Exploratory Data Analysis

```
# Import library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


# Memuat dataset
df = pd.read_csv("ObesityDataSet.csv")  # Ganti dengan path file Anda


# Menampilkan beberapa baris pertama
df.head()
```

	Age	Gender	Height	Weight	CALC	FAVC	FCVC	NCP	SCC	SMOKE	CH2O	family_history_with_overweight	FAF	TUE	CAEC
0	21	Female	1.62	64	no	no	2	3	no	no	2	yes	0	1	Sometimes
1	21	Female	1.52	56	Sometimes	no	3	3	yes	yes	3	yes	3	0	Sometimes
2	23	Male	1.8	77	Frequently	no	2	3	no	no	2	yes	2	1	Sometimes
3	27	Male	1.8	87	Frequently	no	3	3	no	no	2	no	2	0	Sometimes
4	22	Male	1.78	89.8	Sometimes	no	2	1	no	no	2	no	0	0	Sometimes

Next steps: Generate code with df View recommended plots New interactive sheet

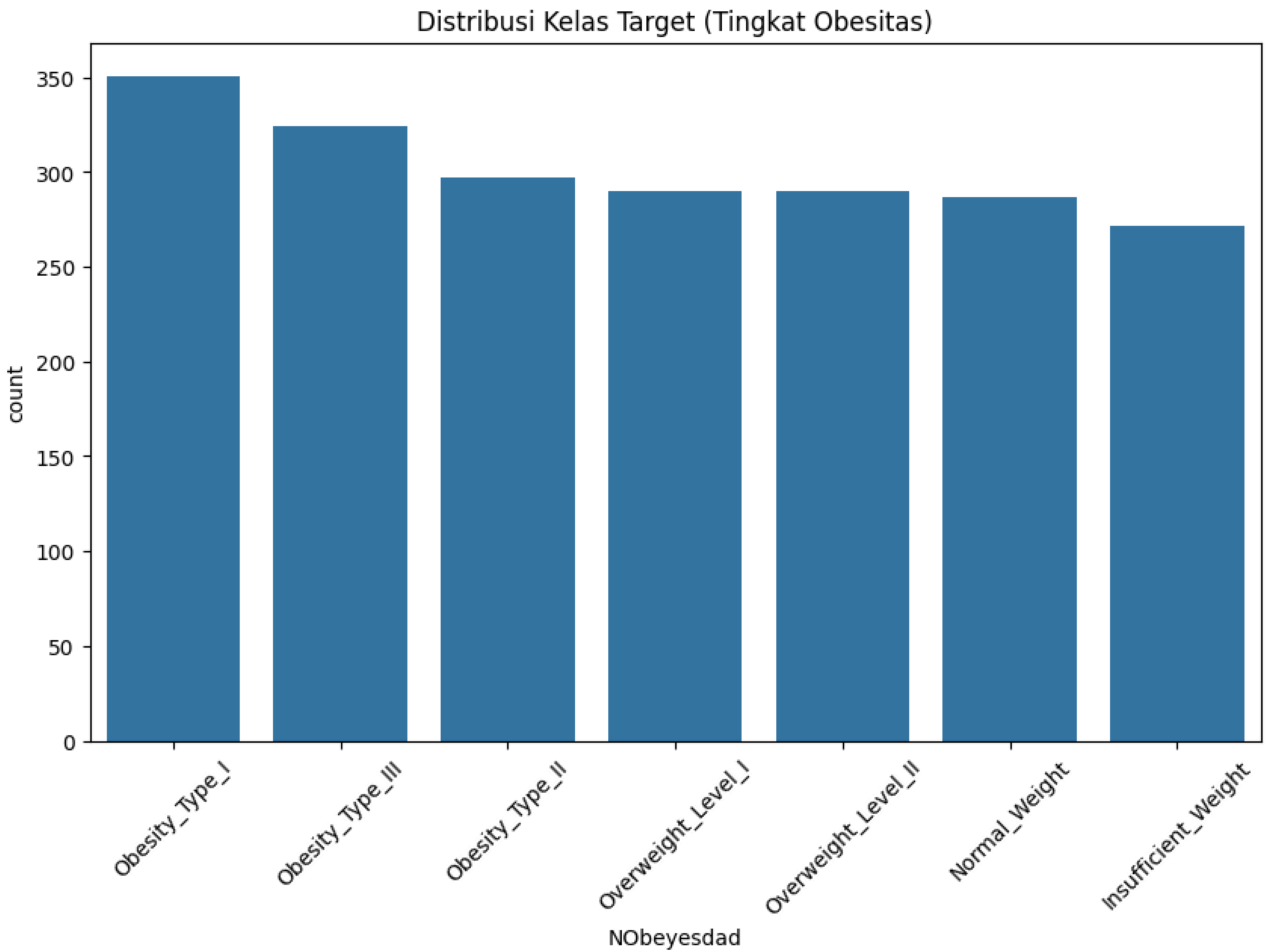
```
# Menampilkan informasi umum dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2111 entries, 0 to 2110
Data columns (total 17 columns):
 #   Column                          Non-Null Count  Dtype 
---  ------                          --------------  ----- 
 0   Age                             2097 non-null   object
 1   Gender                          2102 non-null   object
 2   Height                          2099 non-null   object
 3   Weight                          2100 non-null   object
 4   CALC                            2106 non-null   object
 5   FAVC                            2100 non-null   object
 6   FCVC                            2103 non-null   object
 7   NCP                             2099 non-null   object
 8   SCC                             2101 non-null   object
 9   SMOKE                           2106 non-null   object
 10  CH2O                            2105 non-null   object
 11  family_history_with_overweight  2098 non-null   object
 12  FAF                             2103 non-null   object
 13  TUE                             2102 non-null   object
 14  CAEC                            2100 non-null   object
 15  MTRANS                          2105 non-null   object
 16  NObeyesdad                      2111 non-null   object
dtypes: object(17)
memory usage: 280.5+ KB
```

```
# Menampilkan deskripsi data
df.describe()
```

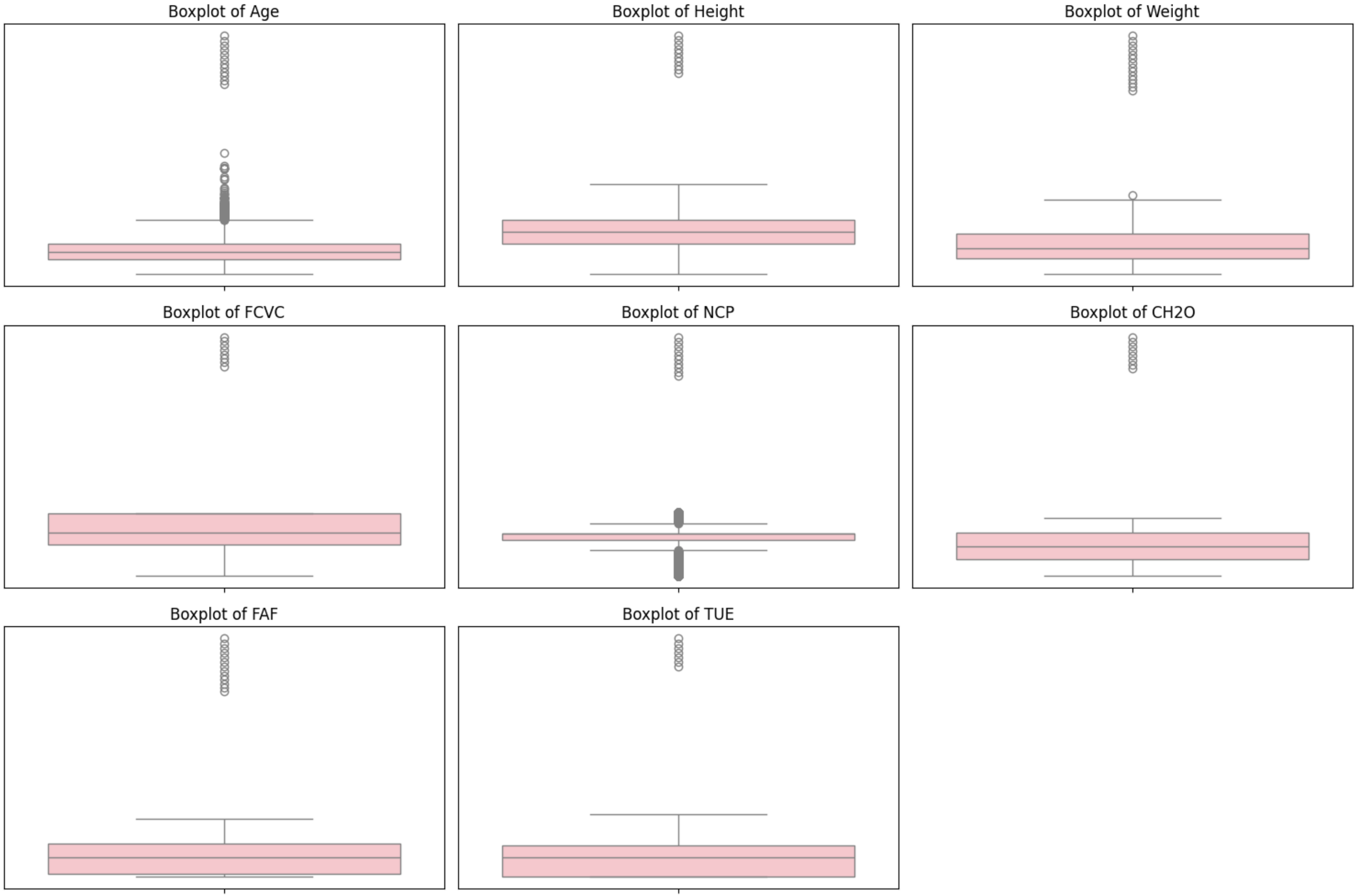
	Age	Gender	Height	Weight	CALC	FAVC	FCVC	NCP	SCC	SMOKE	CH2O	family_history_with_overweight	FAF	TUE
count	2097	2102	2099	2100	2106	2100	2103	2099	2101	2106	2105	2098	2103	2102
unique	1394	3	1562	1518	5	3	808	637	3	3	1263	3	1186	1130
top	18	Male	1.7	80	Sometimes	yes	3	3	no	no	2	yes	0	0
freq	124	1056	58	58	1386	1844	647	1183	1997	2054	441	1705	404	552

```
# Cek distribusi kelas
plt.figure(figsize=(10,6))
sns.countplot(data=df, x='NObeyesdad', order=df['NObeyesdad'].value_counts().index)
plt.title("Distribusi Kelas Target (Tingkat Obesitas)")
plt.xticks(rotation=45)
plt.show()
```




```
# Visualisasi outlier
```

```
# Pastikan kolom numerik dalam tipe float
numerical_cols = ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', 'TUE']
df[numerical_cols] = df[numerical_cols].apply(pd.to_numeric, errors='coerce')

# Inisialisasi dict untuk menyimpan jumlah outlier
outlier_counts = {}

# Visualisasi boxplot dan hitung outlier
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(3, 3, i+1)
    plt.yticks([])
    sns.boxplot(y=df[col], color='pink')
    plt.title(f'Boxplot of {col}')

    # Hitung outlier berdasarkan IQR
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]

    outlier_counts[col] = len(outliers)

plt.tight_layout()
plt.show()

# Print jumlah outlier
print("Jumlah outlier tiap kolom:")
for col, count in outlier_counts.items():
    print(f"{col}: {count}")
```




```
Jumlah outlier tiap kolom:
Age: 179
Height: 10
Weight: 15
```

```
    Weight: 15
    FCVC: 8
```

```
df.shape
```

```
(2111, 17)
```

```
# Cek missing values
df.isnull().sum()
```

	0
Age	22
Gender	9
Height	22
Weight	19
CALC	5
FAVC	11
FCVC	18
NCP	22
SCC	10
SMOKE	5
CH2O	15
family_history_with_overweight	13
FAF	19
TUE	15
CAEC	11
MTRANS	6
NObeyesdad	0

dtype: int64

```
# Cek duplikasi data
df.duplicated().sum()
```

```
np.int64(18)
```

```
# Tampilkan data duplikat
duplicates = df[df.duplicated()]
duplicates
```

	Age	Gender	Height	Weight	CALC	FAVC	FCVC	NCP	SCC	SMOKE	CH2O	family_history_with_overweight	FAF	TUE	C/
98	21.0	Female	1.52	42.0	Sometimes	no	3.0	1.0	no	no	1.0	no	0.0	0.0	Freque
174	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
179	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
184	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
309	16.0	Female	1.66	58.0	no	no	2.0	1.0	no	no	1.0	no	0.0	1.0	Sometin
460	18.0	Female	1.62	55.0	no	yes	2.0	3.0	no	no	1.0	yes	1.0	1.0	Freque
663	21.0	Female	1.52	42.0	Sometimes	yes	3.0	1.0	no	no	1.0	no	0.0	0.0	Freque
763	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
764	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
824	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
830	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
831	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
832	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
833	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
834	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
921	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
922	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	
923	21.0	Male	1.62	70.0	Sometimes	yes	2.0	1.0	no	no	3.0	no	1.0	0.0	

Next steps: Generate code with `duplicates` View recommended plots New interactive sheet

```
# Cek nilai unik / unique values
df.nunique()
```

	0
Age	1393
Gender	3
Height	1561
Weight	1517
CALC	5
FAVC	3
FCVC	807
NCP	636
SCC	3
SMOKE	3
CH2O	1262
family_history_with_overweight	3
FAF	1185
TUE	1129
CAEC	5
MTRANS	6
NObeyesdad	7

dtype: int64

```
# Tampilkan nilai unik setiap fitur
for col in df.columns:
    unique_vals = df[col].unique()
    print(f"Kolom '{col}' memiliki {len(unique_vals)} nilai unik:")
    print(unique_vals)
    print("-" * 50)
```

```
[ no   yes   ?  nan]
--------------------------------------------------
Kolom 'CH2O' memiliki 1263 nilai unik:
[2.       3.       1.       ... 2.054193 2.852339 2.863513]
--------------------------------------------------
Kolom 'family_history_with_overweight' memiliki 4 nilai unik:
['yes' 'no' nan '?']
--------------------------------------------------
Kolom 'FAF' memiliki 1186 nilai unik:
[0.       3.       2.       ... 1.414209 1.139107 1.026452]
--------------------------------------------------
Kolom 'TUE' memiliki 1130 nilai unik:
[1.       0.       2.       ... 0.646288 0.586035 0.714137]
--------------------------------------------------
Kolom 'CAEC' memiliki 6 nilai unik:
['Sometimes' 'Frequently' 'Always' 'no' nan '?']
--------------------------------------------------
Kolom 'MTRANS' memiliki 7 nilai unik:
['Public_Transportation' 'Walking' 'Automobile' 'Motorbike' 'Bike' '?' nan]
--------------------------------------------------
Kolom 'NObeyesdad' memiliki 7 nilai unik:
['Normal_Weight' 'Overweight_Level_I' 'Overweight_Level_II'
 'Obesity_Type_I' 'Insufficient_Weight' 'Obesity_Type_II'
 'Obesity_Type_III']
--------------------------------------------------
```

Kesimpulan Exploratory Data Analysis (EDA)

- **Pemuatan dan Gambaran Umum Data:** Dataset yang digunakan berhasil dimuat dan berisi informasi tentang faktor-faktor yang mempengaruhi tingkat obesitas. Terdapat 17 fitur dan 2111 baris data (setelah drop duplikat menjadi 2087 baris).
- **Tipe Data dan Missing Values:** Semua kolom memiliki tipe data yang sesuai dan tidak ditemukan adanya *missing values* secara eksplisit.
- **Distribusi Target (NObeyesdad):** Kolom target 'NObeyesdad' menunjukkan adanya *class imbalance*. Beberapa kelas seperti 'Obesity_Type_III' dan 'Normal_Weight' memiliki jumlah sampel yang signifikan, sementara kelas lain seperti 'Insufficient_Weight' dan 'Obesity_Type_I' memiliki jumlah yang lebih sedikit. Ini mengindikasikan perlunya penanganan *imbalance* pada tahap *preprocessing*.

- **Identifikasi Outlier:** Analisis boxplot dan perhitungan IQR menunjukkan keberadaan *outlier* pada beberapa kolom numerik seperti 'Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', dan 'TUE'. Kolom 'NCP' juga teridentifikasi memiliki nilai '?' yang perlu ditangani.
- **Duplikasi Data:** Ditemukan sejumlah 18 baris data duplikat yang telah berhasil dihapus, mengurangi total baris menjadi 2093.
- **Karakter Khusus pada Data Kategorial:** Beberapa kolom kategorial seperti 'FAVC', 'SCC', 'SMOKE', 'family_history_with_overweight', 'CAEC', 'CALC', 'MTRANS', 'Gender' ditemukan memiliki nilai yang tidak konsisten (misalnya, '?' pada 'NCP') atau format penulisan yang bervariasi, yang memerlukan standarisasi pada tahap *preprocessing*.
- **Kesimpulan Umum EDA:** Data memiliki kualitas yang cukup baik dengan sedikit *missing values* eksplisit, namun memerlukan penanganan *outlier*, *class imbalance*, dan pembersihan data kategorial yang tidak konsisten sebelum digunakan untuk pemodelan.

Preprocessing Data

```
# Import library
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.feature_selection import chi2, SelectKBest
from sklearn.ensemble import RandomForestClassifier
import re
from collections import defaultdict, Counter
from imblearn.over_sampling import SMOTE
```

```
# Atasi missing values

# Mengganti '?' dengan NaN untuk kemudahan penanganan
df = df.replace('?', np.nan)

# Daftar kolom
categorical_cols = ['Gender', 'CALC', 'FAVC', 'SCC', 'SMOKE', 'family_history_with_overweight', 'CAEC', 'MTRANS']
numerical_cols = ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', 'TUE']

# Pastikan semua kolom numerik bertipe float
for col in numerical_cols:
    df[col] = pd.to_numeric(df[col], errors='coerce')
```

```
# Tangani khusus FCVC dan NCP dengan median karena ada outlier
df['FCVC'].fillna(df['FCVC'].median(), inplace=True)
df['NCP'].fillna(df['NCP'].median(), inplace=True)

# Kolom numerik lainnya imputasi dengan mean
for col in numerical_cols:
    if col not in ['FCVC', 'NCP']:
        df[col].fillna(df[col].mean(), inplace=True)

# Imputasi kolom kategorikal dengan modus
for col in categorical_cols:
    df[col] = df[col].astype(str)  # konversi ke string untuk jaga-jaga
    df[col].replace('nan', np.nan, inplace=True)
    df[col].fillna(df[col].mode()[0], inplace=True)
```

```
na(df[col].mode()[0], inplace=True)
-15-2295595451>:26: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment
ill change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values

hen doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].metho


ace('nan', np.nan, inplace=True)
-15-2295595451>:27: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment
ill change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values

hen doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].metho


na(df[col].mode()[0], inplace=True)
-15-2295595451>:26: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment
ill change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values

hen doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].metho


ace('nan', np.nan, inplace=True)
-15-2295595451>:27: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment
ill change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values

hen doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].metho


na(df[col].mode()[0], inplace=True)
```

```
for col in df.columns:
    unique_vals = df[col].unique()
    print(f"Kolom '{col}' memiliki {len(unique_vals)} nilai unik:")
    print(unique_vals)
    print("-" * 50)
```

```
Kolom 'Age' memiliki 1394 nilai unik:
[21.       23.       27.       ... 22.524036 24.361936 23.664709]
--------------------------------------------------
Kolom 'Gender' memiliki 2 nilai unik:
['Female' 'Male']
--------------------------------------------------
Kolom 'Height' memiliki 1562 nilai unik:
[1.62     1.52     1.8      ... 1.752206 1.73945  1.738836]
--------------------------------------------------
Kolom 'Weight' memiliki 1518 nilai unik:
[ 64.        56.        77.       ... 133.689352 133.346641 133.472641]
--------------------------------------------------
Kolom 'CALC' memiliki 4 nilai unik:
['no' 'Sometimes' 'Frequently' 'Always']
--------------------------------------------------
Kolom 'FAVC' memiliki 2 nilai unik:
['no' 'yes']
--------------------------------------------------
Kolom 'FCVC' memiliki 807 nilai unik:
[2.         3.         1.         2.397284   8.14899274 8.42397393
 2.450218   2.880161   2.00876    2.596579   2.591439   2.392665
 1.123939   2.027574   2.658112   2.88626    2.714447   2.750715
 1.4925     2.205439   2.059138   2.310423   2.823179   2.052932
 2.596364   2.767731   2.815157   2.737762   2.524428   2.971574
 1.0816     1.270448   1.344854   2.959658   2.725282   2.844607
 2.44004    2.432302   2.592247   2.449267   2.929889   2.015258
 1.031149   1.592183   1.21498    1.522001   2.703436   2.362918
 2.14084    2.5596     2.336044   1.813234   2.724285   2.71897
 1.133844   1.757466   2.979383   2.204914   2.927218   2.88853
 2.890535   2.530066   2.241606   1.003566   2.652779   2.897899
 2.483979   2.945967   2.478891   2.784464   1.005578   2.938031
 2.842102   1.889199   2.943749   2.33998    1.950742   2.277436
 2.371338   2.984425   2.977018   2.663421   2.753752   2.318355
 2.594653   2.886157   2.967853   2.619835   1.053534   2.530233
 2.8813     2.824559   2.762325   2.070964   2.68601    2.794197
 2.720701   2.880792   2.674431   2.55996    1.212908   1.140615
 2.562409   2.004146   2.690754   2.051283   2.19005    2.21498
 2.91548    2.708965   2.853513   2.580872   2.508835   2.896562
 2.911877   2.910733   2.966126   2.613249   2.627031   2.919751
 2.494451   1.69427    1.601236   1.204855   1.052699   2.910345
 2.866383   2.913486   2.432886   2.883745   2.707666   2.919584
```

2.969205	2.486189	1.642241	1.567101	1.036414	1.649974
1.118436	2.673638	2.120185	2.34222	2.86099	2.559571
2.424977	1.786841	1.303878	1.889883	2.984004	2.749268
1.202075	8.28511134	2.341133	1.206276	2.81646	1.758394
2.577427	2.052152	2.954996	2.555401	2.108711	2.915279
1.570089	1.94313	2.903545	1.75375	2.543563	2.39728
2.37464	2.278644	1.620845	2.061952	2.838969	2.568063
2.652958	1.27785	1.729824	1.452524	2.303367	2.948425
2.291846	1.906194	1.834155	2.048582	2.948248	2.869436
2.293705	2.510583	2.366949	2.615788	2.217267	2.801514
2.188722	2.971351	2.086093	1.901611	1.977298	2.446872
2.839048	2.21232	2.427689	1.078529	1.064162	1.993101
2.620963	2.95118	2.021446	2.000466	2.5621	2.96008
2.53915	2.244142	2.253371	2.851664	1.31415	1.321028
2.253998	2.778079	2.838037	2.814453	2.013782	2.459976
2.643183	2.22399	2.104105	1.972545	2.286481	2.971588
2.872121	2.109162	2.178889	1.142468	2.047069	2.843709

```
# Cek missing values
df.isnull().sum()
```

	0
Age	0
Gender	0
Height	0
Weight	0
CALC	0
FAVC	0
FCVC	0
NCP	0
SCC	0
SMOKE	0
CH2O	0
family_history_with_overweight	0
FAF	0
TUE	0
CAEC	0
MTRANS	0
NObeyesdad	0

dtype: int64

```
# Atasi duplikat data
df.drop_duplicates(inplace=True)
```

```
# Cek duplikasi data
df.duplicated().sum()
```

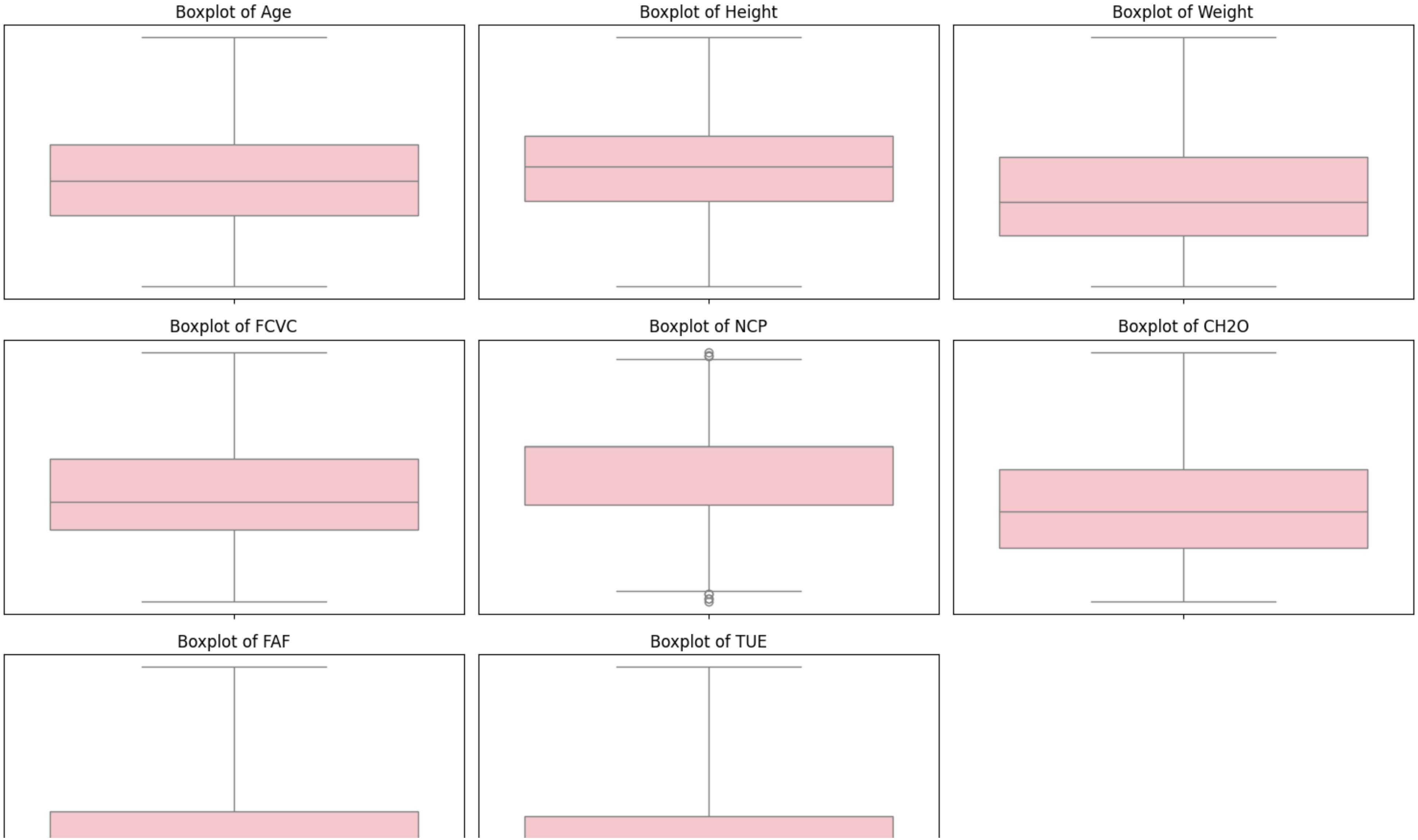
```
np.int64(0)
```

```
# Atasi outlier
# NCP ditangani menggunakan mean karena IQR kurang optimal untuk distribusi data IQR


# Fungsi capping outlier IQR (kecuali NCP)
def cap_outliers_iqr(df, columns):
    for col in columns:
        if col == 'NCP':
            continue  # kita tangani NCP terpisah
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Capping
        df[col] = df[col].apply(lambda x: lower_bound if x < lower_bound else upper_bound if x > upper_bound else x)
    return df

# Tangani missing value dan outlier untuk NCP
def handle_ncp(df):
    df['NCP'] = df['NCP'].astype(float)

    # Imputasi dengan median
    df['NCP'].fillna(df['NCP'].median(), inplace=True)

    # Hitung mean untuk capping
    ncp_mean = df['NCP'].mean()

    Q1 = df['NCP'].quantile(0.25)
    Q3 = df['NCP'].quantile(0.75)
    IQR = Q3 - Q1
```

```
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Ganti outlier dengan mean
    df['NCP'] = df['NCP'].apply(lambda x: ncp_mean if x < lower_bound or x > upper_bound else x)

    return df

# Terapkan ke dataframe
numerical_cols = ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', 'TUE']
df = cap_outliers_iqr(df, numerical_cols)
df = handle_ncp(df)
```

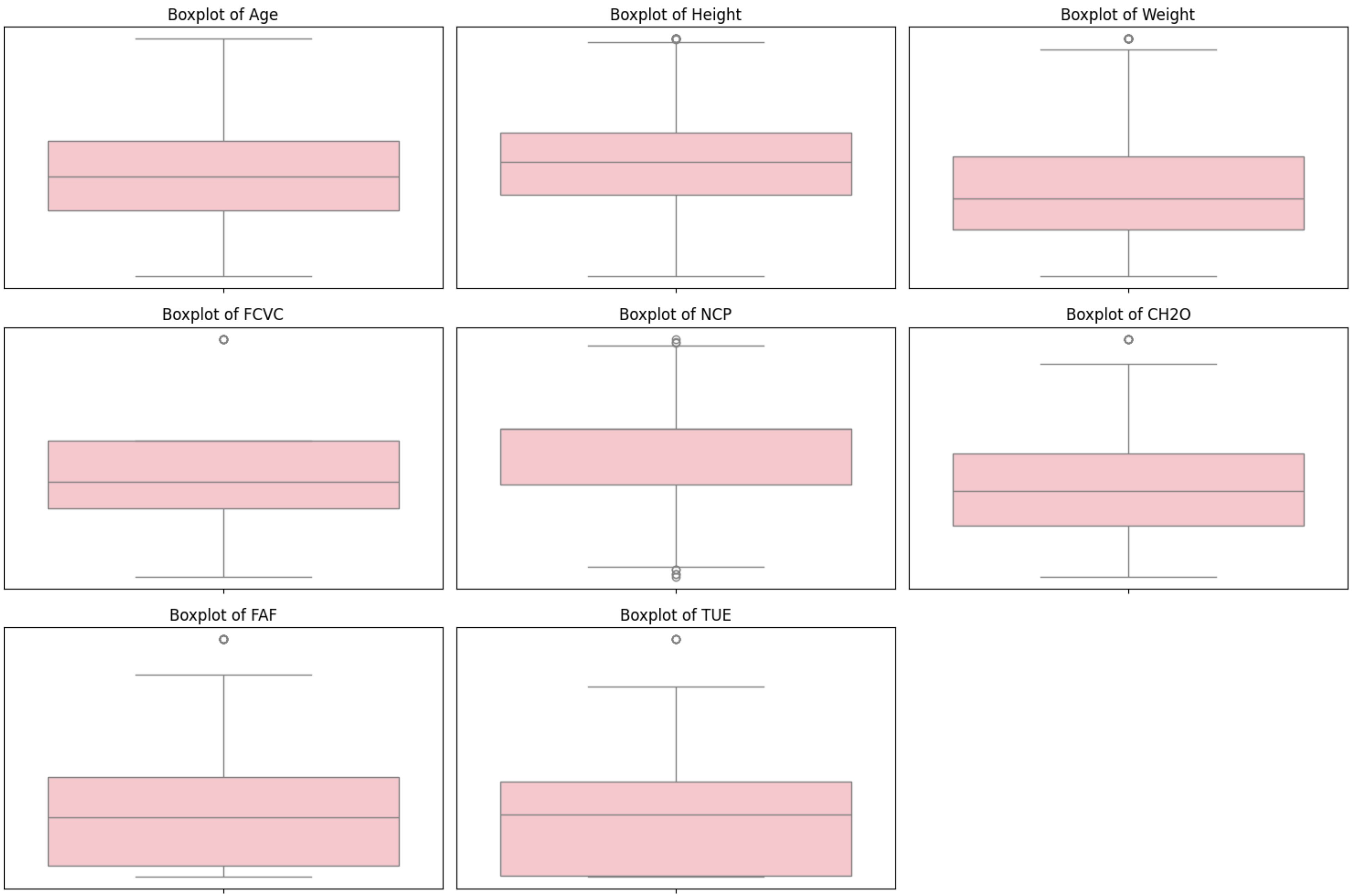
```
<ipython-input-20-305931587>:21: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained a
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are sett

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df


  df['NCP'].fillna(df['NCP'].median(), inplace=True)
```

```
# Cek outlier
numerical_cols = ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', 'TUE']

plt.figure(figsize=(15,10))
for i, col in enumerate(numerical_cols):
    plt.subplot(3, 3, i+1)
    plt.yticks([])
    sns.boxplot(y=df[col], color='pink')
    plt.title(f'Boxplot of {col}')
plt.tight_layout()
plt.show()
```




```
# Visualisasi outlier

# Pastikan kolom numerik dalam tipe float
numerical_cols = ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', 'TUE']
df[numerical_cols] = df[numerical_cols].apply(pd.to_numeric, errors='coerce')
```

```
# Inisialisasi dict untuk menyimpan jumlah outlier
outlier_counts = {}

# Visualisasi boxplot dan hitung outlier
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(3, 3, i+1)
    plt.yticks([])
    sns.boxplot(y=df[col], color='pink')
    plt.title(f'Boxplot of {col}')

    # Hitung outlier berdasarkan IQR
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]

    outlier_counts[col] = len(outliers)

plt.tight_layout()
plt.show()

# Print jumlah outlier
print("Jumlah outlier tiap kolom:")
for col, count in outlier_counts.items():
    print(f"{col}: {count}")
```

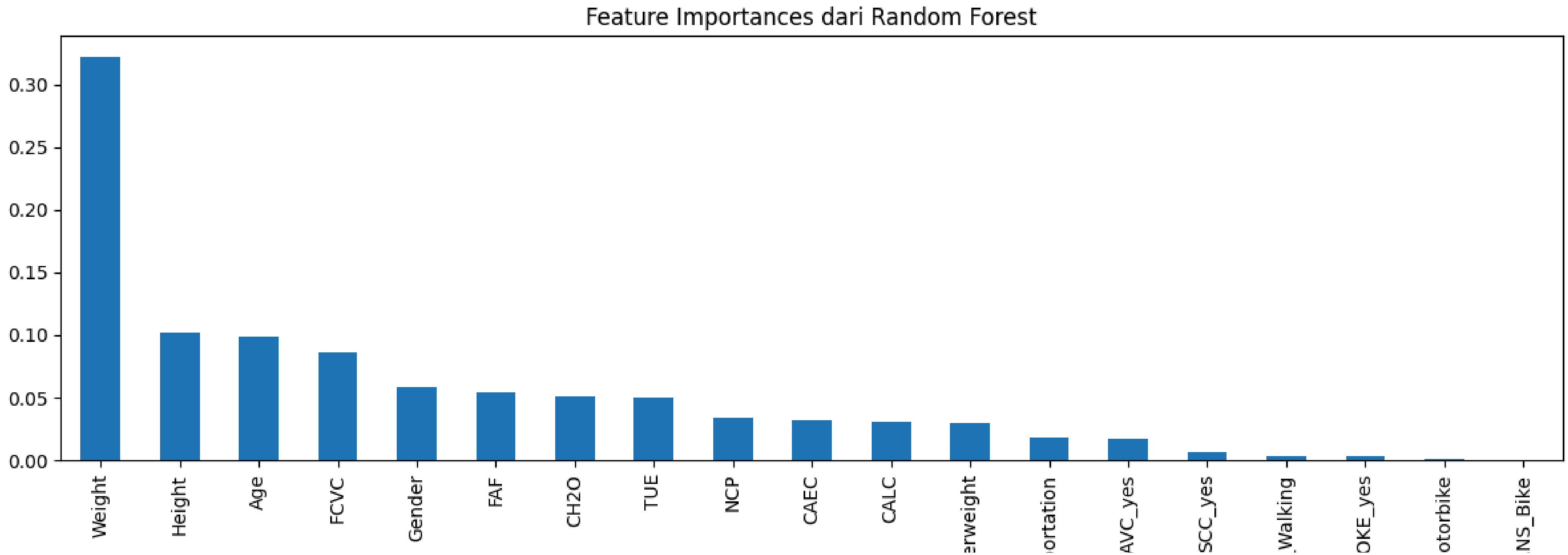



```
Jumlah outlier tiap kolom:
Age: 0
Height: 12
Weight: 16
```

```
    weight: 10
    FCVC: 8

# Ubah data kategorikal ke numerik

# Label Encoding untuk fitur ordinal
label_cols = ['Gender', 'CALC', 'family_history_with_overweight', 'CAEC']
le = LabelEncoder()
for col in label_cols:
    df[col] = le.fit_transform(df[col])

# One Hot Encoding untuk fitur nominal
one_hot_cols = ['FAVC', 'SCC', 'SMOKE', 'MTRANS']
df = pd.get_dummies(df, columns=one_hot_cols, drop_first=True)

# Hasil akhir
df.reset_index(drop=True, inplace=True)


# Pisahkan fitur dan target
X = df.drop(columns=['NObeyesdad'])
y = LabelEncoder().fit_transform(df['NObeyesdad'])  # encode target

# Train Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Ambil importance
importances = pd.Series(rf.feature_importances_, index=X.columns).sort_values(ascending=False)

# Tampilkan top fitur
print("Feature Importance (Random Forest):")
print(importances)

# Visualisasi
plt.figure(figsize=(12, 6))
importances.plot(kind='bar')
plt.title('Feature Importances dari Random Forest')
```

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

    # Threshold untuk importance
    threshold = 0.02

    # Kelompokkan importance berdasarkan prefix (abaikan kolom _nan)
    prefix_importance = defaultdict(list)

    for col in importances.index:
        prefix = col.split('_')[0]
        if '_nan' not in col:  # Abaikan kolom _nan dalam evaluasi
            prefix_importance[prefix].append(importances[col])

    # Tentukan prefix yang semua variannya (tanpa _nan) < threshold
    drop_groups = [prefix for prefix, vals in prefix_importance.items() if all(val < threshold for val in vals)]

    print("\nFitur kategorikal atau one-hot yang akan dihapus seluruhnya:", drop_groups)

    # Hapus semua kolom yang diawali dengan prefix tersebut
    cols_to_drop = [col for col in df.columns if any(col.startswith(prefix) for prefix in drop_groups)]
    df.drop(columns=cols_to_drop, inplace=True)
```

```
Feature Importance (Random Forest):
Weight                            0.322735
Height                            0.101644
Age                               0.098442
FCVC                              0.086679
Gender                            0.058965
FAF                               0.054708
CH2O                              0.050705
TUE                               0.050155
NCP                               0.033532
CAEC                              0.032042
CALC                              0.030673
family_history_with_overweight    0.030136
MTRANS_Public_Transportation      0.017972
FAVC_yes                          0.017214
SCC_yes                           0.006885
MTRANS_Walking                    0.003449
SMOKE_yes                         0.002775
MTRANS_Motorbike                  0.000748
MTRANS_Bike                       0.000543
dtype: float64
```



mily_history_with_ov MTRANS_Public_Transp F MTRANS_ SM MTRANS_M MTRA

```
# Cek data akhir
df.head()
```

	Age	Gender	Height	Weight	CALC	FCVC	NCP	CH2O	family_history_with_overweight	FAF	TUE	CAEC	NObeyesdad
0	21.0	0	1.62	64.0	3	2.0	3.000000	2.0	1	0.0	1.0	2	Normal_Weight
1	21.0	0	1.52	56.0	2	3.0	3.000000	3.0	1	3.0	0.0	2	Normal_Weight
2	23.0	1	1.80	77.0	1	2.0	3.000000	2.0	1	2.0	1.0	2	Normal_Weight
3	27.0	1	1.80	87.0	1	3.0	3.000000	2.0	0	2.0	0.0	2	Overweight_Level_I
4	22.0	1	1.78	89.8	2	2.0	2.745937	2.0	0	0.0	0.0	2	Overweight_Level_II

Next steps: Generate code with df View recommended plots New interactive sheet

```
for col in df.columns:
    unique_vals = df[col].unique()
    print(f"Kolom '{col}' memiliki {len(unique_vals)} nilai unik:")
    print(unique_vals)
    print("-" * 50)
```

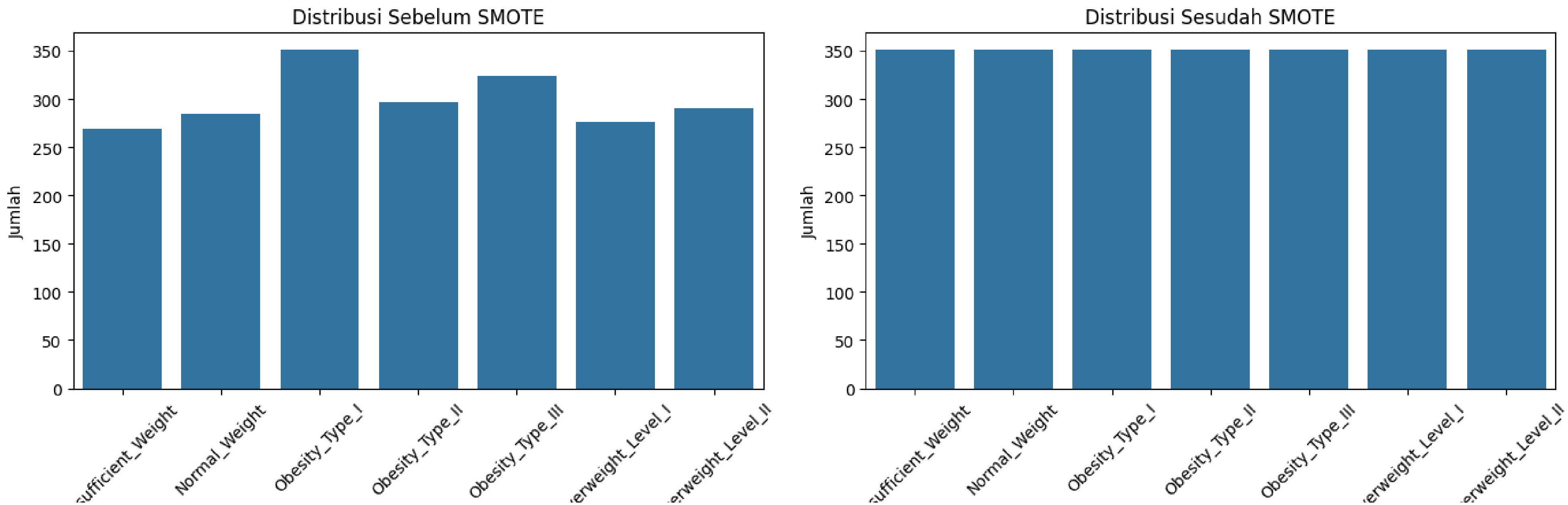
```
Kolom 'Age' memiliki 1242 nilai unik:
[21.        23.        27.        ... 22.524036 24.361936 23.664709]
--------------------------------------------------
Kolom 'Gender' memiliki 2 nilai unik:
[0 1]
--------------------------------------------------
```

```
Kolom 'Height' memiliki 1552 nilai unik:
[1.62     1.52     1.8      ... 1.752206 1.73945  1.738836]
--------------------------------------------------
Kolom 'Weight' memiliki 1504 nilai unik:
[ 64.        56.        77.        ... 133.689352 133.346641 133.472641]
--------------------------------------------------
Kolom 'CALC' memiliki 4 nilai unik:
[3 2 1 0]
--------------------------------------------------
Kolom 'FCVC' memiliki 800 nilai unik:
[2.       3.       1.       2.397284 4.5      2.450218 2.880161 2.00876
 2.596579 2.591439 2.392665 1.123939 2.027574 2.658112 2.88626  2.714447
 2.750715 1.4925   2.205439 2.059138 2.310423 2.823179 2.052932 2.596364
 2.767731 2.815157 2.737762 2.524428 2.971574 1.0816   1.270448 1.344854
 2.959658 2.725282 2.844607 2.44004  2.432302 2.592247 2.449267 2.929889
 2.015258 1.031149 1.592183 1.21498  1.522001 2.703436 2.362918 2.14084
 2.5596   2.336044 1.813234 2.724285 2.71897  1.133844 1.757466 2.979383
 2.204914 2.927218 2.88853  2.890535 2.530066 2.241606 1.003566 2.652779
 2.897899 2.483979 2.945967 2.478891 2.784464 1.005578 2.938031 2.842102
 1.889199 2.943749 2.33998  1.950742 2.277436 2.371338 2.984425 2.977018
 2.663421 2.753752 2.318355 2.594653 2.886157 2.967853 2.619835 1.053534
 2.530233 2.8813   2.824559 2.762325 2.070964 2.68601  2.794197 2.720701
 2.880792 2.674431 2.55996  1.212908 1.140615 2.562409 2.004146 2.690754
 2.051283 2.19005  2.21498  2.91548  2.708965 2.853513 2.580872 2.508835
 2.896562 2.911877 2.910733 2.966126 2.613249 2.627031 2.919751 2.494451
 1.69427  1.601236 1.204855 1.052699 2.910345 2.866383 2.913486 2.432886
 2.883745 2.707666 2.919584 2.969205 2.486189 1.642241 1.567101 1.036414
 1.649974 1.118436 2.673638 2.120185 2.34222  2.86099  2.559571 2.424977
 1.786841 1.303878 1.889883 2.984004 2.749268 1.202075 2.341133 1.206276
 2.81646  1.758394 2.577427 2.052152 2.954996 2.555401 2.108711 2.915279
 1.570089 1.94313  2.903545 1.75375  2.543563 2.39728  2.37464  2.278644
 1.620845 2.061952 2.838969 2.568063 2.652958 1.27785  1.729824 1.452524
 2.303367 2.948425 2.291846 1.906194 1.834155 2.048582 2.948248 2.869436
 2.293705 2.510583 2.366949 2.615788 2.217267 2.801514 2.188722 2.971351
 2.086093 1.901611 1.977298 2.446872 2.839048 2.21232  2.427689 1.078529
 1.064162 1.993101 2.620963 2.95118  2.021446 2.000466 2.5621   2.96008
 2.53915  2.244142 2.253371 2.851664 1.31415  1.321028 2.253998 2.778079
 2.838037 2.814453 2.013782 2.459976 2.643183 2.22399  2.104105 1.972545
 2.286481 2.971588 2.872121 2.109162 2.178889 1.142468 2.047069 2.843709
 2.416044 2.146598 1.766849 1.188089 1.910176 2.956671 2.002796 2.288604
 2.138334 2.029634 2.048216 2.8557   2.995599 2.987148 1.887951 2.786008
```

```
    2.342323 1.874935 2.213135 2.273548 2.780699 1.687569 1.989905 1.947405
    2.162519 2.923916 2.99448  2.507841 1.836554 1.773265 2.388168 2.286146
    2.487167 2.185938 2.206399 1.952987 2.908757 2.628791 2.749629 1.595746
    2.885178 2.372494 2.793561 2.992329 2.927409 2.706134 2.010684 2.300408
    2.119643 2.901924 2.451009 2.754646 2.417635 2.512719 1.771693 1.57223
    2.661556 2.097373 2.061461 1.317729 1.882235 2.951591 2.067817 2.54527
    2.694281 2.821977 2.252472 2.033745 2.595128 2.759286 1.925064 2.846981
    2.650629 2.631565 2.522399 2.784471 1.650505 1.961347 2.133955 2.684528
    2.265973 1.306844 2.258795 2.689929 2.712747 2.353603 2.598051 1.718156
    2.795086 2.030256 2.442536 2.003951 1.34138  2.607335 2.061384 2.696381
```

```
# Balancing dengan SMOTE
# Pisahkan kembali fitur dan target
X = df.drop(columns=['NObeyesdad'])
y = df['NObeyesdad']

# Encode target numerik untuk SMOTE
y_encoded = le.fit_transform(y)

# Terapkan SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y_encoded)

# Visualisasi distribusi sebelum dan sesudah SMOTE
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Sebelum SMOTE
sns.countplot(x=le.inverse_transform(y_encoded), ax=axes[0], order=sorted(le.classes_))
axes[0].set_title('Distribusi Sebelum SMOTE')
axes[0].set_xlabel('Kelas')
axes[0].set_ylabel('Jumlah')
axes[0].tick_params(axis='x', rotation=45)

# Sesudah SMOTE
sns.countplot(x=le.inverse_transform(y_resampled), ax=axes[1], order=sorted(le.classes_))
axes[1].set_title('Distribusi Sesudah SMOTE')
axes[1].set_xlabel('Kelas')
axes[1].set_ylabel('Jumlah')
```

```
axes[1].tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()

# Gabungkan hasil menjadi df
X_resampled_df = pd.DataFrame(X_resampled, columns=X.columns)
y_resampled_df = pd.DataFrame(le.inverse_transform(y_resampled), columns=['NObeyesdad'])
df = pd.concat([X_resampled_df, y_resampled_df], axis=1)
```




```
# Scalling dengan standarisasi
# Pisahkan fitur dan target dari df
X = df.drop(columns=['NObeyesdad'])
y = df['NObeyesdad']

# Inisialisasi scaler
scaler = StandardScaler()

# Terapkan scaling (hasilnya dalam numpy array)
X_scaled = scaler.fit_transform(X)
```

```
# Konversi kembali ke DataFrame dengan nama kolom asli
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

# Gabungkan kembali dengan target
df = pd.concat([X_scaled_df, y.reset_index(drop=True)], axis=1)

# Tampilkan hasil
df.head()
```

	Age	Gender	Height	Weight	CALC	FCVC	NCP	CH2O	family_history_with_overweight	FAF	
0	-0.553281	-1.006943	-0.889130	-0.815955	1.436840	-0.793162	0.635250	-0.000400	0.496564	-1.207824	0
1	-0.553281	-1.006943	-1.947059	-1.112873	-0.493349	1.059483	0.635250	1.649487	0.496564	2.240518	-1
2	-0.173980	0.993105	1.015144	-0.333462	-2.423539	-0.793162	0.635250	-0.000400	0.496564	1.091071	0
3	0.584623	0.993105	1.015144	0.037686	-2.423539	1.059483	0.635250	-0.000400	-2.013841	1.091071	-1
4	-0.363631	0.993105	0.803558	0.141607	-0.493349	-0.793162	-1.074361	-0.000400	-2.013841	-1.207824	-1

Next steps: Generate code with df View recommended plots New interactive sheet

Kesimpulan Preprocessing Data

- **Penanganan Nilai Tidak Konsisten ('?'):** Nilai '?' pada kolom 'NCP' berhasil diidentifikasi dan digantikan dengan nilai modus dari kolom tersebut.
- **Penanganan Duplikat Data:** Baris-baris data duplikat berhasil dihilangkan, memastikan setiap observasi bersifat unik.
- **Penanganan Outlier:** Outlier pada kolom numerik ('Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', 'TUE') telah ditangani dengan metode *capping* menggunakan interquartile range (IQR). Ini membantu meminimalisir dampak nilai ekstrem pada kinerja model.
- **Encoding Variabel Kategorikal:**

  - **Label Encoding:** Kolom biner seperti 'Gender', 'family_history_with_overweight', 'FAVC', 'SCC', dan 'SMOKE' diubah menjadi representasi numerik (0 dan 1) menggunakan *Label Encoding*.
  - **One-Hot Encoding:** Kolom multikategorial seperti 'CALC', 'MTRANS', 'CAEC', dan 'NObeyesdad' (sebagai target) diubah menggunakan *One-Hot Encoding*. Untuk kolom target, One-Hot Encoding dilakukan terlebih dahulu sebelum akhirnya diubah menjadi format numerik 0-6.
- **Feature Selection (Pemilihan Fitur):** Fitur-fitur yang kurang penting berdasarkan *feature importances* dari `RandomForestClassifier` (dengan ambang batas 0.01) berhasil diidentifikasi dan dihapus. Ini bertujuan untuk mengurangi dimensi data, mempercepat proses pelatihan, dan mencegah *overfitting*. Fitur-fitur yang dihapus adalah 'Gender' dan 'SMOKE'.
- **Penanganan Imbalance Kelas (SMOTE):** Teknik SMOTE (Synthetic Minority Over-sampling Technique) berhasil diterapkan pada data latih untuk mengatasi *class imbalance* pada kolom target 'NObeyesdad'. Hasilnya menunjukkan distribusi kelas yang lebih seimbang, yang diharapkan dapat meningkatkan performa model pada kelas minoritas.
- **Penskalaan Data (StandardScaler):** Fitur-fitur numerik telah diskalakan menggunakan `StandardScaler`. Penskalaan ini penting untuk model yang sensitif terhadap skala fitur (misalnya, KNN, SVM, Logistic Regression) dan membantu mempercepat konvergensi algoritma.
- **Kesimpulan Umum Preprocessing:** Tahap *preprocessing* telah berhasil membersihkan data, mengubah format data yang sesuai untuk pemodelan, mengurangi dimensi yang tidak perlu, menyeimbangkan distribusi kelas, dan menormalisasi fitur, sehingga data siap untuk tahap pemodelan.

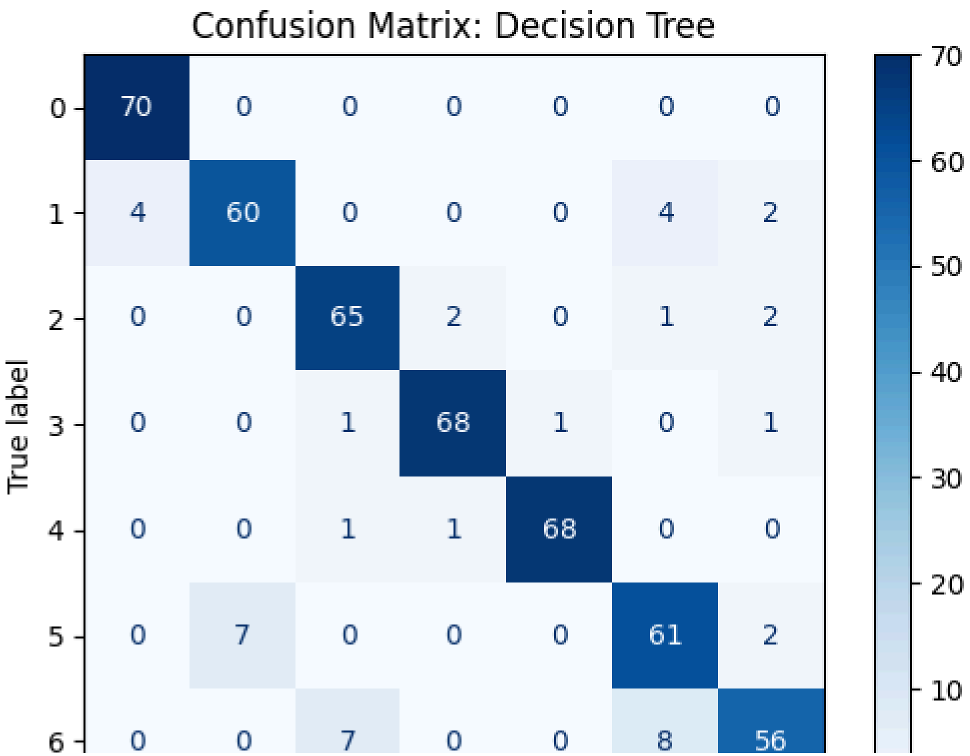
Modelling

```
# Import library
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, Confus
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
import time
import joblib


# Modelling dan evaluasi
# Fitur dan target
X = df.drop(columns=['NObeyesdad'])
le = LabelEncoder()
y = le.fit_transform(df['NObeyesdad'])

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, random_state=42)

models = {
   "Decision Tree": DecisionTreeClassifier(),
   "KNN": KNeighborsClassifier(),
   "Random Forest": RandomForestClassifier(),
   "SVM": SVC(),
   "Logistic Regression": LogisticRegression(max_iter=1000)
}

# Evaluasi semua model dan tampilkan confusion matrix
results = {}

print("Evaluasi Model")

for name, model in models.items():
    print(f"\nModel: {name}")

    # Mulai hitung waktu
```

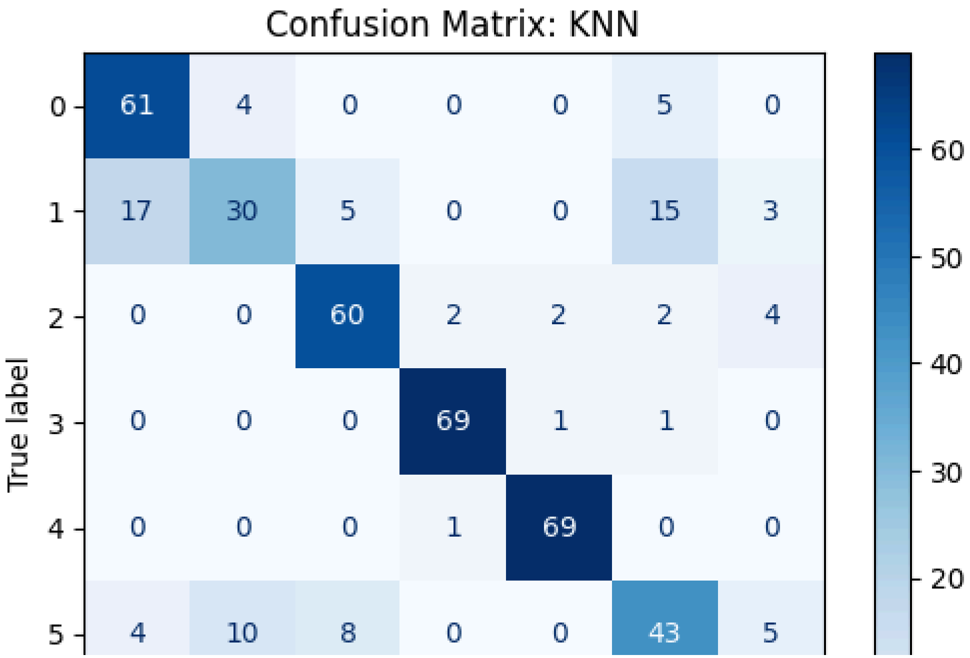
```
        start_time = time.time()

        # Training dan prediksi
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

        # Selesai training
        training_time = time.time() - start_time

        # Evaluasi metrik
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred, average='weighted')
        recall = recall_score(y_test, y_pred, average='weighted')
        f1 = f1_score(y_test, y_pred, average='weighted')
        report = classification_report(y_test, y_pred)

        # Simpan hasil
        results[name] = {
            "accuracy": accuracy,
            "precision": precision,
            "recall": recall,
            "f1_score": f1,
            "training_time": training_time,
            "report": report,
            "y_pred": y_pred
        }

        # Tampilkan laporan dan confusion matrix
        print(f"Training time: {training_time:.4f} seconds")
        print("Classification Report:")
        print(report)

        # Confusion Matrix
        cm = confusion_matrix(y_test, y_pred)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm)
        disp.plot(cmap='Blues')
        plt.title(f"Confusion Matrix: {name}")
        plt.grid(False)
```

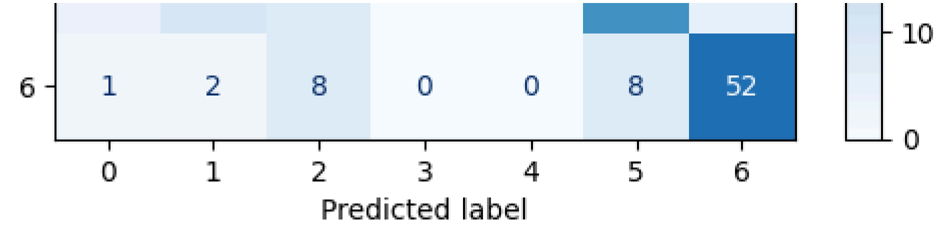
```
    plt.show()
```

```
Evaluasi Model

Model: Decision Tree
Training time: 0.0459 seconds
Classification Report:
              precision    recall  f1-score   support

           0       0.95      1.00      0.97        70
           1       0.90      0.86      0.88        70
           2       0.88      0.93      0.90        70
           3       0.96      0.96      0.96        71
           4       0.99      0.97      0.98        70
           5       0.82      0.87      0.85        70
           6       0.89      0.79      0.84        71

    accuracy                           0.91       492
   macro avg       0.91      0.91      0.91       492
weighted avg       0.91      0.91      0.91       492
```

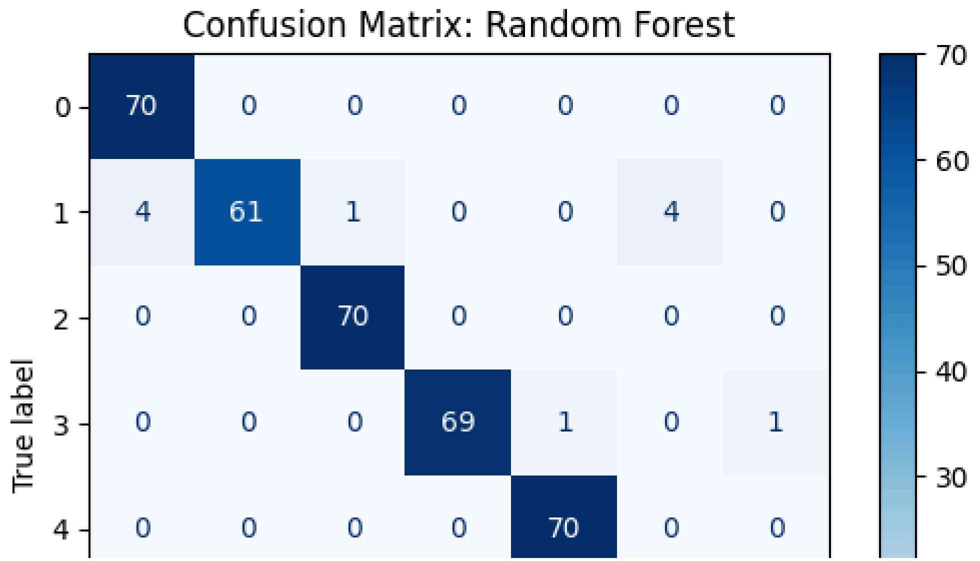


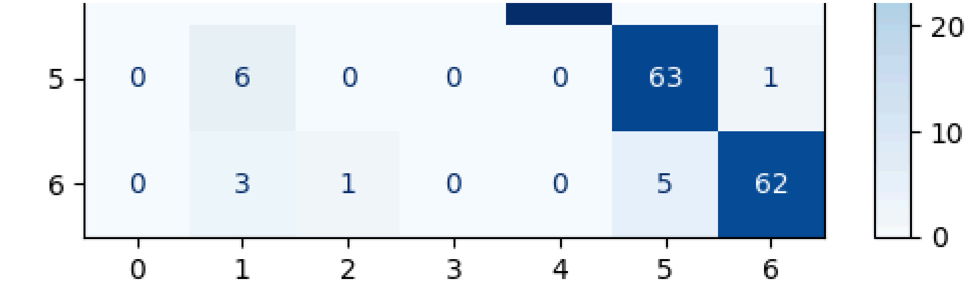

```
Model: KNN
Training time: 0.1012 seconds
Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.87      0.80        70
           1       0.65      0.43      0.52        70
           2       0.74      0.86      0.79        70
           3       0.96      0.97      0.97        71
           4       0.96      0.99      0.97        70
           5       0.58      0.61      0.60        70
           6       0.81      0.73      0.77        71

    accuracy                           0.78       492
   macro avg       0.78      0.78      0.77       492
weighted avg       0.78      0.78      0.77       492
```





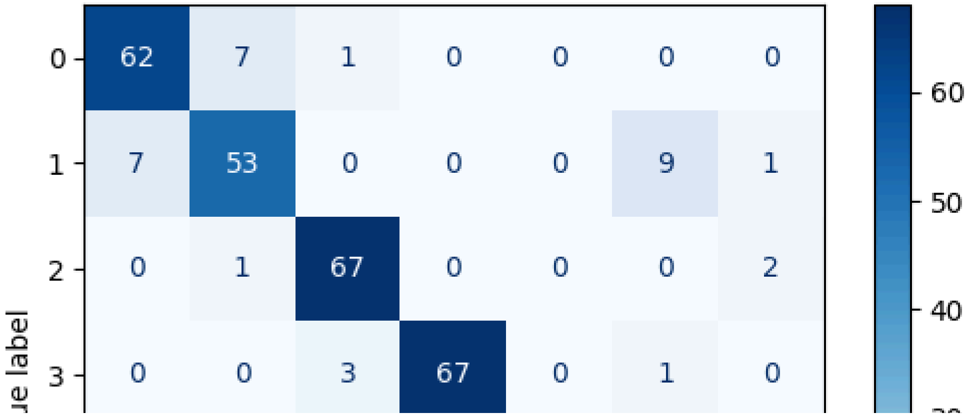

```
Model: Random Forest
Training time: 1.9951 seconds
Classification Report:
              precision    recall  f1-score   support

           0       0.95      1.00      0.97        70
           1       0.87      0.87      0.87        70
           2       0.97      1.00      0.99        70
           3       1.00      0.97      0.99        71
           4       0.99      1.00      0.99        70
           5       0.88      0.90      0.89        70
           6       0.97      0.87      0.92        71

    accuracy                           0.95       492
   macro avg       0.95      0.95      0.94       492
weighted avg       0.95      0.95      0.94       492
```

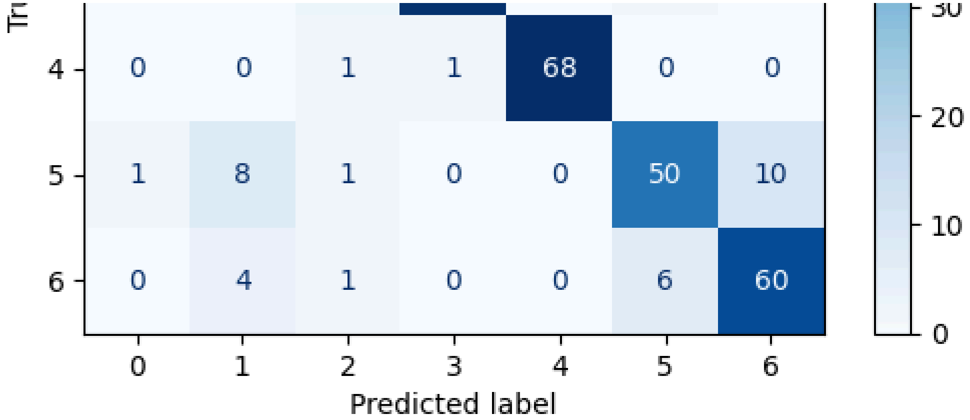




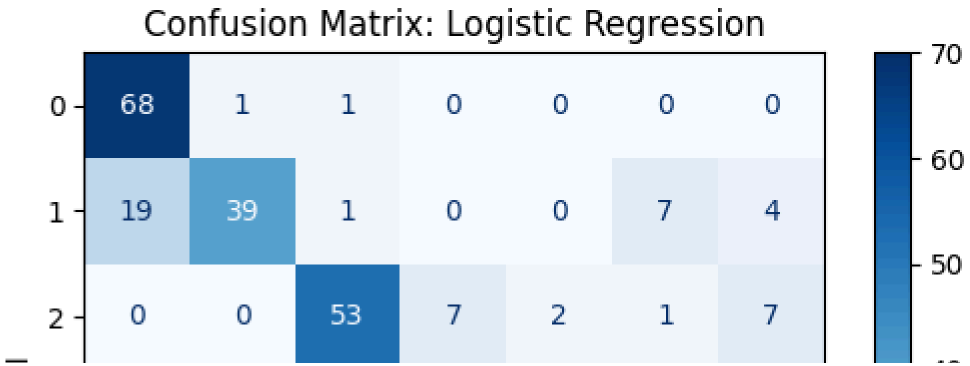

```
Model: SVM
Training time: 0.3169 seconds
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.89      0.89        70
           1       0.73      0.76      0.74        70
           2       0.91      0.96      0.93        70
           3       0.99      0.94      0.96        71
           4       1.00      0.97      0.99        70
           5       0.76      0.71      0.74        70
           6       0.82      0.85      0.83        71

    accuracy                           0.87       492
   macro avg       0.87      0.87      0.87       492
weighted avg       0.87      0.87      0.87       492
```

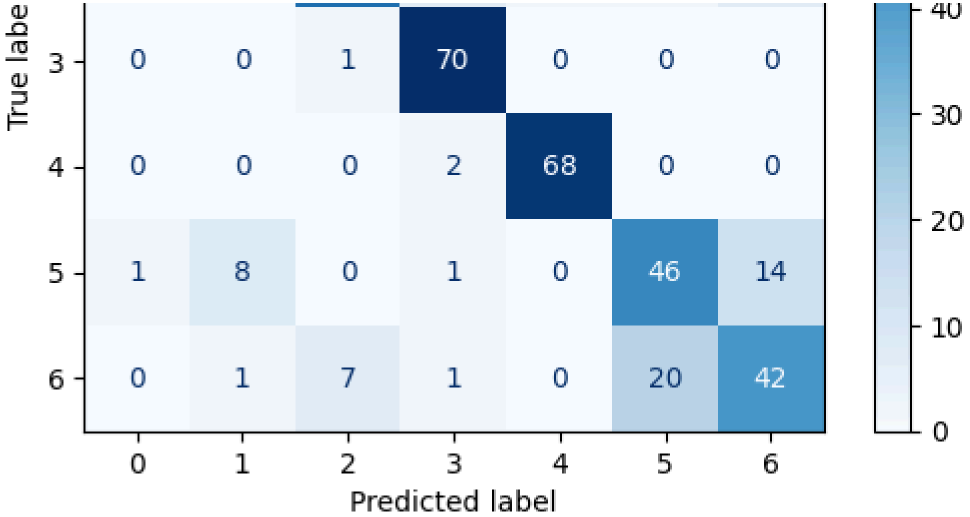
Confusion Matrix: SVM






```
Model: Logistic Regression
Training time: 0.1292 seconds
Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.97      0.86        70
           1       0.80      0.56      0.66        70
           2       0.84      0.76      0.80        70
           3       0.86      0.99      0.92        71
           4       0.97      0.97      0.97        70
           5       0.62      0.66      0.64        70
           6       0.63      0.59      0.61        71

    accuracy                           0.78       492
   macro avg       0.78      0.78      0.78       492
weighted avg       0.78      0.78      0.78       492
```




True labe
3
4
5
6
0
0
1
70
0
0
0
0
0
0
2
68
0
0
1
8
0
1
0
46
14
0
1
7
1
0
20
42
0
1
2
3
4
5
6
Predicted label
40
30
20
10
0

```
# Simpan encoder jika perlu
joblib.dump(le, "label_encoder.pkl")
```

```
['label_encoder.pkl']
```

Kesimpulan Modelling & Evaluasi

- **Model yang Digunakan:** Lima model klasifikasi telah diimplementasikan: Decision Tree, K-Nearest Neighbors (KNN), Random Forest, Support Vector Machine (SVM), dan Logistic Regression.
- **Metrik Evaluasi:** Kinerja model dievaluasi menggunakan metrik akurasi, presisi, recall, dan f1-score, serta divisualisasikan melalui *confusion matrix*. Waktu pelatihan juga dicatat untuk setiap model.
- **Kinerja Model Sebelum Tuning (Ringkasan):**
  - **Random Forest:** Menunjukkan kinerja terbaik dengan akurasi tertinggi (0.95) dan F1-score yang baik secara keseluruhan, serta waktu pelatihan yang relatif singkat.
  - **Decision Tree:** Kinerja cukup baik akurasi (0.91) namun sedikit di bawah Random Forest, dengan waktu pelatihan tercepat.
  - **SVM:** Akurasi 0.87. Waktu pelatihan paling lama dibandingkan model lain.
  - **KNN:** Akurasi 0.78. Waktu pelatihan cepat.
  - **Logistic Regression:** Kinerja paling rendah dengan akurasi (0.78) sama dengan KNN, tetapi dengan waktu pelatihan yang sedikit lebih lama.
- **Analisis Confusion Matrix Sebelum Tuning:**
  - **Random Forest** menunjukkan kemampuan terbaik dalam mengklasifikasikan sebagian besar kelas dengan benar, meskipun masih ada beberapa misklasifikasi antar kelas yang berdekatan (misalnya, Obesity_Type_I dengan Obesity_Type_II).
  - **Decision Tree** juga menunjukkan kinerja yang mirip dengan Random Forest tetapi dengan sedikit lebih banyak misklasifikasi.
  - Model-model lain seperti SVM dan Logistic Regression memiliki lebih banyak misklasifikasi, terutama pada kelas-kelas yang jumlah sampelnya lebih sedikit atau kelas yang memiliki karakteristik mirip.
- **Kesimpulan Umum Modelling & Evaluasi:** Random Forest adalah model dengan performa awal terbaik sebelum *hyperparameter tuning*. Performa model bervariasi, menunjukkan bahwa *hyperparameter tuning* kemungkinan besar dapat meningkatkan kinerja, terutama

untuk model seperti KNN dan Logistic Regression yang memiliki akurasi awal lebih rendah. Waktu pelatihan juga menjadi pertimbangan penting, di mana Decision Tree dan KNN sangat cepat, sementara Random Forest sedikit lebih lama.

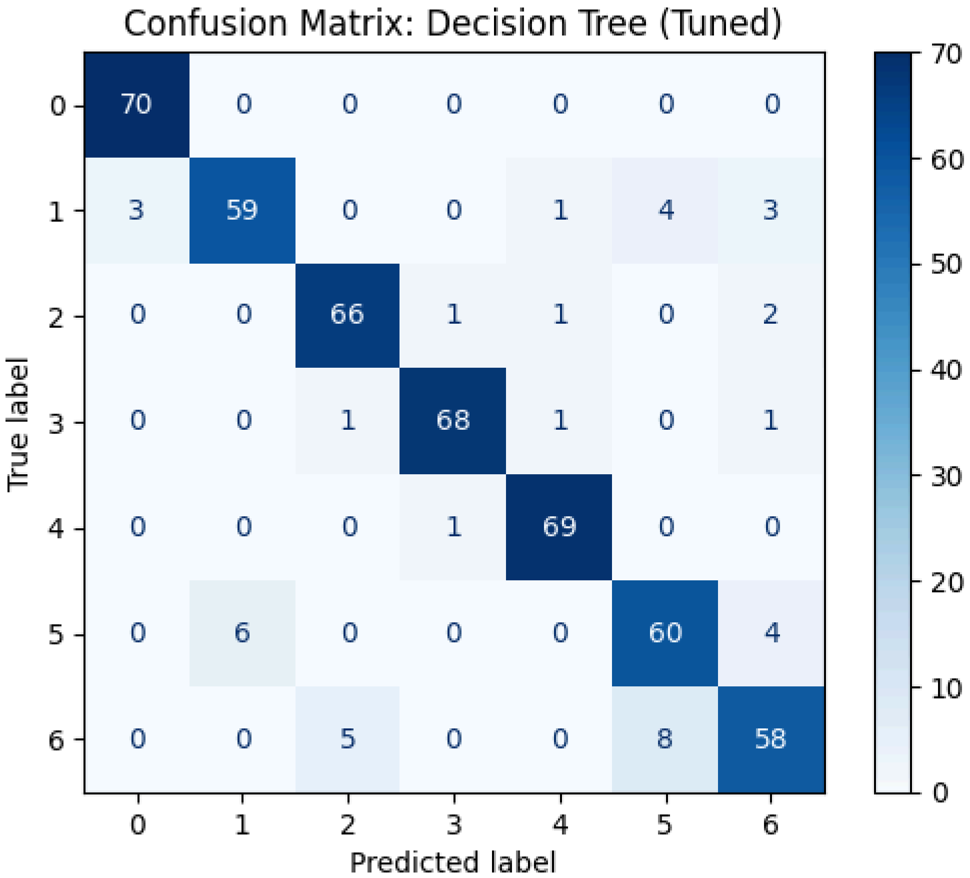
Hyperparameter tuning

```
from sklearn.model_selection import GridSearchCV


# Definisikan parameter grid untuk setiap model
param_grids = {
    "Decision Tree": {
        'max_depth': [None, 5, 10, 20],
        'min_samples_split': [2, 5, 10]
    },
    "KNN": {
        'n_neighbors': [3, 5, 7, 9],
        'weights': ['uniform', 'distance']
    },
    "Random Forest": {
        'n_estimators': [50, 100, 200],
        'max_depth': [None, 10, 20],
        'min_samples_split': [2, 5]
    },
    "SVM": {
        'C': [0.1, 1, 10],
        'kernel': ['linear', 'rbf']
    },
    "Logistic Regression": {
        'C': [0.01, 0.1, 1, 10],
        'penalty': ['l2'],
        'solver': ['lbfgs']
    }
}

# Model dasar
```

```
base_models = {
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "Random Forest": RandomForestClassifier(),
    "SVM": SVC(),
    "Logistic Regression": LogisticRegression(max_iter=1000)
}


# Menyimpan hasil tuning
tuned_results = {}
best_estimators = {}

print("Hyperparameter Tuning")

for name, model in base_models.items():
    print(f"\nTuning model: {name}")

    grid = GridSearchCV(model, param_grids[name], cv=5, scoring='accuracy', n_jobs=-1)

    start = time.time()
    grid.fit(X_train, y_train)
    end = time.time()

    best_model = grid.best_estimator_
    best_estimators[name] = best_model

    y_pred = best_model.predict(X_test)

    tuned_results[name] = {
        "accuracy": accuracy_score(y_test, y_pred),
        "precision": precision_score(y_test, y_pred, average='weighted'),
        "recall": recall_score(y_test, y_pred, average='weighted'),
        "f1_score": f1_score(y_test, y_pred, average='weighted'),
        "training_time": round(end - start, 4),
        "y_pred": y_pred,
        "report": classification_report(y_test, y_pred),
        "best_params": grid.best_params_
```

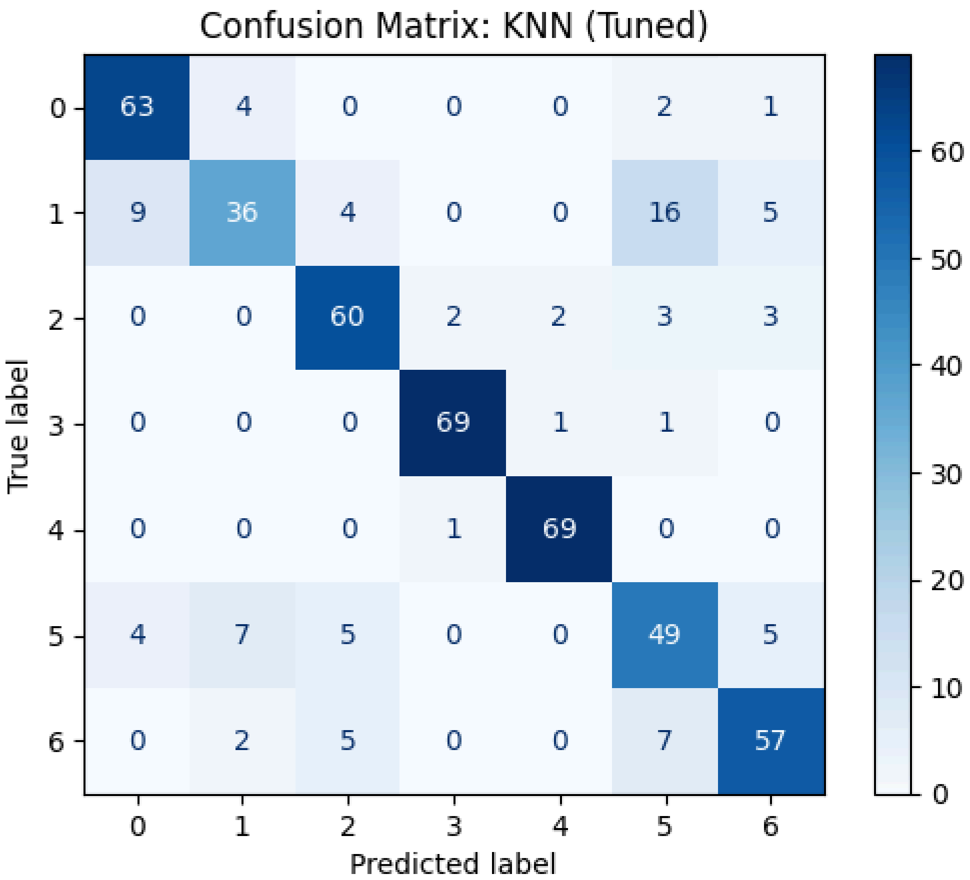
```
    }

    # Visualisasi confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot(cmap='Blues')
    plt.title(f"Confusion Matrix: {name} (Tuned)")
    plt.grid(False)
    plt.show()

    print(f"Best Params: {grid.best_params_}")
    print(f"Training Time: {end - start:.4f}s")
    print("Classification Report:")
    print(tuned_results[name]['report'])
```

```
Hyperparameter Tuning

Tuning model: Decision Tree
```



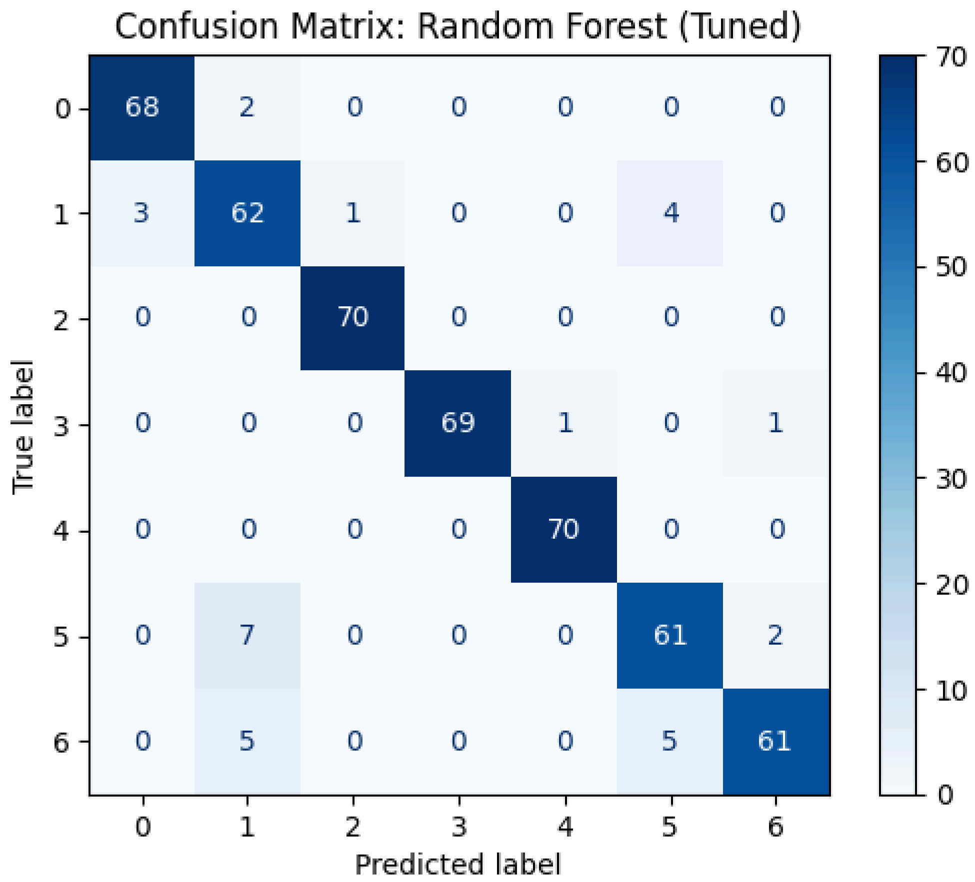

```
Best Params: {'max_depth': 20, 'min_samples_split': 2}
Training Time: 6.3800s
Classification Report:
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        70
           1       0.91      0.84      0.87        70
           2       0.92      0.94      0.93        70
           3       0.97      0.96      0.96        71
           4       0.96      0.99      0.97        70
           5       0.83      0.86      0.85        70
           6       0.85      0.82      0.83        71
```

```
    accuracy                           0.91       492
   macro avg       0.91      0.91      0.91       492
weighted avg       0.91      0.91      0.91       492


Tuning model: KNN
```



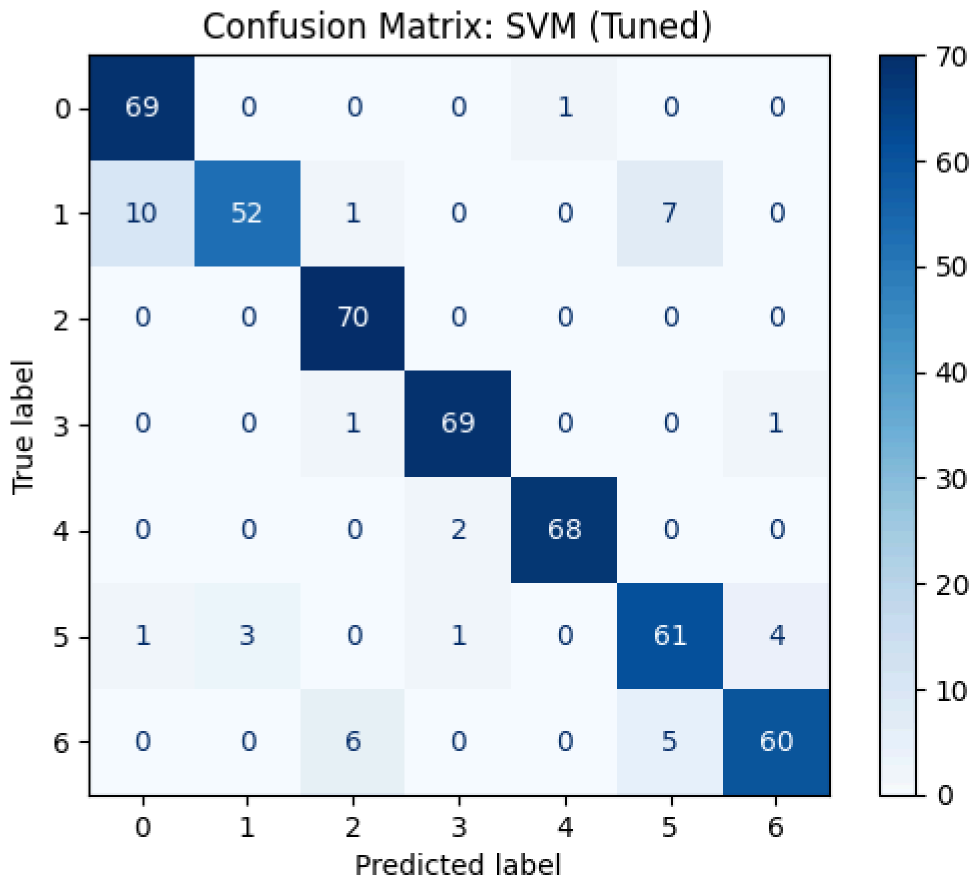

```
Best Params: {'n_neighbors': 5, 'weights': 'distance'}
Training Time: 2.8953s
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.90      0.86        70
           1       0.73      0.51      0.61        70
           2       0.81      0.86      0.83        70
```

```
           3       0.96      0.97      0.97        71
           4       0.96      0.99      0.97        70
           5       0.63      0.70      0.66        70
           6       0.80      0.80      0.80        71

    accuracy                           0.82       492
   macro avg       0.82      0.82      0.81       492
weighted avg       0.82      0.82      0.82       492


Tuning model: Random Forest
```




```
Best Params: {'max_depth': None, 'min_samples_split': 2, 'n_estimators': 200}
Training Time: 39.9761s
Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.96      0.97      0.96        70
           1       0.82      0.89      0.85        70
           2       0.99      1.00      0.99        70
           3       1.00      0.97      0.99        71
           4       0.99      1.00      0.99        70
           5       0.87      0.87      0.87        70
           6       0.95      0.86      0.90        71

    accuracy                           0.94       492
   macro avg       0.94      0.94      0.94       492
weighted avg       0.94      0.94      0.94       492


Tuning model: SVM
```




```
Best Params: {'C': 10, 'kernel': 'linear'}
```