Tugas Capstone Bengkel Koding

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Link file all : https://drive.google.com/drive/folders/1b5TbkWHwxtVNNOFI72Z9qYzi8ObxFzeK?usp=sharing

Link github : https://github.com/syallomchristian/Capstone_Project_BengKod_DataScience

Informasi Fitur Dataset

- Gender : Fitur, Kategorikal — "Jenis kelamin"
- Age : Fitur, Kontinu — "Usia"
- Height : Fitur, Kontinu — "Tinggi badan"
- Weight : Fitur, Kontinu — "Berat badan"
- family_history_with_overweight : Fitur, Biner — "Apakah ada anggota keluarga yang pernah atau sedang mengalami kelebihan berat badan?"
- FAVC : Fitur, Biner — "Apakah Anda sering mengonsumsi makanan tinggi kalori?"
- FCVC : Fitur, Integer — "Apakah Anda biasanya makan sayuran dalam setiap kali makan?"
- NCP : Fitur, Kontinu — "Berapa kali Anda makan besar dalam sehari?"
- CAEC : Fitur, Kategorikal — "Apakah Anda makan camilan di antara waktu makan?"
- SMOKE : Fitur, Biner — "Apakah Anda merokok?"
- CH2O : Fitur, Kontinu — "Berapa banyak air yang Anda minum setiap hari?"
- SCC : Fitur, Biner — "Apakah Anda memantau asupan kalori harian Anda?"
- FAF : Fitur, Kontinu — "Seberapa sering Anda melakukan aktivitas fisik?"
- TUE : Fitur, Integer — "Berapa lama Anda menggunakan perangkat teknologi seperti ponsel, video game, televisi, komputer, dan lainnya?"
- CALC : Fitur, Kategorikal — "Seberapa sering Anda mengonsumsi alkohol?"
- MTRANS : Fitur, Kategorikal — "Jenis transportasi apa yang biasa Anda gunakan?"
- NObeyesdad : Target, Kategorikal — "Tingkat obesitas"

1. Import Lib

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import LabelEncoder, StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.feature_selection import mutual_info_classif
```

2. Import Dataset

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

import sys
sys.path.append('/content/drive/My Drive/Project_CAPSTONE_BengKod')

df = pd.read_csv('/content/drive/My Drive/Project_CAPSTONE_BengKod/ObesityDataSet.csv')
```

```
Mounted at /content/drive
```

```
df.info()
df.head()

# Cek distribusi kelas
print(df['NObeyesdad'].value_counts())
print("\nProporsi kelas:")
print(df['NObeyesdad'].value_counts(normalize=True))
```

```
<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
NObeyesdad
Obesity_Type_I         351
Obesity_Type_III       324
Obesity_Type_II        297
Overweight_Level_I     290
Overweight_Level_II    290
Normal_Weight          287
Insufficient_Weight    272
Name: count, dtype: int64

Proporsi kelas:
NObeyesdad
Obesity_Type_I         0.166272
Obesity_Type_III       0.153482
Obesity_Type_II        0.140692
Overweight_Level_I     0.137376
Overweight_Level_II    0.137376
Normal_Weight          0.135955
Insufficient_Weight    0.128849
Name: proportion, dtype: float64
```

3. EDA

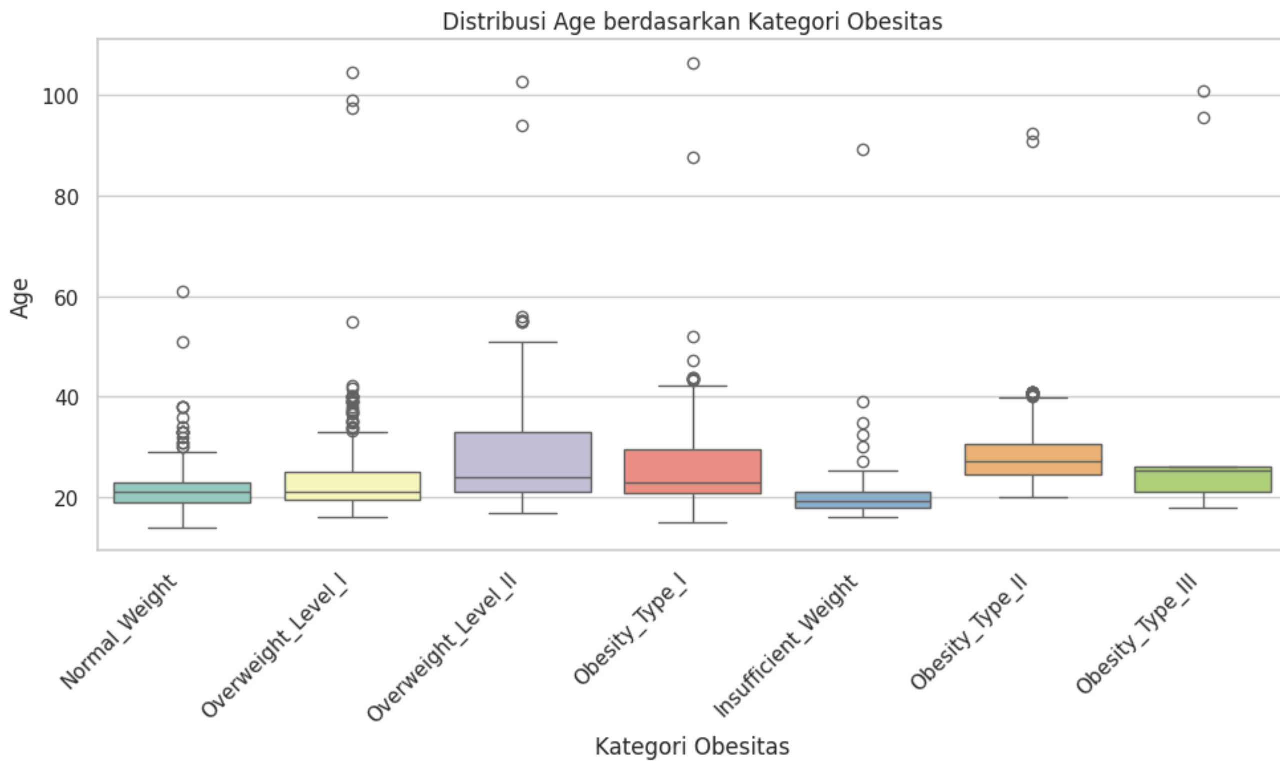
```
# Ringkasan informasi dataset
info = df.info()

# Cek nilai yang hilang
missing_values = df.isnull().sum()

# Statistik deskriptif untuk kolom numerik
desc_stats = df.describe()

info, missing_values, desc_stats
```

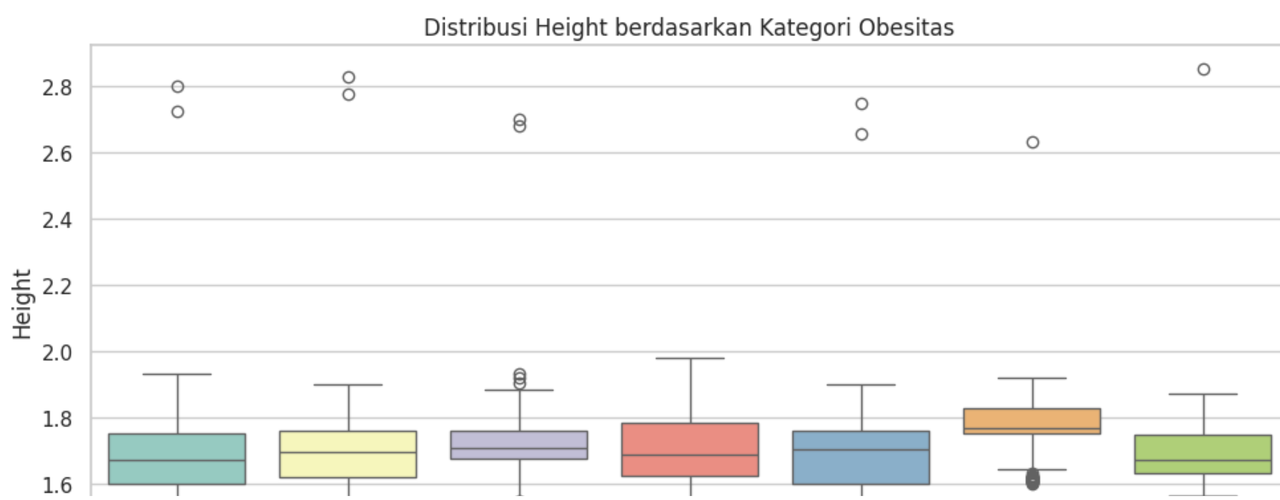
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2111 entries, 0 to 2110
Data columns (total 17 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Age                             2097 non-null   object
 1   Gender                          2102 non-null   object
 2   Height                          2099 non-null   object
 3   Weight                          2100 non-null   object
```

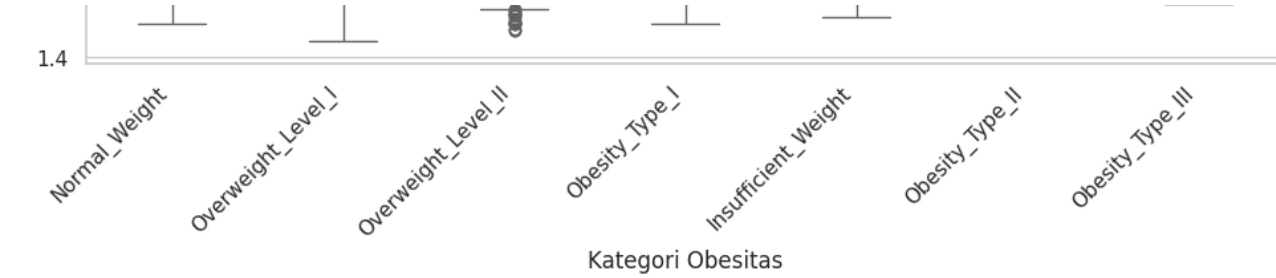
```
 4   CALC                            2106 non-null   object
 5   FAVC                            2100 non-null   object
 6   FCVC                            2103 non-null   object
 7   NCP                             2099 non-null   object
 8   SCC                             2101 non-null   object
 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
(None,
 Age                               14
 Gender                             9
 Height                            12
 Weight                            11
 CALC                               5
 FAVC                              11
 FCVC                               8
 NCP                               12
 SCC                               10
 SMOKE                              5
 CH2O                               6
 family_history_with_overweight    13
 FAF                                8
 TUE                                9
 CAEC                              11
 MTRANS                             6
 NObeyesdad                         0
 dtype: int64,
          Age Gender Height Weight       CALC  FAVC  FCVC   NCP   SCC SMOKE  \
 count   2097   2102   2099   2100       2106  2100  2103  2099  2101  2106
 unique  1394      3   1562   1518          5     3   808   637     3     3
 top       18   Male    1.7     80  Sometimes   yes     3     3    no    no
 freq     124   1056     58     58       1386  1844   647  1183  1997  2054

         CH2O family_history_with_overweight   FAF   TUE       CAEC  \
 count   2105                           2098  2103  2102       2100
 unique  1263                              3  1186  1130          5
 top        2                            yes     0     0  Sometimes
 freq     441                           1705   404   552       1747

                        MTRANS      NObeyesdad
 count                    2105            2111
 unique                      6               7
```

```
numerical_columns = ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF', 'TUE']

# Ubah nilai tidak valid menjadi NaN pada kolom numerik
for col in numerical_columns:
    df[col] = pd.to_numeric(df[col], errors='coerce')
```

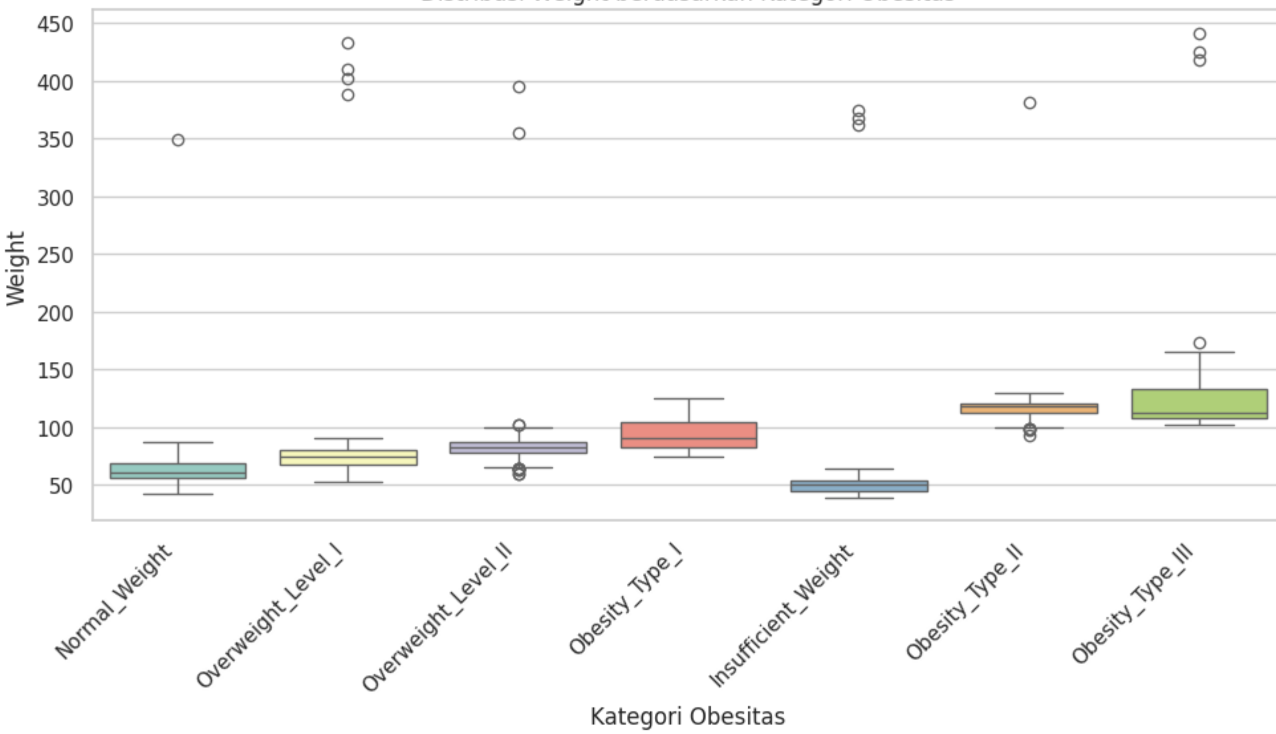
```
    df[col] = pd.to_numeric(df[col], errors='coerce')

# Hapus NaN
df_cleaned = df.dropna(subset=numerical_columns + ['NObeyesdad']) # Hapus baris dengan Na

# Buat boxplot
sns.set_theme(style="whitegrid")
for col in numerical_columns:
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='NObeyesdad', y=col, hue='NObeyesdad', data=df_cleaned, palette='Set3',
    plt.title(f'Distribusi {col} berdasarkan Kategori Obesitas')
    plt.xlabel('Kategori Obesitas')
    plt.ylabel(col)
    plt.xticks(rotation=45, ha='right')      # Putar dan rapikan label
    plt.subplots_adjust(bottom=0.25)         # Tambah jarak bawah agar tidak bertabrakan
    plt.tight_layout()
    plt.show()
```



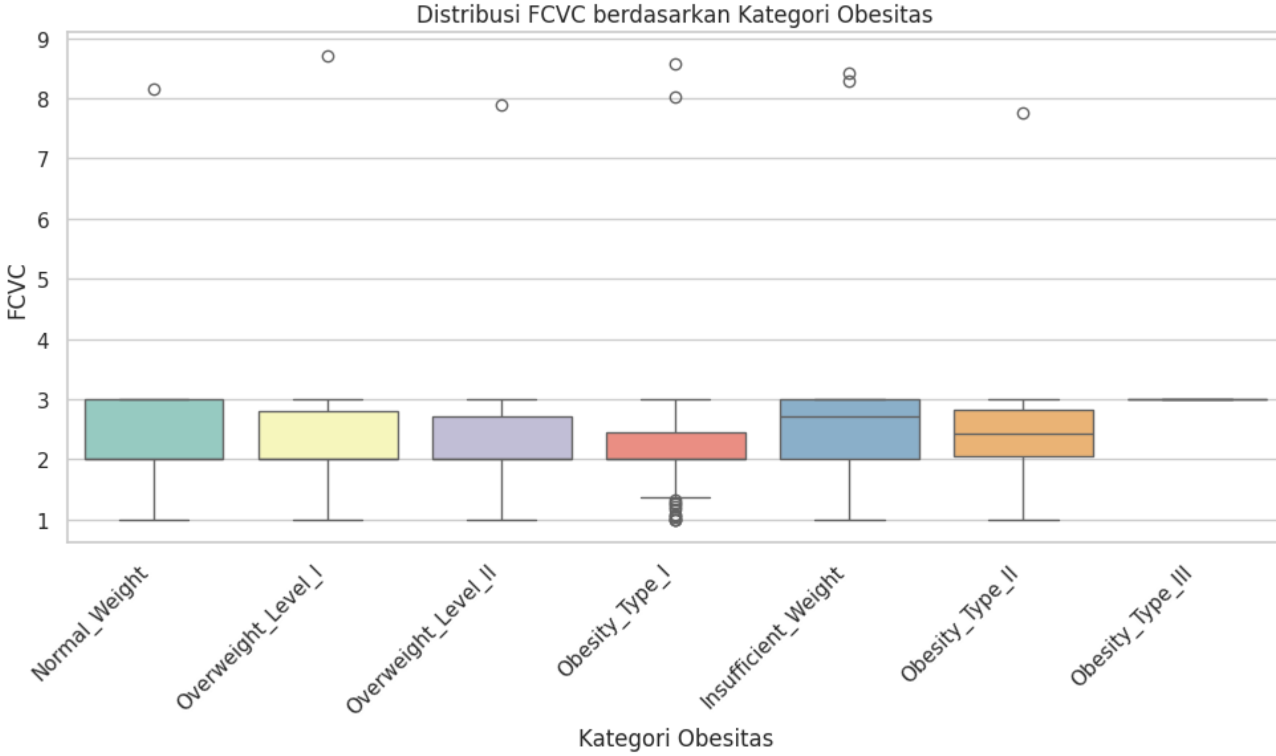




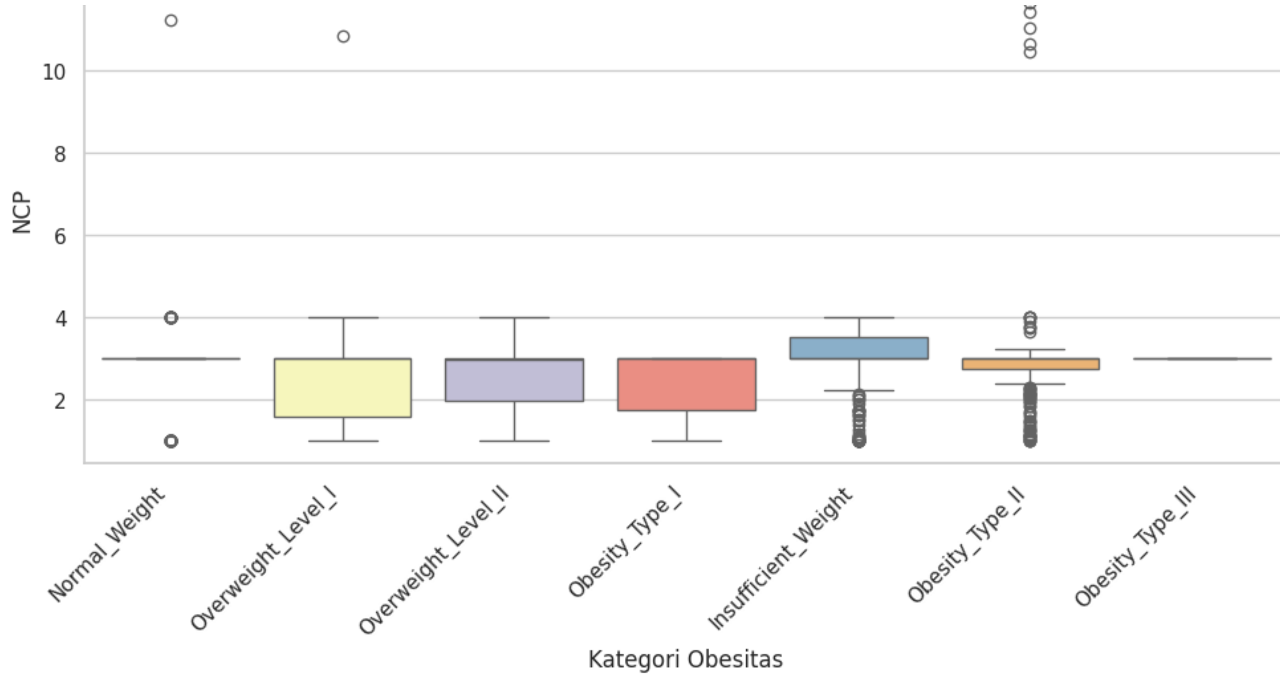
Distribusi Weight berdasarkan Kategori Obesitas

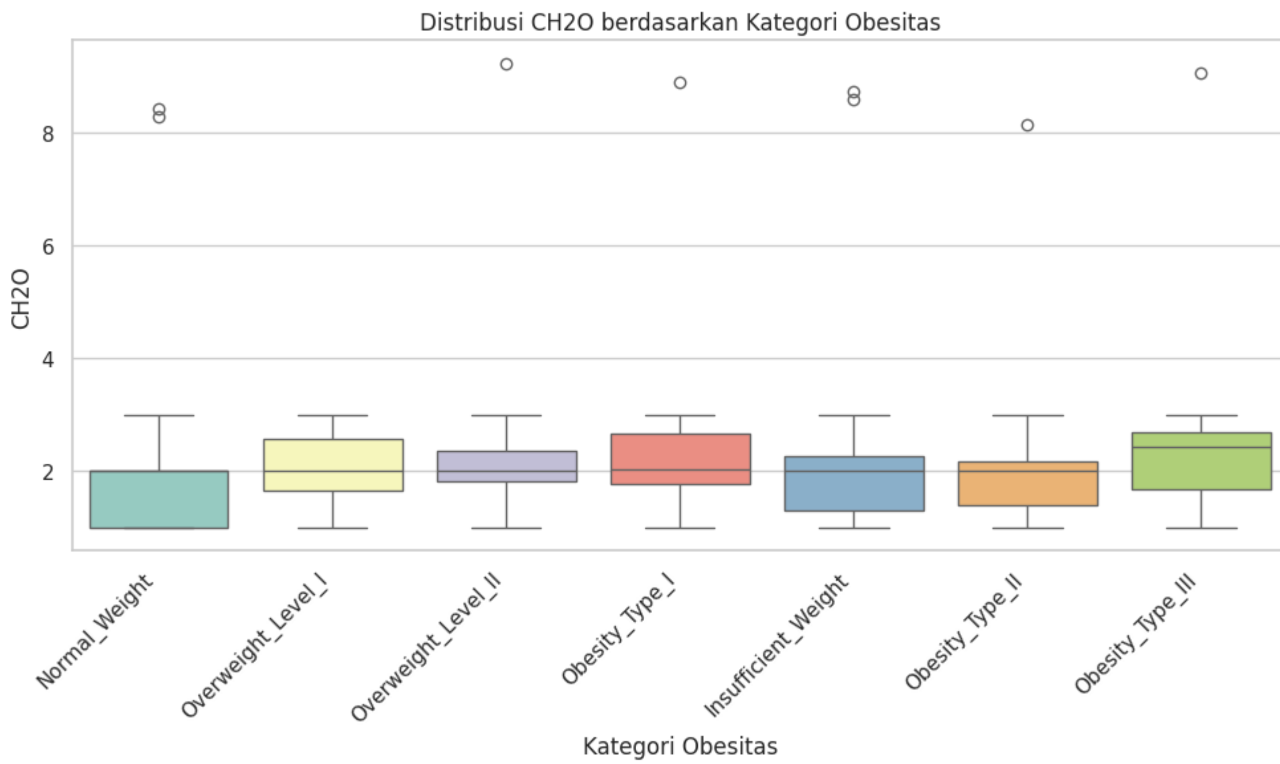


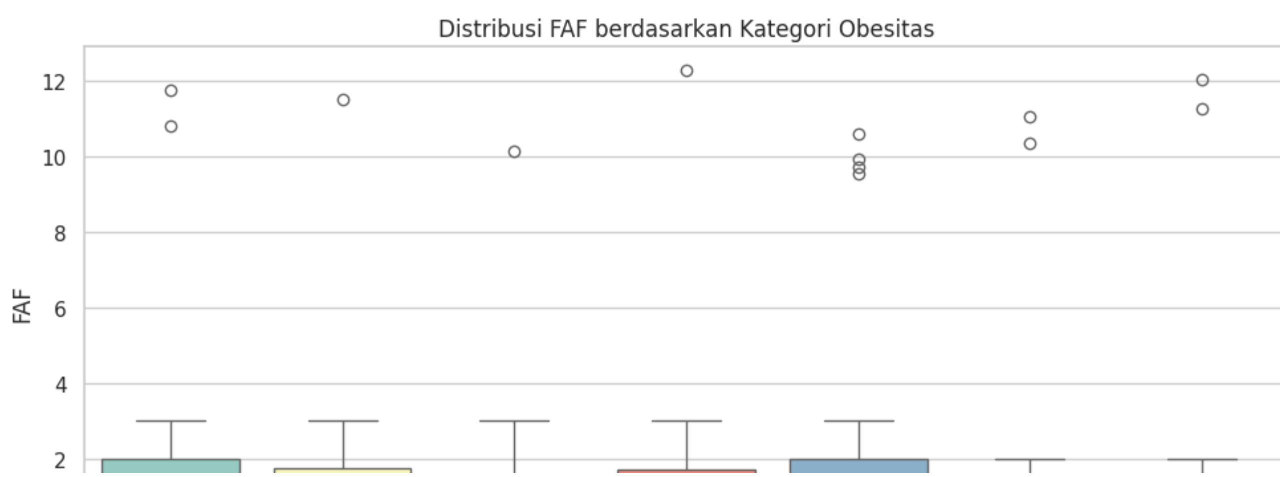
Distribusi FCVC berdasarkan Kategori Obesitas



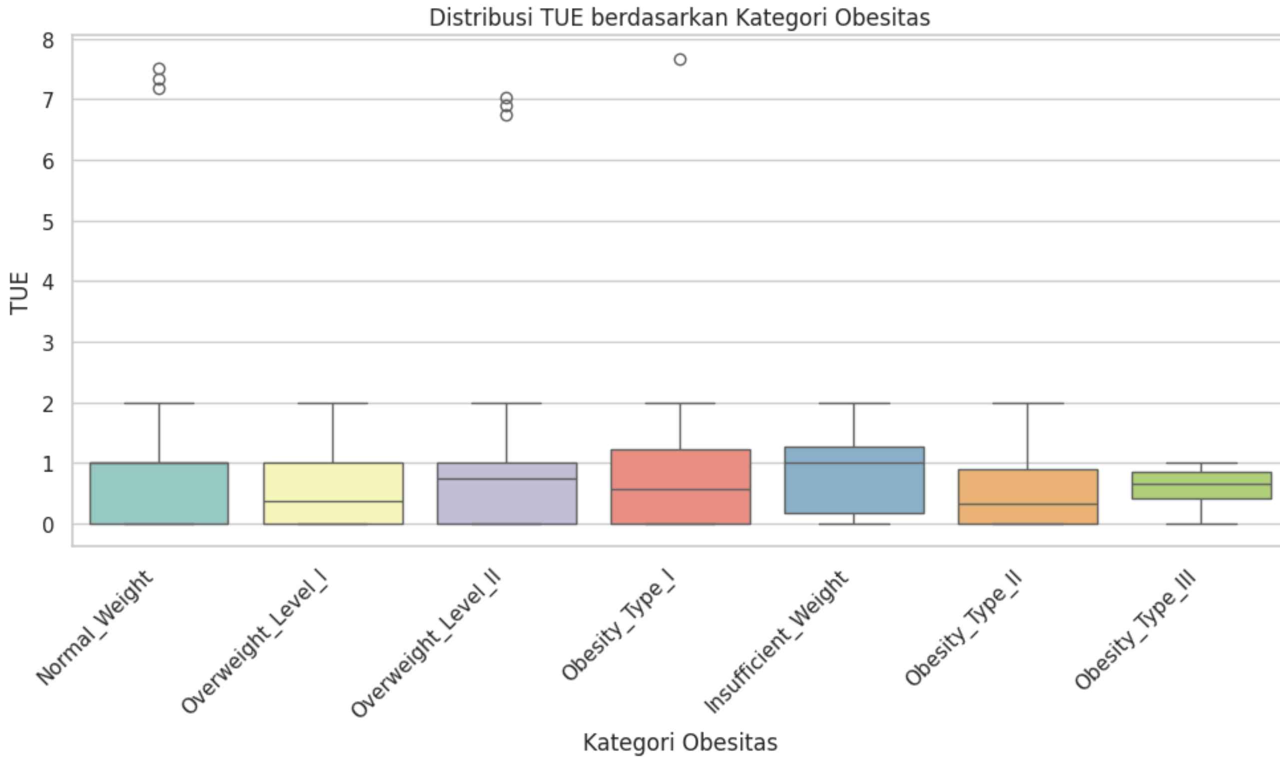
Distribusi NCP berdasarkan Kategori Obesitas


NCP
10
8
6
4
2
Normal_Weight
Overweight_Level_I
Overweight_Level_II
Obesity_Type_I
Insufficient_Weight
Obesity_Type_II
Obesity_Type_III
Kategori Obesitas


Distribusi CH2O berdasarkan Kategori Obesitas
CH2O
8
6
4
2
Normal_Weight
Overweight_Level_I
Overweight_Level_II
Obesity_Type_I
Insufficient_Weight
Obesity_Type_II
Obesity_Type_III
Kategori Obesitas


Distribusi FAF berdasarkan Kategori Obesitas
FAF
12
10
8
6
4
2


0
Normal_Weight
Overweight_Level_I
Overweight_Level_II
Obesity_Type_I
Insufficient_Weight
Obesity_Type_II
Obesity_Type_III
Kategori Obesitas


Distribusi TUE berdasarkan Kategori Obesitas
TUE
0
1
2
3
4
5
6
7
8
Normal_Weight
Overweight_Level_I
Overweight_Level_II
Obesity_Type_I
Insufficient_Weight
Obesity_Type_II
Obesity_Type_III
Kategori Obesitas

```
# Cek missing values per kolom
missing_values = df.isnull().sum()
#print("Jumlah Missing Values per Kolom:\n", missing_values)
print(missing_values)
```

```
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 unique values per kolom
unique_values = df.nunique()
print("\nJumlah Unique Values per Kolom:\n", unique_values)
```

```
Jumlah Unique Values per Kolom:
 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
```

```
print("\nUnique values pada semua kolom:")
for col in df.columns:
    print(f"- {col}: {df[col].unique()}")
```

```
Unique values pada semua kolom:
- Age: [21.       23.       27.       ... 22.524036 24.361936 23.664709]
- Gender: ['Female' 'Male' '?' nan]
- Height: [1.62     1.52     1.8      ... 1.752206 1.73945  1.738836]
- Weight: [ 64.        56.        77.        ... 133.689352 133.346641 133.472641]
- CALC: ['no' 'Sometimes' 'Frequently' '?' 'Always' nan]
- FAVC: ['no' 'yes' '?' nan]
- FCVC: [2.         3.         1.                nan 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
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
8.7067947  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
```

```
# Cek data duplikat
# Jumlah total baris duplikat (seluruh baris sama persis)
total_duplikat = df.duplicated().sum()
print("Total baris duplikat:", total_duplikat)
print("--------------------------------")

# Tampilkan baris yang terduplikat
duplikat = df[df.duplicated()]
print("Baris duplikat:")
print(duplikat)

# Ambil satu contoh baris duplikat
if not duplikat.empty:
    ref = duplikat.iloc[0]
    matching_cols = df.columns[(df == ref).all(axis=0)]
    print("Kolom yang identik di baris duplikat contoh:", list(matching_cols))
```

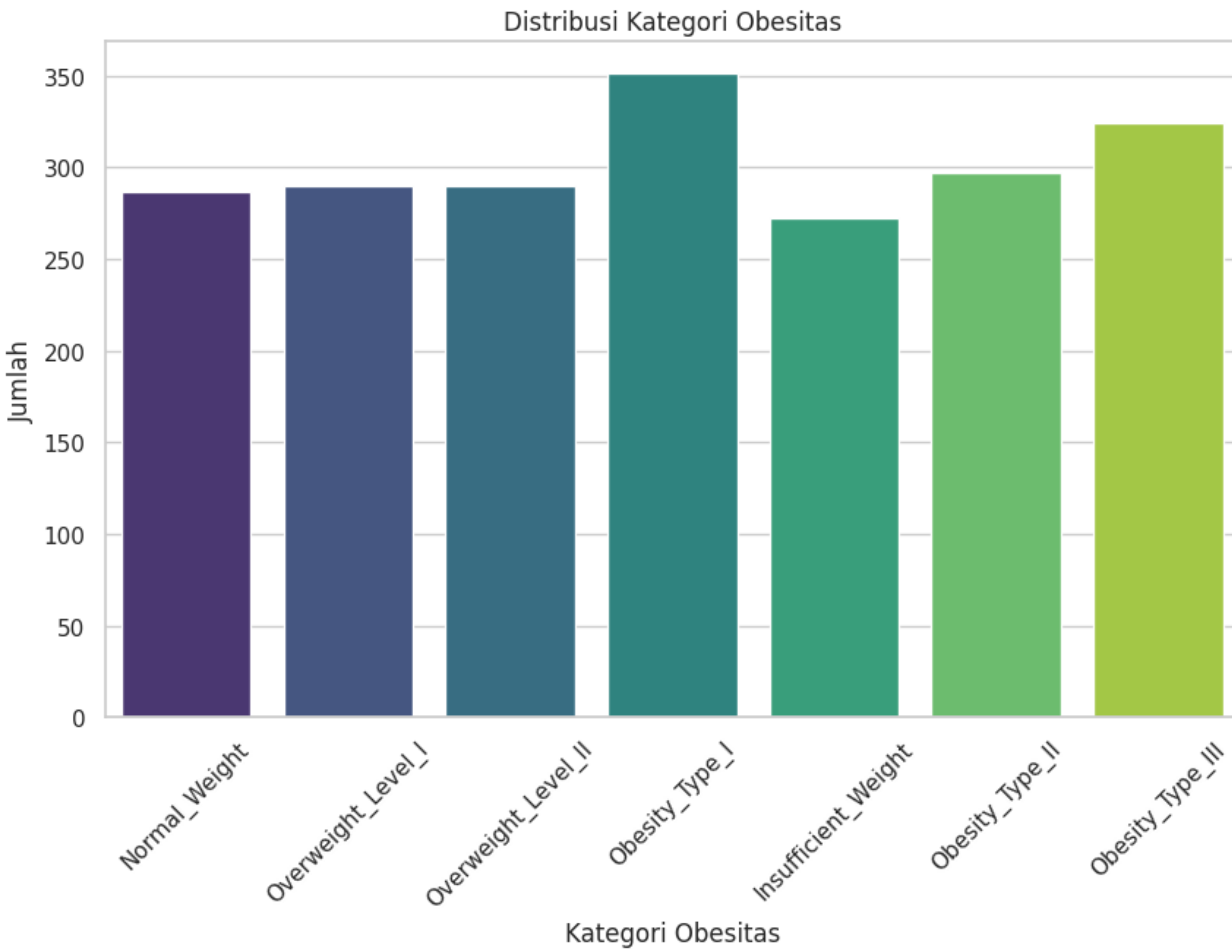
```
Total baris duplikat: 18
--------------------------------
Baris duplikat:
      Age  Gender  Height  Weight       CALC FAVC  FCVC  NCP SCC SMOKE  CH2O  \
98   21.0  Female    1.52    42.0  Sometimes   no   3.0  1.0  no    no   1.0
174  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
179  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
184  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
309  16.0  Female    1.66    58.0         no   no   2.0  1.0  no    no   1.0
460  18.0  Female    1.62    55.0         no  yes   2.0  3.0  no    no   1.0
663  21.0  Female    1.52    42.0  Sometimes  yes   3.0  1.0  no    no   1.0
763  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
764  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
824  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
830  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
831  21.0    Male    1.62    70.0  Sometimes  yes   2.0  1.0  no    no   3.0
```

```
832  21.0    Male    1.62    70.0  Sometimes  yes    2.0  1.0  no    no   3.0
833  21.0    Male    1.62    70.0  Sometimes  yes    2.0  1.0  no    no   3.0
834  21.0    Male    1.62    70.0  Sometimes  yes    2.0  1.0  no    no   3.0
921  21.0    Male    1.62    70.0  Sometimes  yes    2.0  1.0  no    no   3.0
922  21.0    Male    1.62    70.0  Sometimes  yes    2.0  1.0  no    no   3.0
923  21.0    Male    1.62    70.0  Sometimes  yes    2.0  1.0  no    no   3.0

    family_history_with_overweight  FAF  TUE        CAEC  \
98                              no  0.0  0.0  Frequently
174                             no  1.0  0.0          no
179                             no  1.0  0.0          no
184                             no  1.0  0.0          no
309                             no  0.0  1.0   Sometimes
460                            yes  1.0  1.0  Frequently
663                             no  0.0  0.0  Frequently
763                             no  1.0  0.0          no
764                             no  1.0  0.0          no
824                             no  1.0  0.0          no
830                             no  1.0  0.0          no
831                             no  1.0  0.0          no
832                             no  1.0  0.0          no
833                             no  1.0  0.0          no
834                             no  1.0  0.0          no
921                             no  1.0  0.0          no
922                             no  1.0  0.0          no
923                             no  1.0  0.0          no

                    MTRANS           NObeyesdad
98   Public_Transportation  Insufficient_Weight
174  Public_Transportation   Overweight_Level_I
179  Public_Transportation   Overweight_Level_I
184  Public_Transportation   Overweight_Level_I
309                Walking        Normal_Weight
460  Public_Transportation        Normal_Weight
663  Public_Transportation  Insufficient_Weight
763  Public_Transportation   Overweight_Level_I
764  Public_Transportation   Overweight_Level_I
824  Public_Transportation   Overweight_Level_I
830  Public_Transportation   Overweight_Level_I
831  Public_Transportation   Overweight_Level_I
832  Public_Transportation   Overweight_Level_I
833  Public_Transportation   Overweight_Level_I
```

```
# Cek keseimbangan data pada kolom target 'NObeyesdad'
class_distribution = df['NObeyesdad'].value_counts()
print("\nDistribusi Keseimbangan Data (NObeyesdad):\n", class_distribution)


plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='NObeyesdad', hue='NObeyesdad', palette='viridis', legend=False)
plt.title('Distribusi Kategori Obesitas')
plt.xlabel('Kategori Obesitas')
plt.ylabel('Jumlah')
plt.xticks(rotation=45)
```

```
plt.show()
```

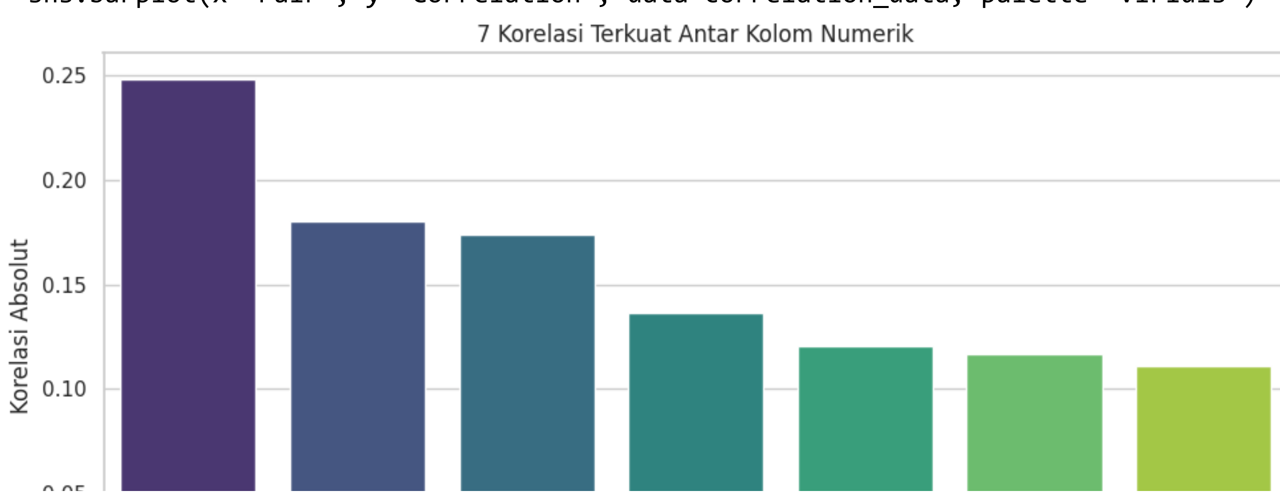
```
Distribusi Keseimbangan Data (NObeyesdad):
 NObeyesdad
Obesity_Type_I         351
Obesity_Type_III       324
Obesity_Type_II        297
Overweight_Level_I     290
Overweight_Level_II    290
Normal_Weight          287
Insufficient_Weight    272
Name: count, dtype: int64
```

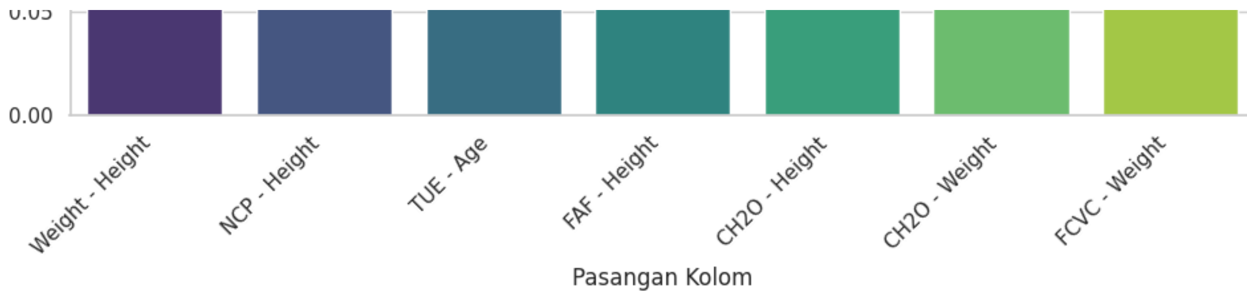



```
# Konversi kolom numerik ke tipe data numerik
for col in numerical_columns:
```

```
for col in numerical_columns:
    df[col] = pd.to_numeric(df[col], errors='coerce')

# Hapus baris dengan missing values di kolom numerik
df_cleaned = df.dropna(subset=numerical_columns)

# Hitung matriks korelasi
correlation_matrix = df_cleaned[numerical_columns].corr()

# Ambil nilai korelasi absolut dan urutkan
abs_corr_matrix = np.abs(correlation_matrix)
upper_triangle = abs_corr_matrix.where(np.triu(np.ones(abs_corr_matrix.shape), k=1).astyp
strong_correlations = upper_triangle.unstack().sort_values(ascending=False)
strong_correlations = strong_correlations.dropna()  # Hapus NaN

# Pilih 7 korelasi teratas
top_7_correlations = strong_correlations.head(7)

# Siapkan data untuk diagram batang
correlation_data = pd.DataFrame({
    'Pair': [f"{pair[0]} - {pair[1]}" for pair in top_7_correlations.index],
    'Correlation': top_7_correlations.values
})

# Visualisasikan dalam diagram batang
plt.figure(figsize=(10, 6))
sns.barplot(x='Pair', y='Correlation', data=correlation_data, palette='viridis')
plt.title('7 Korelasi Terkuat Antar Kolom Numerik')
plt.xlabel('Pasangan Kolom')
plt.ylabel('Korelasi Absolut')
plt.xticks(rotation=45, ha='right')  # Rotasi label sumbu x agar terbaca
plt.tight_layout()  # Untuk mencegah label tumpang tindih
plt.show()
```

```
<ipython-input-239-139b094f1198>:28: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

  sns.barplot(x='Pair', y='Correlation', data=correlation_data, palette='viridis')
```





Top 7 Korelasi Tertinggi (dalam nilai absolut)

Pasangan Fitur	Korelasi	Analisis
Weight – Height	0.248	Positif lemah: Orang dengan tinggi badan lebih besar cenderung memiliki berat lebih tinggi, meskip
NCP – Height	0.180	Korelasi lemah: Orang dengan tinggi tertentu cenderung memiliki pola makan besar tertentu, tetapi
TUE – Age	0.174	Korelasi lemah: Usia memengaruhi durasi penggunaan teknologi; kemungkinan, kelompok usia mu
FAF – Height	0.136	Korelasi sangat lemah: Tinggi badan sedikit berkorelasi dengan aktivitas fisik, bisa jadi orang lebih
CH2O – Height	0.121	Korelasi sangat lemah: Tinggi badan sedikit berkaitan dengan konsumsi air harian, tetapi tidak sign
CH2O – Weight	0.117	Korelasi sangat lemah: Berat badan memiliki sedikit hubungan dengan konsumsi air, tetapi tidak cu
FCVC – Weight	0.111	Korelasi sangat lemah: Konsumsi sayuran berkaitan sedikit dengan berat badan; bisa berarti diet se

Kesimpulan Analisis Korelasi

- Tidak ada korelasi yang **kuat** antar fitur numerik (semuanya < 0.3).
- Korelasi tertinggi pun (`Weight – Height`) hanya 0.25, yang termasuk **lemah**.
- Ini menunjukkan bahwa **tidak ada dua fitur numerik** dalam dataset ini yang sangat linear satu sama lain.
- Hal ini baik untuk pemodelan, karena tidak ada multikolinearitas tinggi yang bisa merusak performa model prediktif berbasis regresi atau pohon keputusan.

Preprocessing Data

```
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                             2089 non-null   float64
 1   Gender                          2102 non-null   object 
 2   Height                          2089 non-null   float64
 3   Weight                          2092 non-null   float64
 4   CALC                            2106 non-null   object 
 5   FAVC                            2100 non-null   object 
 6   FCVC                            2093 non-null   float64
 7   NCP                             2089 non-null   float64
 8   SCC                             2101 non-null   object 
 9   SMOKE                           2106 non-null   object 
 10  CH2O                            2096 non-null   float64
 11  family_history_with_overweight  2098 non-null   object 
 12  FAF                             2092 non-null   float64
 13  TUE                             2096 non-null   float64
 14  CAEC                            2100 non-null   object 
 15  MTRANS                          2105 non-null   object 
 16  NObeyesdad                      2111 non-null   object 
dtypes: float64(8), object(9)
memory usage: 280.5+ KB
```

```
#cek fitur kategorikal
fitur_kategorikal = ['Gender', 'family_history_with_overweight', 'FAVC', 'CAEC', 'SMOKE',

for fitur in fitur_kategorikal:
    print(f"\nUnique values pada kolom '{fitur}':")
    print(df[fitur].unique())
```

```
Unique values pada kolom 'Gender':
['Female' 'Male' '?' nan]

Unique values pada kolom 'family_history_with_overweight':
['yes' 'no' nan '?']

Unique values pada kolom 'FAVC':
['no' 'yes' '?' nan]

Unique values pada kolom 'CAEC':
['Sometimes' 'Frequently' 'Always' 'no' nan '?']

Unique values pada kolom 'SMOKE':
['no' 'yes' '?' nan]

Unique values pada kolom 'SCC':
['no' 'yes' nan '?']

Unique values pada kolom 'CALC':
['no' 'Sometimes' 'Frequently' '?' 'Always' nan]
```

```
Unique values pada kolom 'MTRANS':
['Public_Transportation' 'Walking' 'Automobile' 'Motorbike' 'Bike' '?' nan]

Unique values pada kolom 'NObeyesdad':
['Normal_Weight' 'Overweight_Level_I' 'Overweight_Level_II'
 'Obesity_Type_I' 'Insufficient_Weight' 'Obesity_Type_II'
 'Obesity_Type_III']
```

test

```
for col in df.columns:
    print(f"\nUnique values pada kolom '{col}':")
    print(df[col].unique())
```

```
Unique values pada kolom 'Age':
[21.       23.       27.       ... 22.524036 24.361936 23.664709]

Unique values pada kolom 'Gender':
['Female' 'Male' '?' nan]

Unique values pada kolom 'Height':
[1.62     1.52     1.8      ... 1.752206 1.73945  1.738836]

Unique values pada kolom 'Weight':
[ 64.        56.        77.        ... 133.689352 133.346641 133.472641]

Unique values pada kolom 'CALC':
['no' 'Sometimes' 'Frequently' '?' 'Always' nan]

Unique values pada kolom 'FAVC':
['no' 'yes' '?' nan]

Unique values pada kolom 'FCVC':
[2.         3.         1.                nan 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

```python
gender_map = {
    'Female': 0,
    'Male': 1
}

family_history_map = {
    'no': 0,
    'yes': 1
}

favc_map = {
    'no': 0,
    'yes': 1
}

caec_map = {
    'no': 0,
    'Sometimes': 1,
    'Frequently': 2,
    'Always': 3
}

smoke_map = {
    'no': 0,
    'yes': 1
}

scc_map = {
    'no': 0,
    'yes': 1
```

```
    }

    calc_map = {
        'no': 0,
        'Sometimes': 1,
        'Frequently': 2,
        'Always': 3
    }

    mtrans_map = {
        'Public_Transportation': 0,
        'Walking': 1,
        'Automobile': 2,
        'Motorbike': 3,
        'Bike': 4
    }

    nobeyesdad_map = {
        'Insufficient_Weight': 0,
        'Normal_Weight': 1,
        'Overweight_Level_I': 2,
        'Overweight_Level_II': 3,
        'Obesity_Type_I': 4,
        'Obesity_Type_II': 5,
        'Obesity_Type_III': 6
    }


    df['Gender'] = df['Gender'].map(gender_map)
    df['family_history_with_overweight'] = df['family_history_with_overweight'].map(family_hi
    df['FAVC'] = df['FAVC'].map(favc_map)
    df['CAEC'] = df['CAEC'].map(caec_map)
    df['SMOKE'] = df['SMOKE'].map(smoke_map)
    df['SCC'] = df['SCC'].map(scc_map)
    df['CALC'] = df['CALC'].map(calc_map)
    df['MTRANS'] = df['MTRANS'].map(mtrans_map)
    df['NObeyesdad'] = df['NObeyesdad'].map(nobeyesdad_map)

    print("\nDataFrame setelah Label Encoding:")
    print(df.head())
    '''
    # Identifikasi kolom kategorikal dan target
    categorical_cols = ['Gender', 'family_history_with_overweight', 'FAVC', 'CAEC', 'SMOKE',
    target_col = 'NObeyesdad'

    # Inisialisasi LabelEncoder
    label_encoder = LabelEncoder()

    # Terapkan Label Encoding pada setiap kolom kategorikal
    for col in categorical_cols:
```

```
    df[col] = label_encoder.fit_transform(df[col])

# Terapkan Label Encoding pada kolom target
df[target_col] = label_encoder.fit_transform(df[target_col])


# Tampilkan info DataFrame setelah encoding untuk memastikan perubahan
df.info()

# Tampilkan beberapa baris pertama untuk melihat hasil encoding
print("\nDataFrame setelah Label Encoding:")
print(df.head())
'''
```

```
DataFrame setelah Label Encoding:
    Age  Gender  Height  Weight  CALC  FAVC  FCVC  NCP  SCC  SMOKE  CH2O  \
0  21.0     0.0    1.62    64.0   0.0   0.0   2.0  3.0  0.0    0.0   2.0
1  21.0     0.0    1.52    56.0   1.0   0.0   3.0  3.0  1.0    1.0   3.0
2  23.0     1.0    1.80    77.0   2.0   0.0   2.0  3.0  0.0    0.0   2.0
3  27.0     1.0    1.80    87.0   2.0   0.0   3.0  3.0  0.0    0.0   2.0
4  22.0     1.0    1.78    89.8   1.0   0.0   2.0  1.0  0.0    0.0   2.0

   family_history_with_overweight  FAF  TUE  CAEC  MTRANS  NObeyesdad
0                             1.0  0.0  1.0   1.0     0.0           1
1                             1.0  3.0  0.0   1.0     0.0           1
2                             1.0  2.0  1.0   1.0     0.0           1
3                             0.0  2.0  0.0   1.0     1.0           2
4                             0.0  0.0  0.0   1.0     0.0           3
'\n# Identifikasi kolom kategorikal dan target\ncategorical_cols = [\'Gender\', \'fa
mily_history_with_overweight\', \'FAVC\', \'CAEC\', \'SMOKE\', \'SCC\', \'CALC\',
\'MTRANS\']\ntarget_col = \'NObeyesdad\'\n\n# Inisialisasi LabelEncoder\nlabel_encod
er = LabelEncoder()\n\n# Terapkan Label Encoding pada setiap kolom kategorikal\nfor
col in categorical_cols:\n    df[col] = label_encoder.fit_transform(df[col])\n\n# Te
rapkan Label Encoding pada kolom target\ndf[target_col] = label_encoder.fit_transfor
```

```
# Cek kembali jumlah missing values
missing_values_after_encoding = df.isnull().sum()
print("Jumlah Missing Values setelah Encoding:\n", missing_values_after_encoding)
```

```
Jumlah Missing Values setelah Encoding:
 Age                               22
Gender                            22
Height                            22
Weight                            19
CALC                              20
FAVC                              22
FCVC                              18
NCP                               22
SCC                               18
SMOKE                             13
CH2O                              15
family_history_with_overweight    23
FAF                               19
```

```
TUE                              15
CAEC                             18
MTRANS                           12
NObeyesdad                        0
dtype: int64
```

```
# Jika ada missing values, beberapa strategi umum adalah:
# 1. Imputasi dengan mean/median (untuk numerik)
# 2. Imputasi dengan mode (untuk kategorikal)
# 3. Menghapus baris/kolom dengan missing values (jika jumlahnya sedikit)

# Loop ke seluruh kolom di dataframe
for kolom in df.columns:
    # Ganti '?' menjadi NaN (jika ada)
    df[kolom] = df[kolom].replace('?', np.nan)

    # Hitung modus (nilai terbanyak) — bisa string atau angka
    if df[kolom].isnull().sum() > 0:
        modus = df[kolom].mode()[0]
        df[kolom] = df[kolom].fillna(modus)
        print(f"Kolom '{kolom}' telah diisi dengan modus: {modus}")

print("\nSisa missing values setelah imputasi:")
print("----------------------------------------")
print(df.isnull().sum())
print("----------------------------------------")
df.info()
```

```
Kolom 'Age' telah diisi dengan modus: 18.0
Kolom 'Gender' telah diisi dengan modus: 1.0
Kolom 'Height' telah diisi dengan modus: 1.7
Kolom 'Weight' telah diisi dengan modus: 80.0
Kolom 'CALC' telah diisi dengan modus: 1.0
Kolom 'FAVC' telah diisi dengan modus: 1.0
Kolom 'FCVC' telah diisi dengan modus: 3.0
Kolom 'NCP' telah diisi dengan modus: 3.0
Kolom 'SCC' telah diisi dengan modus: 0.0
Kolom 'SMOKE' telah diisi dengan modus: 0.0
Kolom 'CH2O' telah diisi dengan modus: 2.0
Kolom 'family_history_with_overweight' telah diisi dengan modus: 1.0
Kolom 'FAF' telah diisi dengan modus: 0.0
Kolom 'TUE' telah diisi dengan modus: 0.0
Kolom 'CAEC' telah diisi dengan modus: 1.0
Kolom 'MTRANS' telah diisi dengan modus: 0.0

Sisa missing values setelah imputasi:
----------------------------------------
Age                              0
Gender                           0
Height                           0
Weight                           0
CALC                             0
```

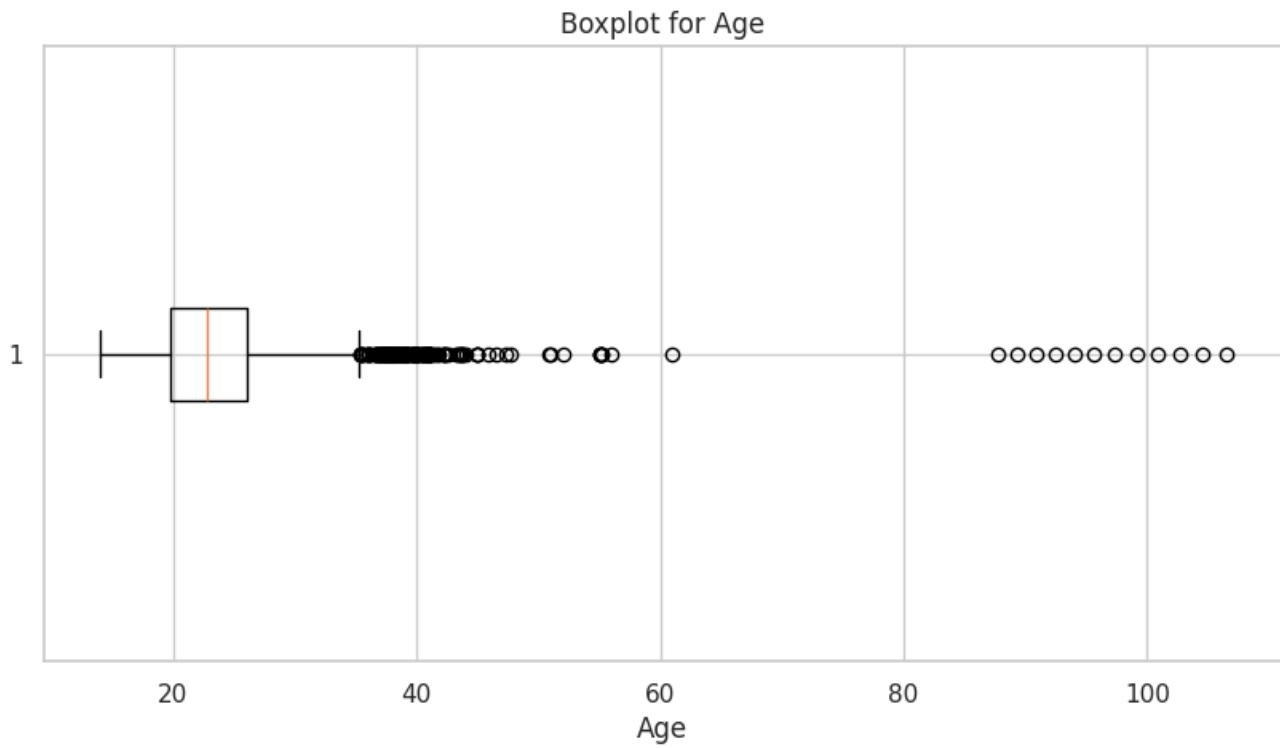
```
FAVC                              0
FCVC                              0
NCP                               0
SCC                               0
SMOKE                             0
CH2O                              0
family_history_with_overweight    0
FAF                               0
TUE                               0
CAEC                              0
MTRANS                            0
NObeyesdad                        0
dtype: int64
-----------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2111 entries, 0 to 2110
Data columns (total 17 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   Age                             2111 non-null   float64
 1   Gender                          2111 non-null   float64
 2   Height                          2111 non-null   float64
 3   Weight                          2111 non-null   float64
 4   CALC                            2111 non-null   float64
 5   FAVC                            2111 non-null   float64
 6   FCVC                            2111 non-null   float64
 7   NCP                             2111 non-null   float64
 8   SCC                             2111 non-null   float64
 9   SMOKE                           2111 non-null   float64
 10  CH2O                            2111 non-null   float64
 11  family_history_with_overweight  2111 non-null   float64
 12  FAF                             2111 non-null   float64
 13  TUE                             2111 non-null   float64
 14  CAEC                            2111 non-null   float64
```

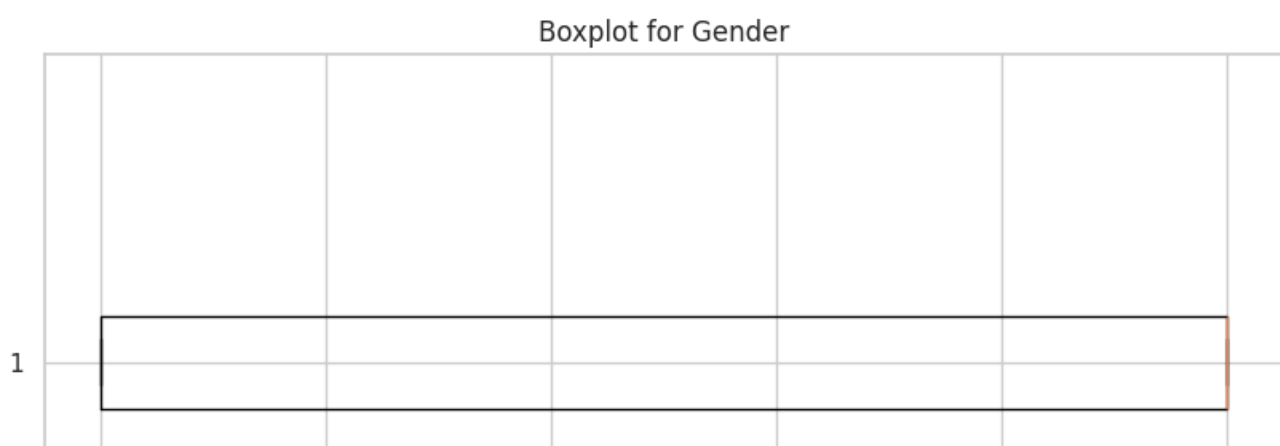
```
# Mengidentifikasi duplikasi per kolom
duplikat_per_kolom = df.apply(lambda x: x.duplicated().sum())
print("\nDuplikasi per Kolom:")
print(duplikat_per_kolom)
```

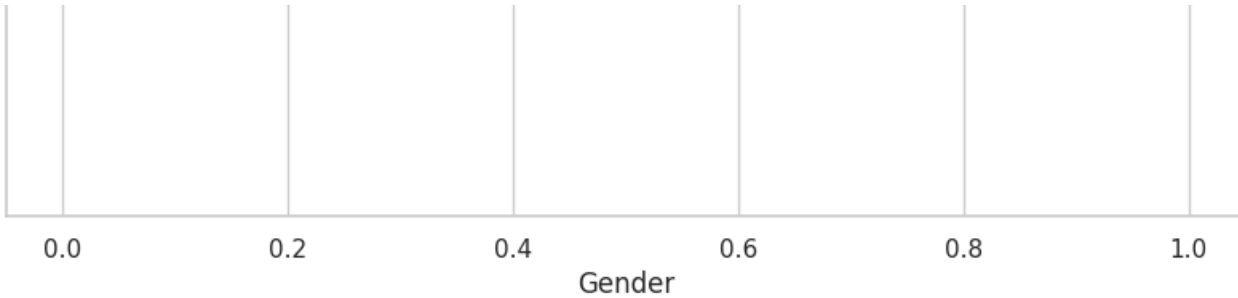
```
Duplikasi per Kolom:
Age                                718
Gender                            2109
Height                             550
Weight                             594
CALC                              2107
FAVC                              2109
FCVC                              1304
NCP                               1475
SCC                               2109
SMOKE                             2109
CH2O                               849
family_history_with_overweight    2109
```

```
FAF                               926
TUE                               982
CAEC                             2107
MTRANS                           2106
NObeyesdad                       2104
dtype: int64
```

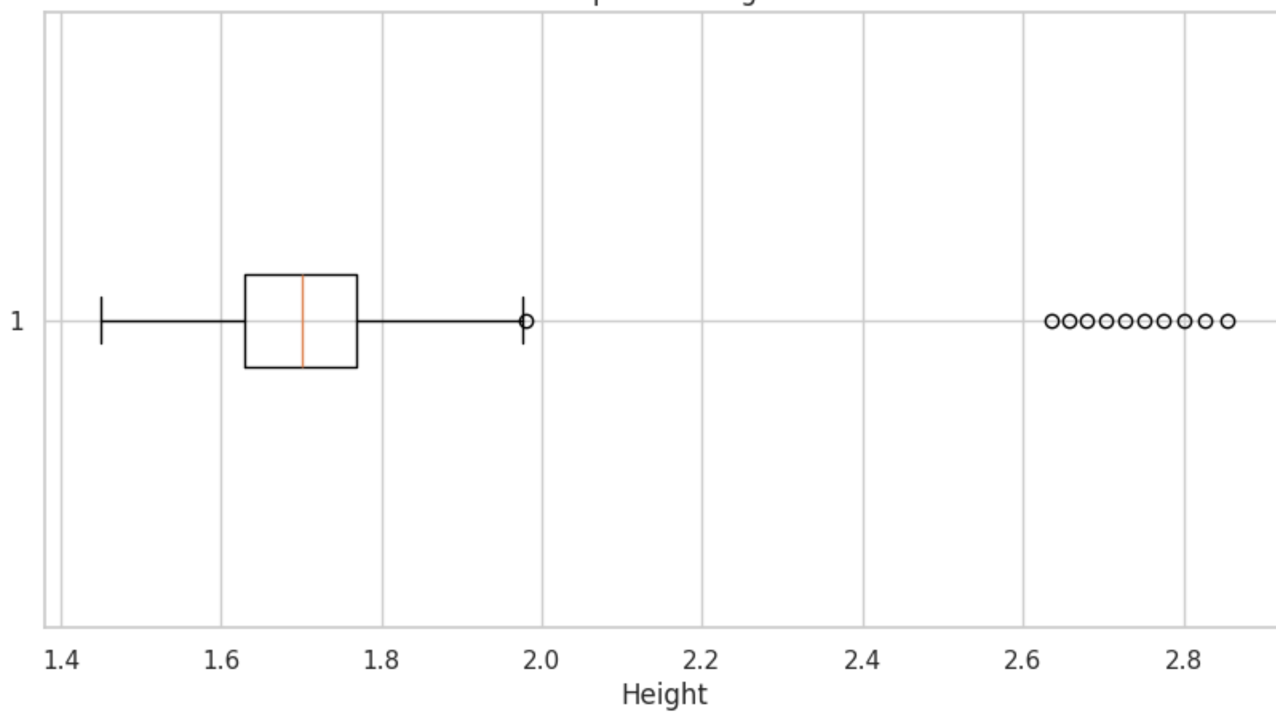
```
# Pilih hanya kolom numerik
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns

# Buat boxplot untuk setiap kolom numerik
for col in numerical_cols:
    plt.figure(figsize=(10, 5))
    plt.boxplot(df[col], vert=False)
    plt.title(f'Boxplot for {col}')
    plt.xlabel(col)
    plt.show()
```



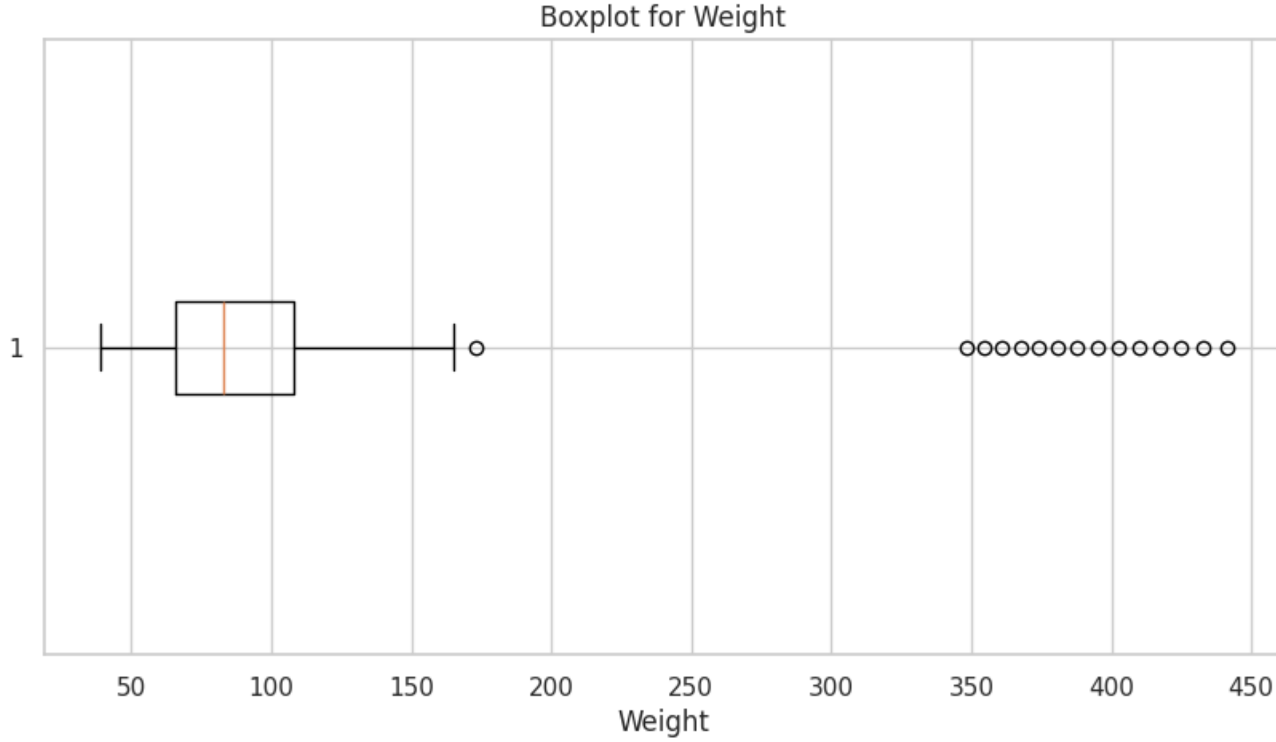




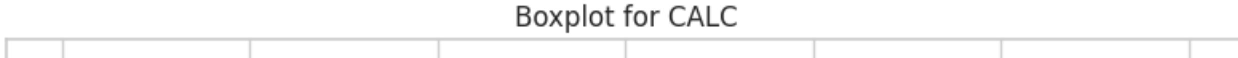
Boxplot for Height

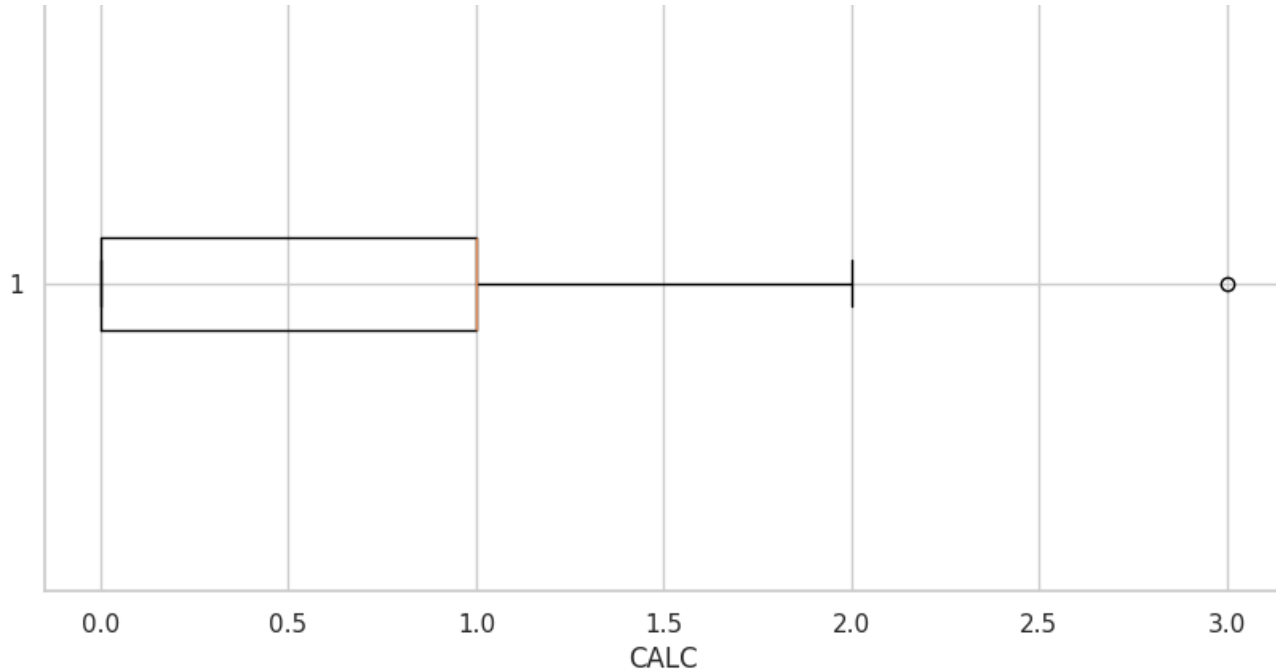


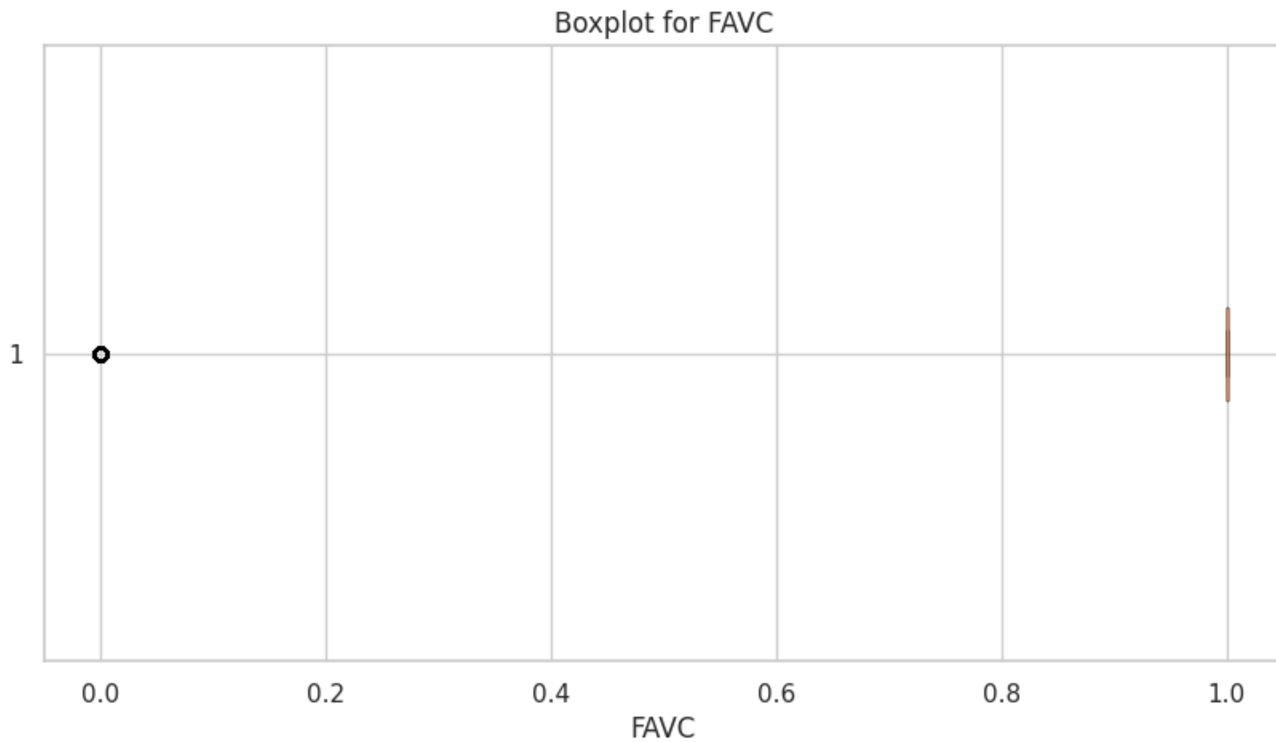
Boxplot for Weight

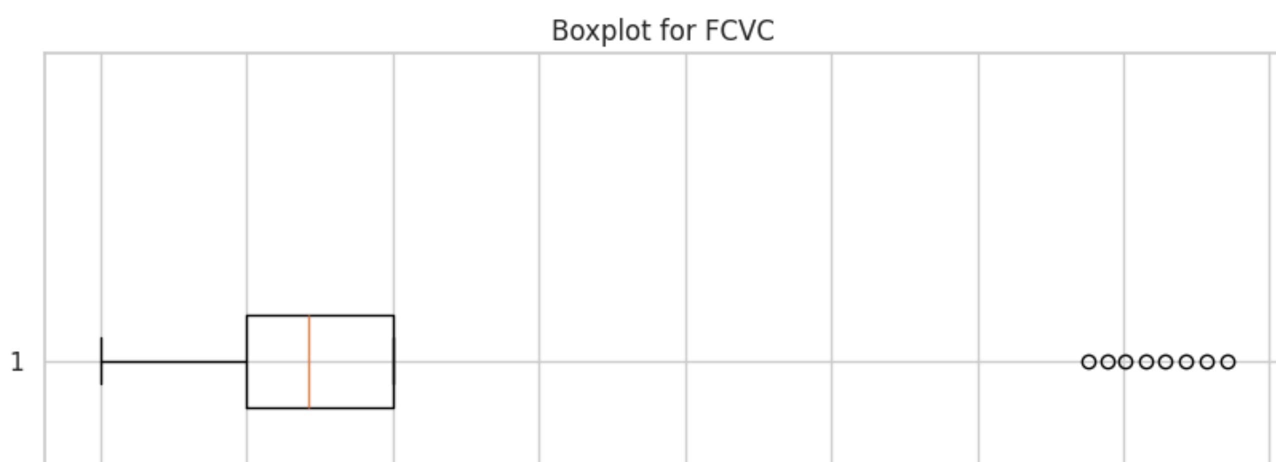


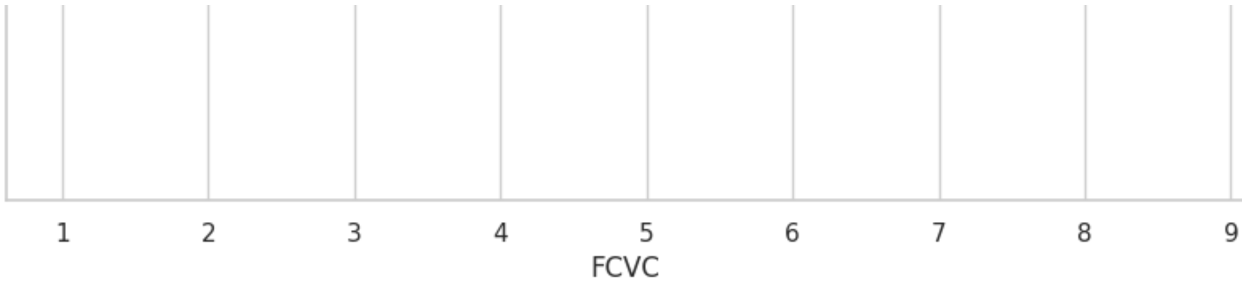
Boxplot for CALC



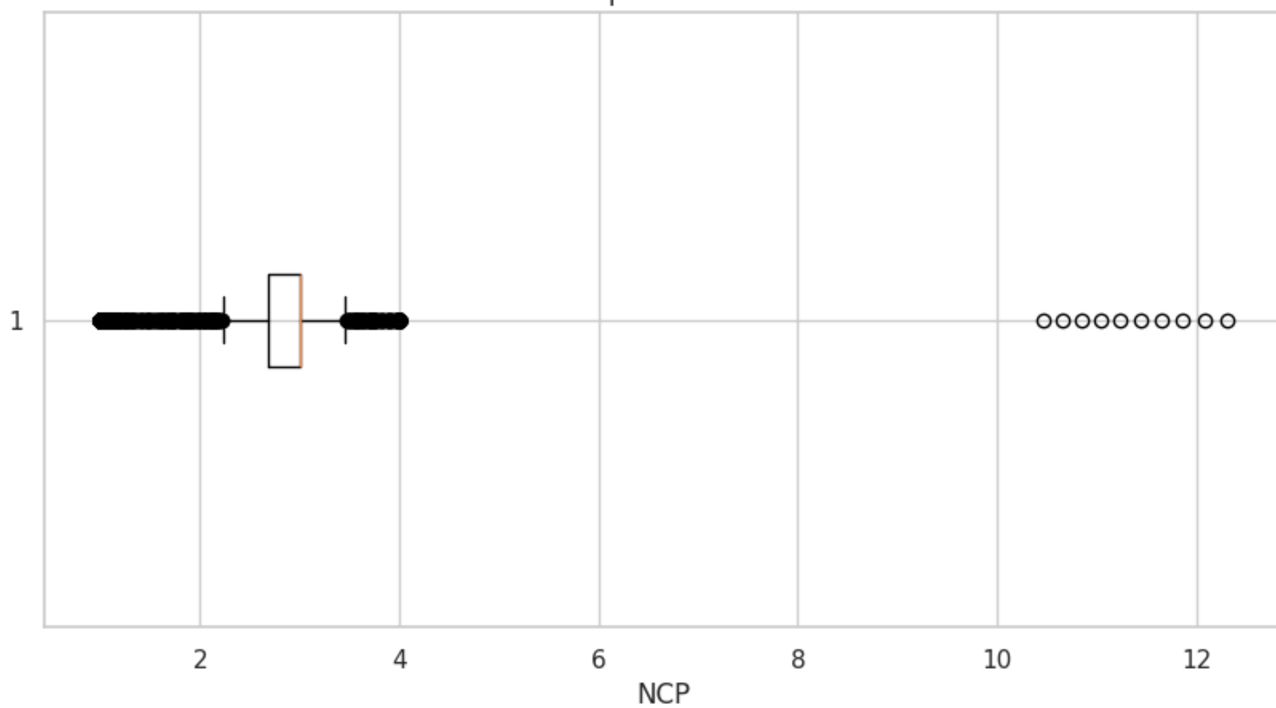

1
0.0
0.5
1.0
1.5
2.0
2.5
3.0
CALC


Boxplot for FAVC
1
0.0
0.2
0.4
0.6
0.8
1.0
FAVC

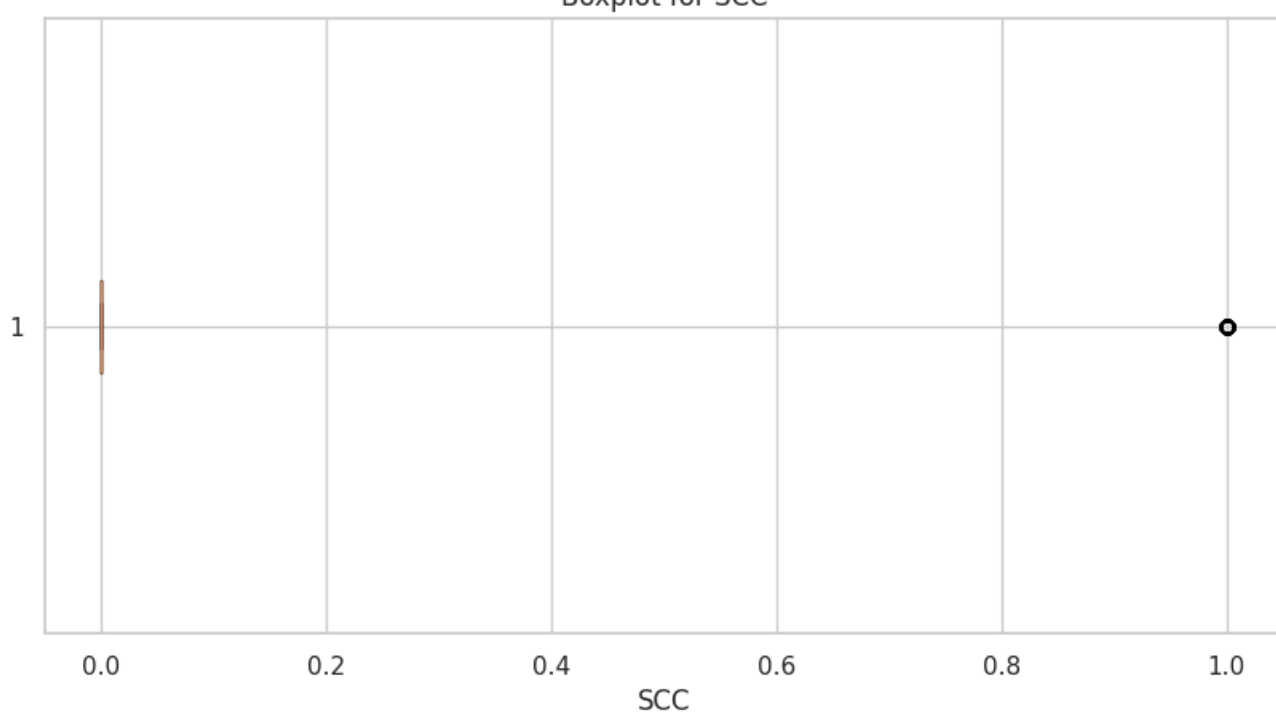

Boxplot for FCVC
1



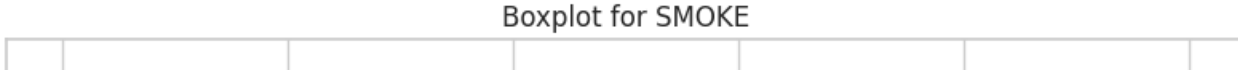
Boxplot for NCP

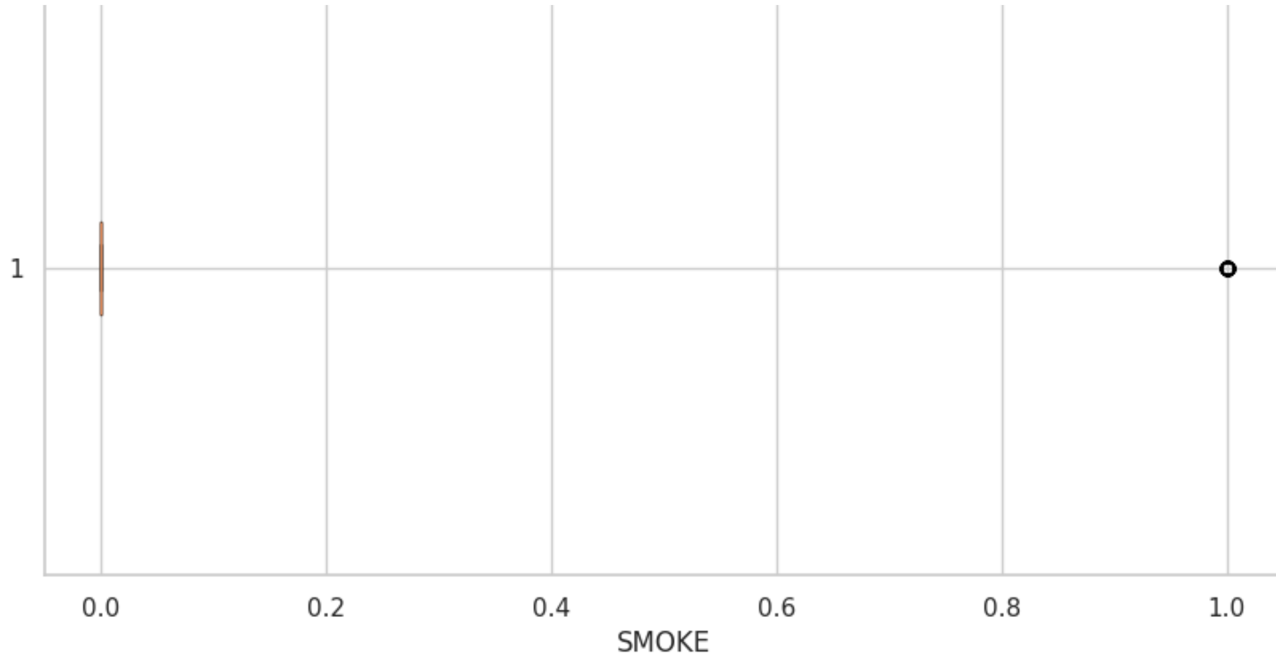


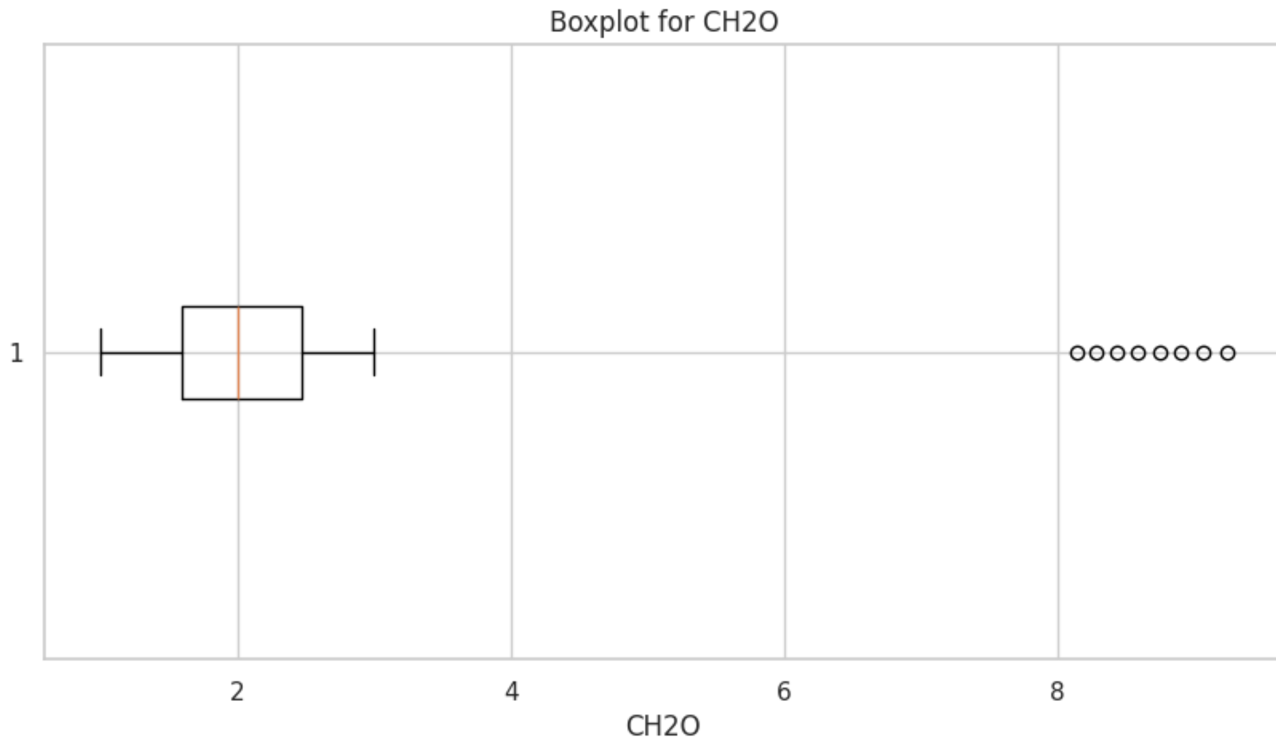
Boxplot for SCC

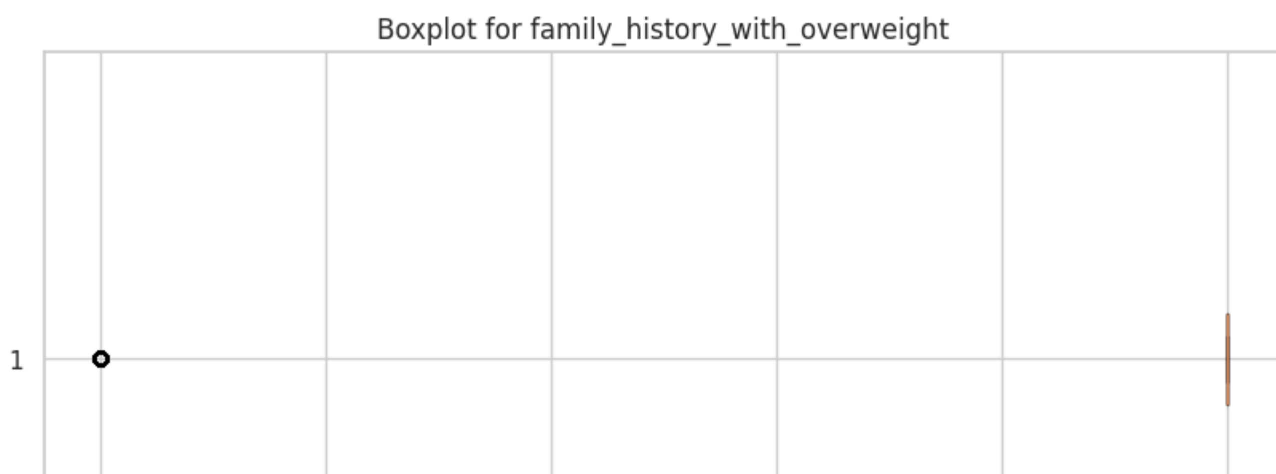


Boxplot for SMOKE

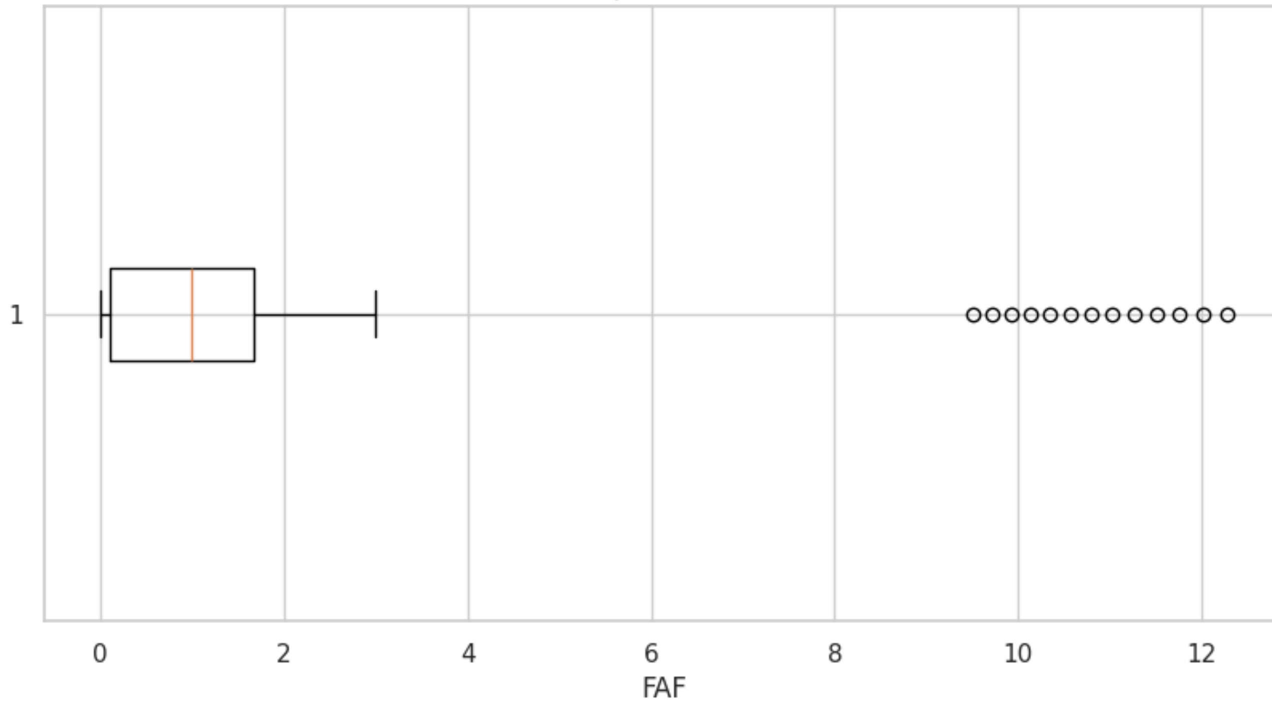



1
0.0
0.2
0.4
0.6
0.8
1.0
SMOKE

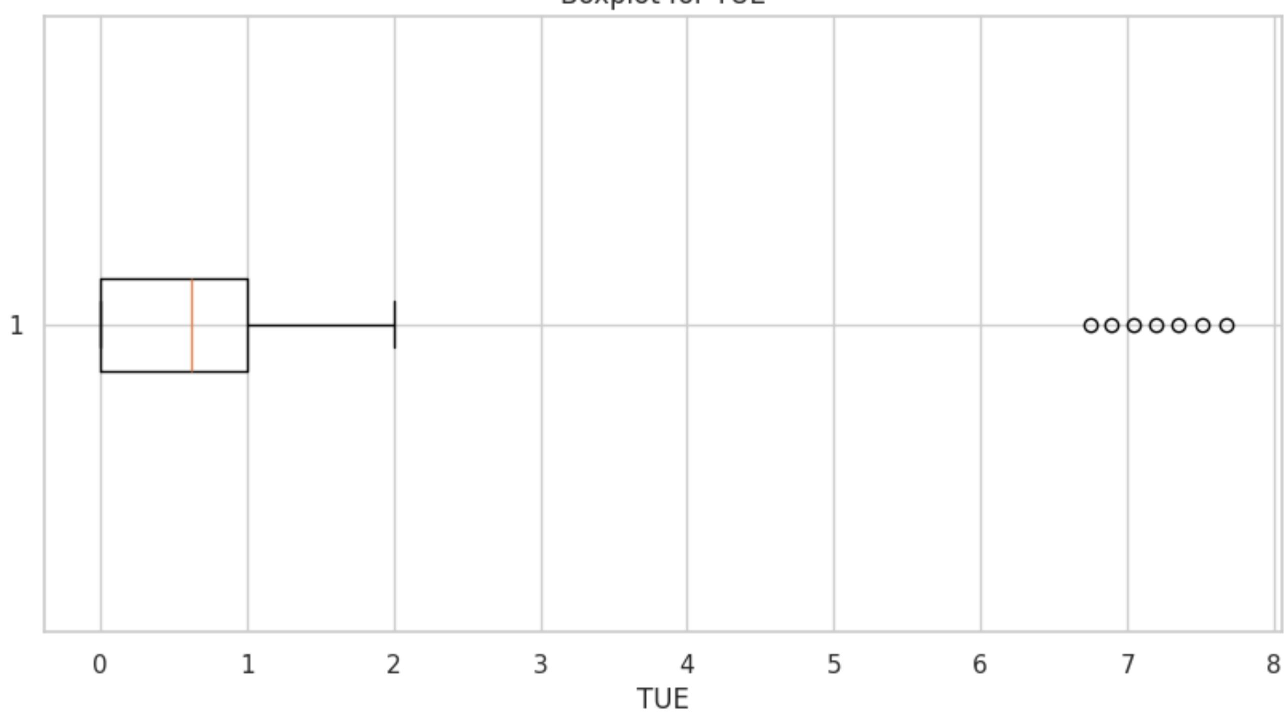

Boxplot for CH2O
1
2
4
6
8
CH2O


Boxplot for family_history_with_overweight
1

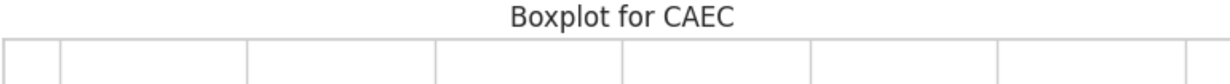
Boxplot for FAF

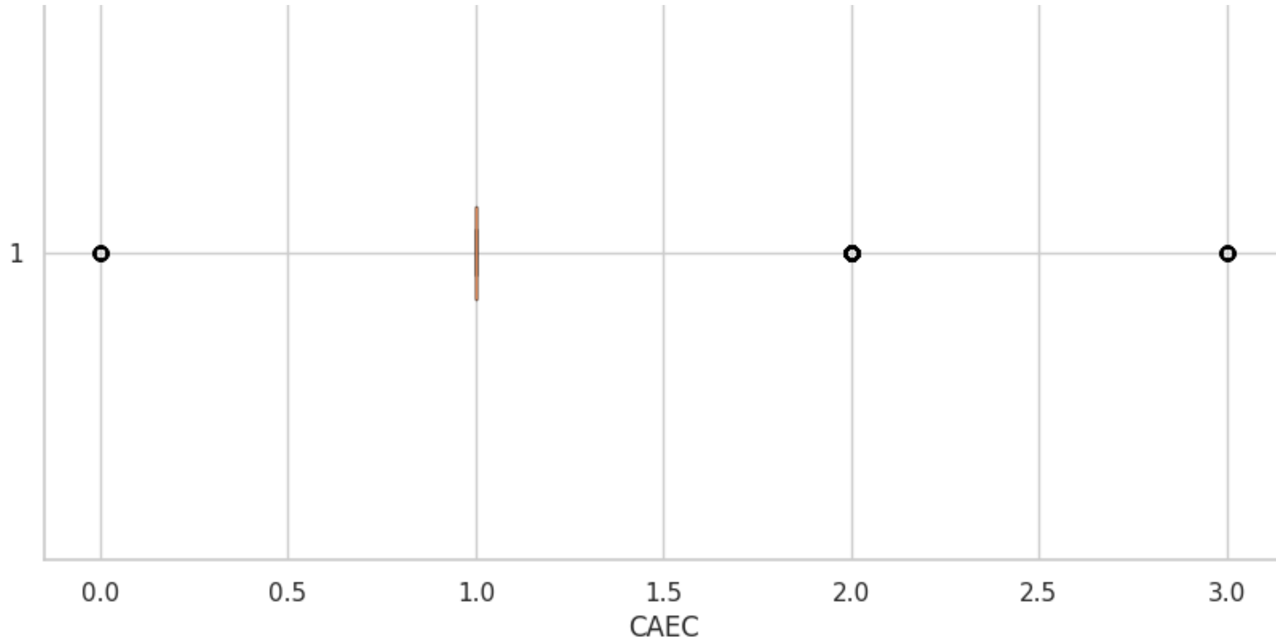


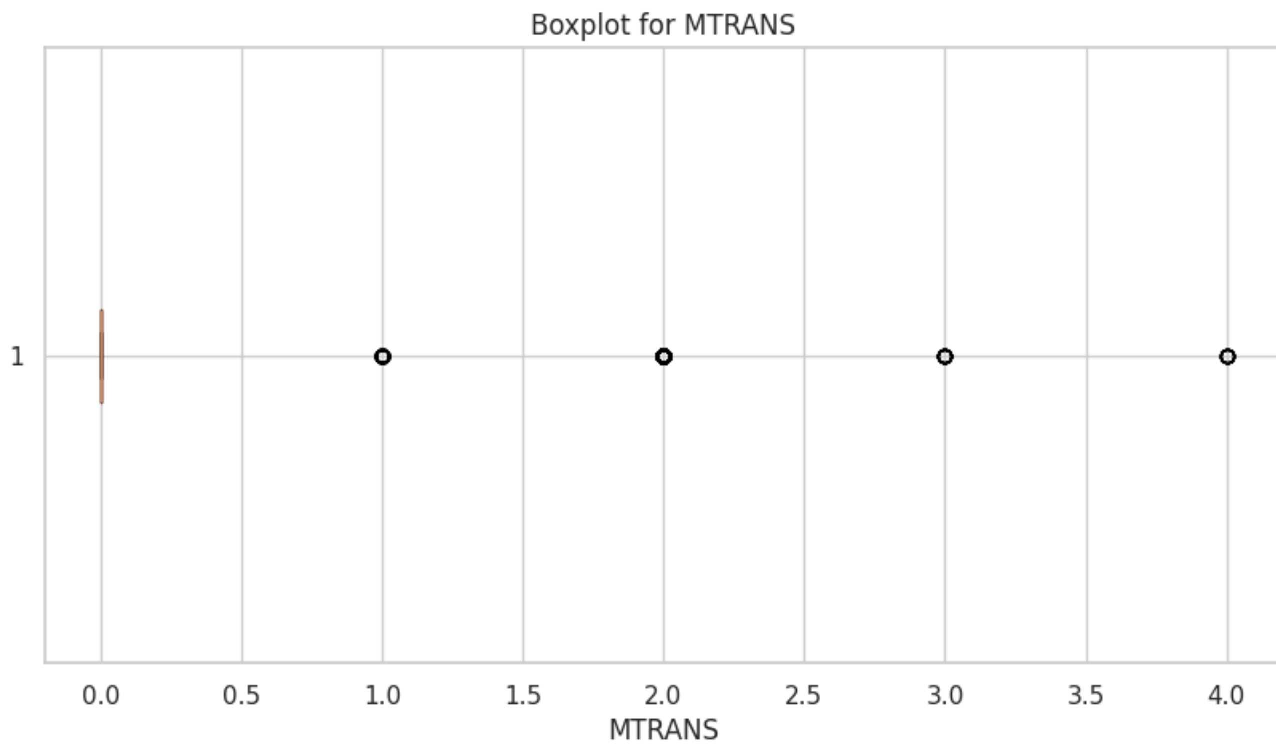
Boxplot for TUE

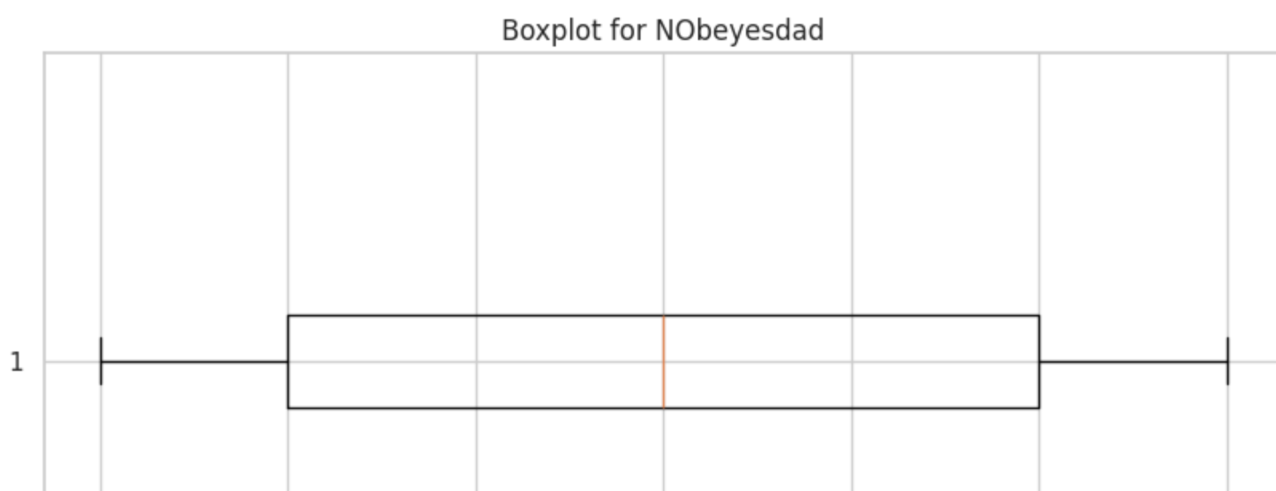


Boxplot for CAEC




1
0.0
0.5
1.0
1.5
2.0
2.5
3.0
CAEC


Boxplot for MTRANS
1
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
MTRANS


Boxplot for NObeyesdad
1


0
1
2
3
4
5
6
NObeyesdad

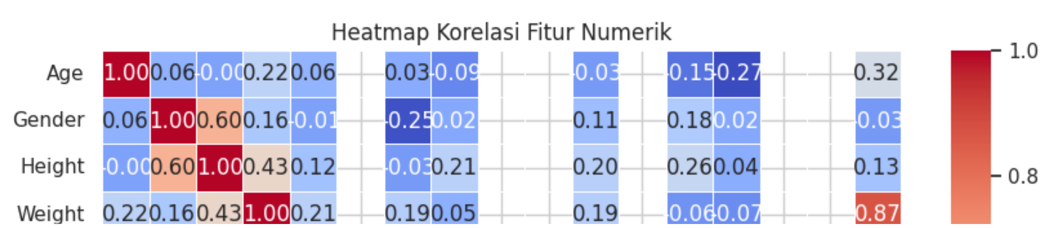
```
# Tangani outlier menggunakan metode IQR
for col in numerical_cols:
    Q1 = df[col].quantile(0.25)  # Kuartil pertama
    Q3 = df[col].quantile(0.75)  # Kuartil ketiga
    IQR = Q3 - Q1  # Rentang interkuartil
```

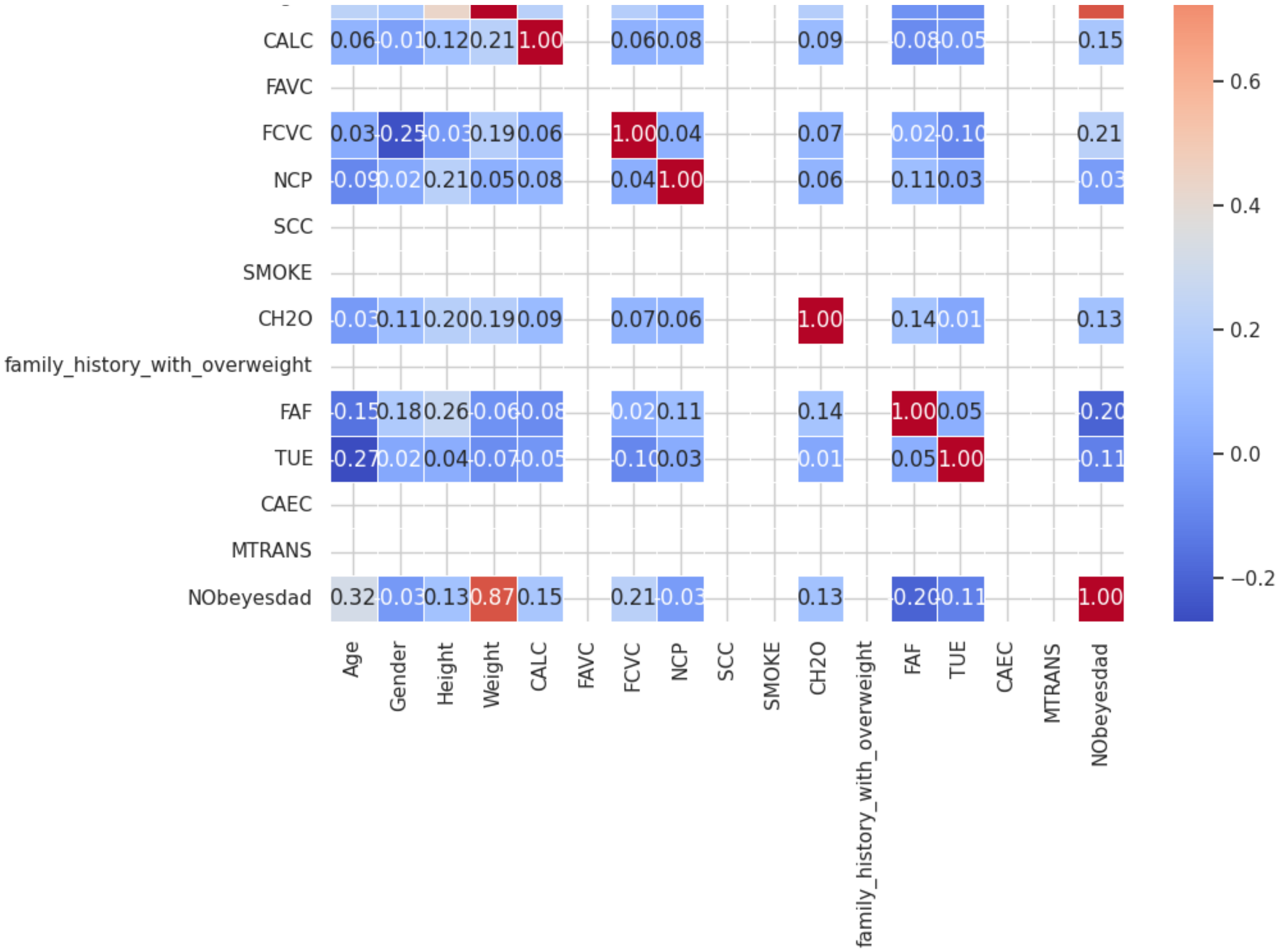
```
    # Tentukan batas bawah dan atas
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Ganti outlier dengan nilai batas bawah atau atas
    df[col] = df[col].apply(lambda x: lower_bound if x < lower_bound else (upper_bound if
```

```
print("Tipe data pada masing-masing kolom:")
print(df.dtypes)
```

```
Tipe data pada masing-masing kolom:
Age                                float64
Gender                             float64
Height                             float64
Weight                             float64
CALC                               float64
FAVC                               float64
FCVC                               float64
NCP                                float64
SCC                                float64
SMOKE                              float64
CH2O                               float64
family_history_with_overweight     float64
FAF                                float64
TUE                                float64
CAEC                               float64
MTRANS                             float64
NObeyesdad                           int64
dtype: object
```

```
# Pilih hanya kolom numerik
numerical_df = df.select_dtypes(include=['int64', 'float64'])

# Hitung korelasi
correlation_matrix = numerical_df.corr()

# Plot heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Heatmap Korelasi Fitur Numerik")
plt.show()
```





```
# Korelasi antar kolom numerik
correlation_matrix = df.select_dtypes(include=['int64', 'float64']).corr()

# Cetak sebagai tabel biasa
print(correlation_matrix.round(2).to_markdown())
```

	Age	Gender	Height	Weight	CALC
Age	1	0.06	-0	0.22	0.06
Gender	0.06	1	0.6	0.16	-0.01
Height	-0	0.6	1	0.43	0.12
Weight	0.22	0.16	0.43	1	0.21
CALC	0.06	-0.01	0.12	0.21	1
FAVC	nan	nan	nan	nan	nan
FCVC	0.03	-0.25	-0.03	0.19	0.06
NCP	-0.09	0.02	0.21	0.05	0.08
SCC	nan	nan	nan	nan	nan
SMOKE	nan	nan	nan	nan	nan
CH2O	-0.03	0.11	0.2	0.19	0.09
family_history_with_overweight	nan	nan	nan	nan	nan
FAF	-0.15	0.18	0.26	-0.06	-0.08
TUE	-0.27	0.02	0.04	-0.07	-0.05
CAEC	nan	nan	nan	nan	nan
MTRANS	nan	nan	nan	nan	nan
NObeyesdad	0.32	-0.03	0.13	0.87	0.15

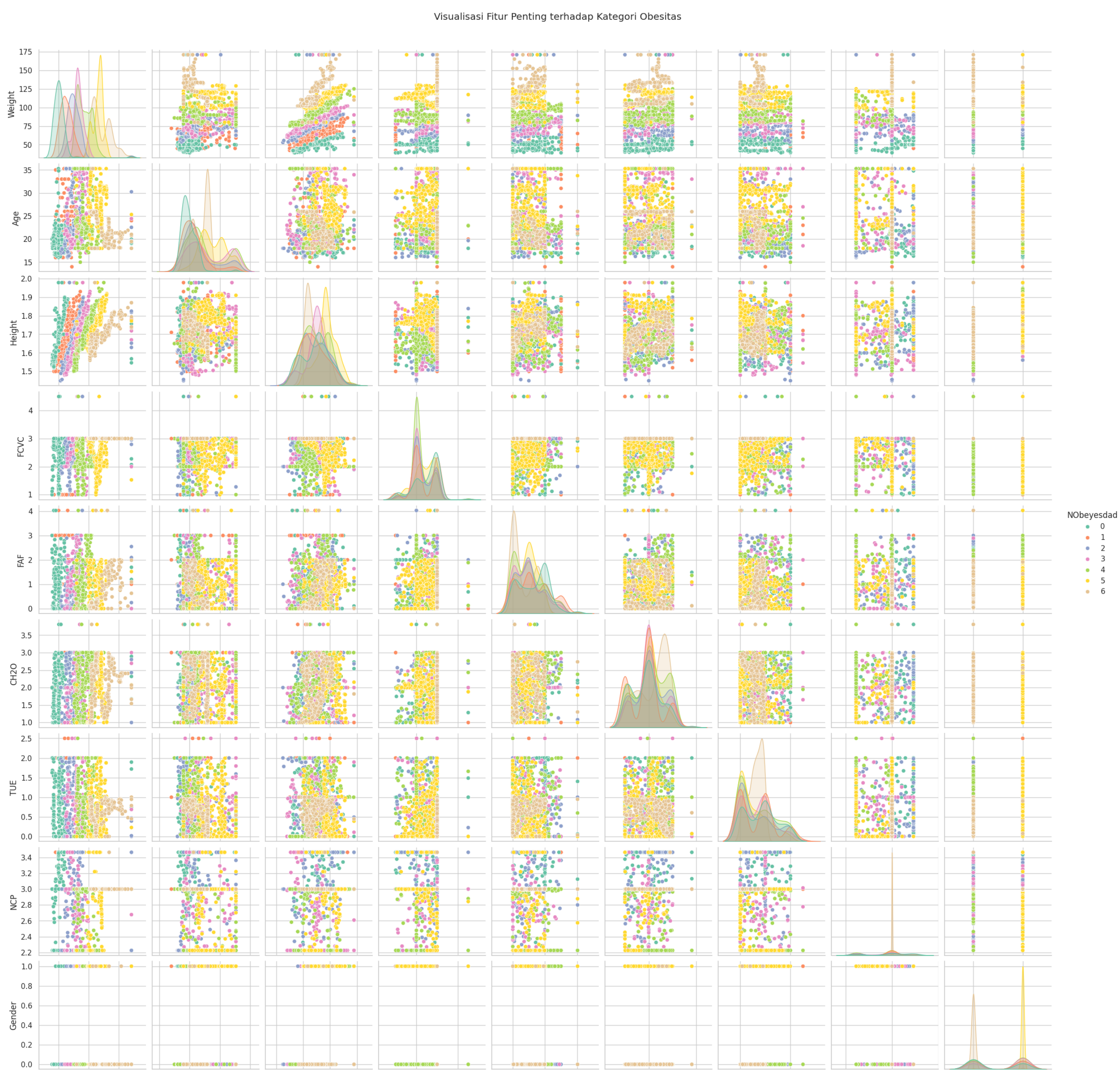
```
# Pastikan semua fitur sudah numerik
X = df.drop(columns=['NObeyesdad'])
y = df['NObeyesdad']
mi = mutual_info_classif(X, y, discrete_features='auto')
mi_series = pd.Series(mi, index=X.columns)
print(mi_series.sort_values(ascending=False))
```

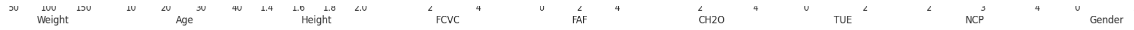
```
Weight                            1.209718
Age                               0.555901
Height                            0.406596
FCVC                              0.389864
FAF                               0.283103
CH2O                              0.270877
TUE                               0.266764
NCP                               0.214830
Gender                            0.197914
CALC                              0.092914
family_history_with_overweight    0.031171
SMOKE                             0.014734
FAVC                              0.014381
CAEC                              0.001399
SCC                               0.000000
MTRANS                            0.000000
dtype: float64
```

Fitur	Nilai MI	Keterangan
Weight	**1.21**	Sangat penting
Age	0.56	Penting
Height	0.41	Cukup penting

FCVC (makan sayur)	0.39	Cukup penting
FAF (aktivitas fisik)	0.28	Relevan
CH2O (minum air)	0.27	Relevan
TUE (teknologi)	0.27	Relevan
NCP (makan besar)	0.21	Masih berkontribusi
Gender	0.20	Marginal, tapi bisa dipakai
`CALC → MTRANS`	< 0.1	Bisa diabaikan / low impact

```
fitur_penting = ['Weight', 'Age', 'Height', 'FCVC', 'FAF', 'CH2O', 'TUE', 'NCP', 'Gender']

# Buat pairplot untuk visualisasi distribusi dan relasi antar fitur terhadap target
sns.pairplot(df[fitur_penting + ['NObeyesdad']], hue='NObeyesdad', palette='Set2', diag_kir
plt.suptitle("Visualisasi Fitur Penting terhadap Kategori Obesitas", y=1.02)
plt.show()
```




Weight
Age
Height
FCVC
FAF
CH2O
TUE
NCP
Gender