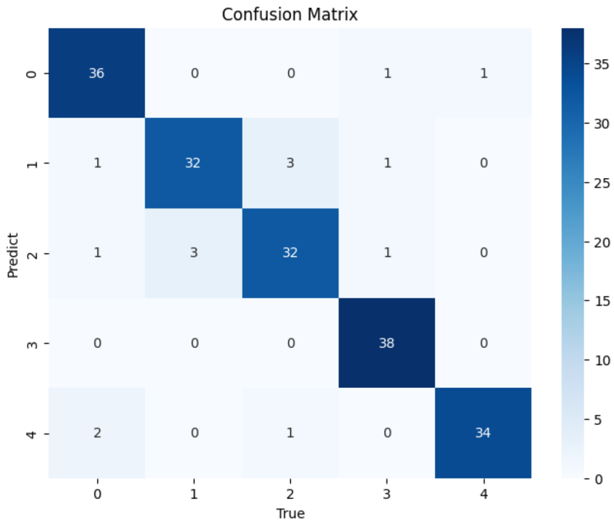
```
y_pred_xgb = xgb_model.predict(X_test_normal)

# 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
```

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



8) Evaluasi

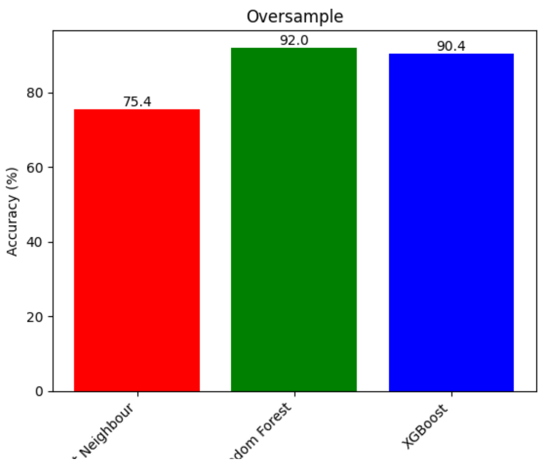
Selanjutnya kita akan melakukan evaluasi data sekaligus membandingkan antar algoritma guna dengan tujuan mengetahui jenis model algoritma yang menghasilkan hasil akurasi terbaik.

```
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()
```

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

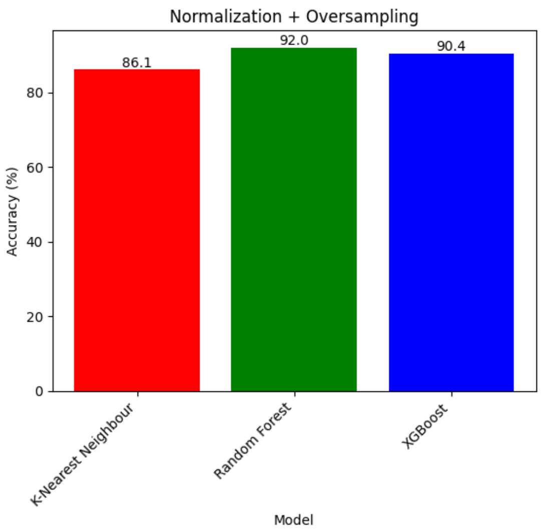
```
# Membuat bar plot dengan keterangan jumlah
fig, ax = plt.subplots()
bars = plt.bar(model_comp1['Model'], model_comp1['Accuracy'], color=['red', 'green', 'blue'])
plt.xlabel('Model')
plt.ylabel('Accuracy (%)')
plt.title('Oversample')
plt.xticks(rotation=45, ha='right')  # Untuk memutar label sumbu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




```
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()
```

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

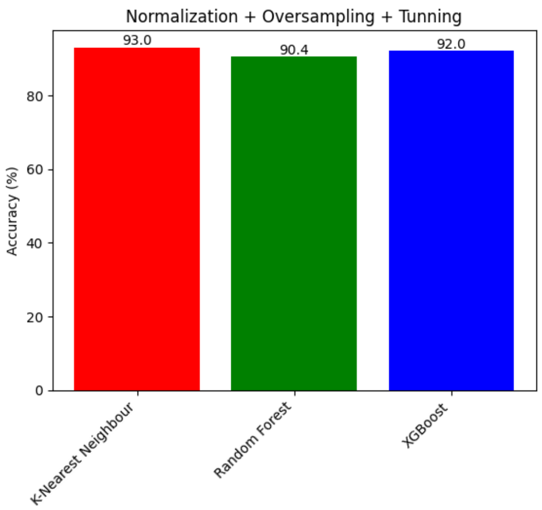
```
# Membuat bar plot dengan keterangan jumlah
fig, ax = plt.subplots()
bars = plt.bar(model_comp2['Model'], model_comp2['Accuracy'], color=['red', 'green', 'blue'])
plt.xlabel('Model')
plt.ylabel('Accuracy (%)')
plt.title('Normalization + Oversampling')
plt.xticks(rotation=45, ha='right')  # Untuk 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()
```



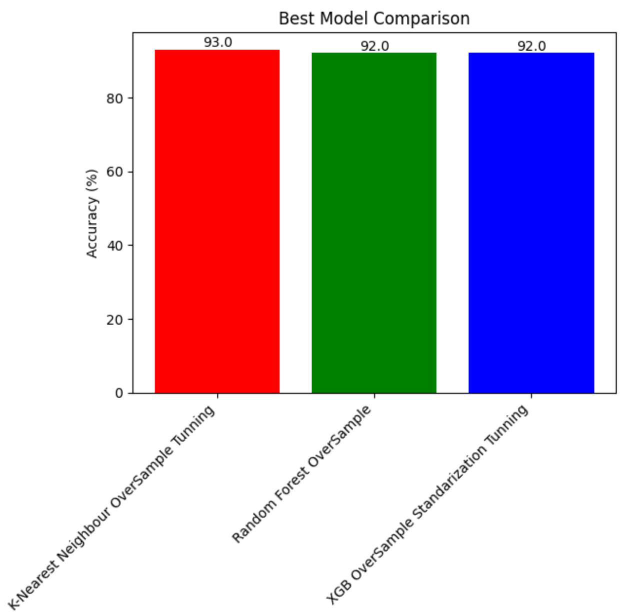

```
model_comp3 = pd.DataFrame({'Model': ['K-Nearest Neighbour','Random Forest',
                    'XGBoost'], 'Accuracy': [accuracy_knn_smote_normal_Tun*100,
                    accuracy_rf_smote_normal_Tun*100,accuracy_xgb_smote_normal_Tun*100]})
model_comp3.head()
```

	Model	Accuracy
0	K-Nearest Neighbour	93.0
1	Random Forest	90.4
2	XGBoost	92.0

```
# 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()
```




```
# 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]
})


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



9) Streamlit

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.

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