

**A MAJOR PROJECT REPORT ON**  
**Machine Learning-Based Obesity Risk Analysis**  
**with LightGBM**

*Project report Submitted*

In partial fulfilment of the requirement for the award of degree of

**MASTER OF COMPUTER APPLICATIONS**

**SUBMITTED BY**

**GUNTIMADUGU SUNIL**

**Reg. No:(11400240020)**

**Batch: 2023-2025**

**Under the guidance of**

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**DEPARTMENT OF COMPUTER SCIENCE AND TECHNOLOGY**

**DRAVIDIAN UNIVERSITY**  
**KUPPAM – 517426, A.P., INDIA**



# DRAVIDIAN UNIVERSITY

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## **BONAFIDE CERTIFICATE**

This is to certify that the project work entitled "**Machine Learning-Based Obesity Risk Analysis with LightGBM**" is a Bonafide work carried out by **GUNTIMADUGU SUNIL (Reg. No: 11400240020)** of Dravidian University, Kuppam, for the award of the degree of **MASTER OF COMPUTER APPLICATIONS** a record of bonafide major project work carried out by the candidates under my supervision and guidance. The major project has reached the standard of fulfilling the requirements of the regulation for the award of the degree of **DRAVIDIAN UNIVERSITY** Kuppam during the academic year 2023-2025.

**Internal Guide**

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## **DECLARATION**

*I, GUNTIMADUGU SUNIL (Reg. No:11400240020) hereby declare that the project entitled "Obesity Risk Analysis with LightGBM" using Machine Learning is done by me under the guidance of **Dr. D. Mabuni**. submitted in partial fulfillment of the requirements for the award of the degree of Master of Computer Applications at Dravidian University, kuppam during the academic year 2023-2025. This work has not been submitted by anybody towards of any degree.*

*Date:*

*[Signature of the student]*

*Place: Kuppam*

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## **ACKNOWLEDGEMENT**

I would like to express my special thanks of gratitude to my guide **Dr. D. Mabuni**. and our Head of the Department of Computer Science **Prof. K. AMMULU**, who gave me the excellent opportunity to do this project on the topic of the In this study, I explore the application of machine learning techniques to predict obesity risk levels based on various physiological, behavioral, and lifestyle factors. I focus on the Light Gradient Boosting Machine (LightGBM), a high-performance gradient boosting framework that offers efficiency and accuracy. The model is trained on a well-preprocessed dataset and evaluated using multiple performance metrics. My goal is to provide an interpretable and scalable solution to aid in early identification of obesity

## **ABSTRACT**

Obesity is a rapidly growing global health issue, significantly contributing to a range of chronic diseases and increasing healthcare burdens. This project presents a comprehensive machine learning-based approach for analyzing and predicting obesity risk levels using the Light Gradient Boosting Machine (LightGBM) algorithm. Utilizing a robust dataset comprising physiological, behavioral, and lifestyle attributes such as age, diet, physical activity, and technology usage, the study emphasizes the importance of early detection and personalized risk assessment.

The project encompasses extensive data preprocessing, exploratory data analysis, feature engineering, and model training using advanced classification algorithms, including LightGBM, XGBoost, and CatBoost. The LightGBM model demonstrated high predictive accuracy while maintaining computational efficiency, making it suitable for scalable deployment. Through feature importance analysis and visualizations, the model also provides interpretable insights into the key factors influencing obesity.

This research highlights the potential of machine learning in public health by enabling proactive and data-driven obesity prevention strategies. The proposed system serves as a valuable tool for healthcare professionals to identify high-risk individuals and implement timely interventions.

# **COMPREHENSIVE ANALYSIS AND PREDICTION OF OBESITY RISK LEVELS USING MACHINE LEARNING TECHNIQUES WITH - (LightGBM) MODEL**

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Conclusion: □

## Section: 1. Introduction:

### **What is Obesity:**

**Obesity** is a complex health condition affecting millions globally, with significant implications for morbidity, mortality, and healthcare costs. Obesity is a global concern, with statistics indicating a significant rise in the number of obese individuals, now accounting for approximately 30% of the global population, triple the figures from 1975. This escalating trend highlights the pressing need to address the multifaceted risks associated with excess weight. Obesity is a major contributor to various health complications, including diabetes, heart disease, osteoarthritis, sleep apnea, strokes, and high blood pressure, thereby significantly reducing life expectancy and increasing mortality rates. Effective prediction of obesity risk is crucial for implementing targeted interventions and promoting public health.

In this project, we undertake a comprehensive analysis to predict obesity risk levels using advanced machine learning techniques.

# **Understanding Obesity and Risk Prediction:**

- **Understanding Obesity:**
  - Obesity stems from excessive body fat accumulation, influenced by genetic, environmental, and behavioral factors.
  - Risk prediction involves analyzing demographics, lifestyle habits, and physical activity to classify individuals into obesity risk categories.
- **Global Impact:**
  - Worldwide obesity rates have tripled since 1975, affecting 30% of the global population.
  - Urgent action is needed to develop effective risk prediction and management strategies.
- **Factors Influencing Risk:**
  - Obesity risk is shaped by demographics, lifestyle habits, diet, physical activity, and medical history.
  - Analyzing these factors reveals insights into obesity's mechanisms and identifies high-risk populations.
- **Data-Driven Approach:**
  - Advanced machine learning and large datasets enable the development of predictive models for stratifying obesity risk.
  - These models empower healthcare professionals and policymakers to implement tailored interventions for improved public health outcomes.
- **Proactive Health Initiatives:**
  - Our proactive approach aims to combat obesity by leveraging data and technology for personalized prevention and management.
  - By predicting obesity risk, we aspire to create a future where interventions are precise, impactful, and tailored to individual needs.

**Source:** World Health Organization. (2022). [Obesity and overweight](#).

## **Dataset Overview:**

The dataset contains comprehensive information encompassing eating habits, physical activity, and demographic variables, comprising a total of 17

## Key Attributes Related to Eating Habits:

- **Frequent Consumption of High-Caloric Food (FAVC):** Indicates the frequency of consuming high-caloric food items.
- **Frequency of Consumption of Vegetables (FCVC):** Measures the frequency of consuming vegetables.
- **Number of Main Meals (NCP):** Represents the count of main meals consumed per day.
- **Consumption of Food Between Meals (CAEC):** Describes the pattern of food consumption between main meals.
- **Consumption of Water Daily (CH20):** Quantifies the daily water intake.
- **Consumption of Alcohol (CALC):** Indicates the frequency of alcohol consumption.

## Attributes Related to Physical Condition:

- **Calories Consumption Monitoring (SCC):** Reflects the extent to which individuals monitor their calorie intake.
- **Physical Activity Frequency (FAF):** Measures the frequency of engaging in physical activities.
- **Time Using Technology Devices (TUE):** Indicates the duration spent using technology devices.
- **Transportation Used (MTRANS):** Describes the mode of transportation typically used.

Additionally, the dataset includes essential demographic variables such as gender, age, height, and weight, providing a comprehensive overview of individuals' characteristics.

## Target Variable:

The target variable, NObesity, represents different obesity risk levels, categorized as:

- **Underweight (BMI < 18.5):0**
- **Normal (18.5 <= BMI < 20):1**
- **Overweight I (20 <= BMI < 25):2**
- **Overweight II (25 <= BMI < 30):3**
- **Obesity I (30 <= BMI < 35):4**
- **Obesity II (35 <= BMI < 40):5**
- **Obesity III (BMI >= 40):6**

## Section: 2.Importing Libraries and Dataset:

### Importing Relevant Libraries:

```
import os # Operating system specific functionalities
import numpy as np # Linear algebra
```

```

import pandas as pd # Data processing, CSV file I/O (e.g.
pd.read_csv)
from IPython.display import Image # Displaying images in Jupyter
Notebook
import matplotlib.pyplot as plt # Plotting library
import seaborn as sns # Statistical data visualization
%matplotlib inline
import pickle as pkl # Python object serialization
import altair as alt # Declarative statistical visualization library
from tabulate import tabulate # Pretty-print tabular data
from colorama import Fore, Style # ANSI escape sequences for colored
terminal text
from scipy.stats import pearsonr # Pearson correlation coefficient
and p-value computation
from mpl_toolkits.mplot3d import Axes3D # 3D plotting toolkit for
Matplotlib
from sklearn.cluster import KMeans # K-Means clustering algorithm
from sklearn.preprocessing import StandardScaler # Standardization of
features
from sklearn.decomposition import PCA # Principal Component Analysis
from scipy.stats import chi2 # Chi-square distribution
from sklearn.ensemble import RandomForestClassifier # Random Forest
classifier
import xgboost as xgb # XGBoost library for gradient boosting
import lightgbm as lgb # LightGBM library for gradient boosting

# Import necessary libraries for model training and evaluation
from sklearn.model_selection import train_test_split # Splitting data
into train and test sets
from xgboost import XGBClassifier # XGBoost classifier
from lightgbm import LGBMClassifier # LightGBM classifier
from catboost import CatBoostClassifier # CatBoost classifier
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix # For model evaluation

import warnings # Suppress warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None) # Display all columns in
DataFrame
pd.set_option('display.max_rows', None) # Display all rows in
DataFrame

```

## Loading Datasets:

```

# Loading Datasets:
# Define filepath
filepath = os.path.join("/kaggle/input/playground-series-s4e2")

```

```

# Function for reading file from your current directory
def read_csv(filepath, filename):
    # Read file from the specified path
    df = pd.read_csv(os.path.join(filepath, filename))
    return df

# Give filepath and access all three file to read (In my case, it is
# 'train.csv', 'test.csv' and 'sample_submission.csv')
df_train = read_csv(filepath, 'train.csv')
test = read_csv(filepath, 'test.csv')
test_sub=test.copy()
submission_df = read_csv(filepath, 'sample_submission.csv')

```

## Section: 3. Descriptive Analysis:

```

print('Number of rows and columns:\n')
df_train.shape

```

Number of rows and columns:

```
(20758, 18)
```

```
df_train.head()
```

	id	Gender	Age	Height	Weight				
family_history_with_overweight \	0	Male	24.443011	1.699998	81.669950	yes			
1	1	Female	18.000000	1.560000	57.000000	yes			
2	2	Female	18.000000	1.711460	50.165754	yes			
3	3	Female	20.952737	1.710730	131.274851	yes			
4	4	Male	31.641081	1.914186	93.798055	yes			
FAVC		FCVC	NCP	CAEC	SMOKE	CH2O	SCC		
FAF \	0	yes	2.000000	2.983297	Sometimes	no	2.763573	no	0.000000
1	yes	2.000000	3.000000	Frequently		no	2.000000	no	1.000000
2	yes	1.880534	1.411685	Sometimes		no	1.910378	no	0.866045
3	yes	3.000000	3.000000	Sometimes		no	1.674061	no	1.467863
4	yes	2.679664	1.971472	Sometimes		no	1.979848	no	1.967973

```

      TUE          CALC          MTRANS          NObeyesdad
0  0.976473  Sometimes  Public_Transportation  Overweight_Level_II
1  1.000000        no        Automobile  Normal_Weight
2  1.673584        no  Public_Transportation  Insufficient_Weight
3  0.780199  Sometimes  Public_Transportation  Obesity_Type_III
4  0.931721  Sometimes  Public_Transportation  Overweight_Level_II

test.head()

      id  Gender      Age     Height     Weight \
0  20758    Male  26.899886  1.848294  120.644178
1  20759  Female  21.000000  1.600000   66.000000
2  20760  Female  26.000000  1.643355  111.600553
3  20761    Male  20.979254  1.553127  103.669116
4  20762  Female  26.000000  1.627396  104.835346

family_history_with_overweight FAVC          FCVC          NCP          CAEC
SMOKE \
0                      yes  yes  2.938616  3.000000  Sometimes
no
1                      yes  yes  2.000000  1.000000  Sometimes
no
2                      yes  yes  3.000000  3.000000  Sometimes
no
3                      yes  yes  2.000000  2.977909  Sometimes
no
4                      yes  yes  3.000000  3.000000  Sometimes
no

      CH2O  SCC          FAF          TUE          CALC          MTRANS
0  2.825629  no  0.855400  0.000000  Sometimes  Public_Transportation
1  3.000000  no  1.000000  0.000000  Sometimes  Public_Transportation
2  2.621877  no  0.000000  0.250502  Sometimes  Public_Transportation
3  2.786417  no  0.094851  0.000000  Sometimes  Public_Transportation
4  2.653531  no  0.000000  0.741069  Sometimes  Public_Transportation

df_train.tail()

      id  Gender      Age     Height     Weight \
20753  20753    Male  25.137087  1.766626  114.187096
20754  20754    Male  18.000000  1.710000  50.000000
20755  20755    Male  20.101026  1.819557  105.580491
20756  20756    Male  33.852953  1.700000   83.520113
20757  20757    Male  26.680376  1.816547  118.134898

```

```

family_history_with_overweight   FAVC        FCVC        NCP
CAEC \
20753                           yes  yes  2.919584  3.000000
Sometimes
20754                           no   yes  3.000000  4.000000
Frequently
20755                           yes  yes  2.407817  3.000000
Sometimes
20756                           yes  yes  2.671238  1.971472
Sometimes
20757                           yes  yes  3.000000  3.000000
Sometimes

SMOKE      CH2O  SCC      FAF        TUE        CALC \
20753     no    2.151809  no    1.330519  0.196680  Sometimes
20754     no    1.000000  no    2.000000  1.000000  Sometimes
20755     no    2.000000  no    1.158040  1.198439  no
20756     no    2.144838  no    0.000000  0.973834  no
20757     no    2.003563  no    0.684487  0.713823  Sometimes

MTRANS          NOBYESDAD
20753  Public_Transportation  Obesity_Type_II
20754  Public_Transportation  Insufficient_Weight
20755  Public_Transportation  Obesity_Type_II
20756          Automobile  Overweight_Level_II
20757  Public_Transportation  Obesity_Type_II

df_train.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20758 entries, 0 to 20757
Data columns (total 18 columns):
 #   Column           Non-Null Count Dtype
 --- 
 0   id               20758 non-null  int64
 1   Gender            20758 non-null  object
 2   Age                20758 non-null  float64
 3   Height              20758 non-null  float64
 4   Weight              20758 non-null  float64
 5   family_history_with_overweight  20758 non-null  object
 6   FAVC                20758 non-null  object
 7   FCVC                20758 non-null  float64
 8   NCP                 20758 non-null  float64
 9   CAEC                20758 non-null  object
 10  SMOKE               20758 non-null  object
 11  CH2O                20758 non-null  float64
 12  SCC                  20758 non-null  object
 13  FAF                  20758 non-null  float64
 14  TUE                  20758 non-null  float64

```

```

15    CALC                         20758 non-null   object
16    MTRANS                        20758 non-null   object
17    NObeyesdad                     20758 non-null   object
dtypes: float64(8), int64(1), object(9)
memory usage: 2.9+ MB

print("size of dataframe:",df_train.size)
df_train.dtypes

size of dataframe: 373644

id                               int64
Gender                          object
Age                            float64
Height                          float64
Weight                          float64
family_history_with_overweight  object
FAVC                           object
FCVC                           float64
NCP                            float64
CAEC                           object
SMOKE                          object
CH2O                           float64
SCC                            object
FAF                            float64
TUE                            float64
CALC                           object
MTRANS                          object
NObeyesdad                      object
dtype: object

```

## 1. Summary Statistic of dataframe:

```

df_train.describe().transpose().style.background_gradient(cmap='viridis').format("{:.2f}")
<pandas.io.formats.style.Styler at 0x7c3698339600>

```

- **Count:** Number of non-null values for each feature. For instance, the 'Age' feature has 20,758 non-null values.
- **Mean:** Average value of each feature across all observations. The mean age in the dataset is approximately 23.84 years.
- **Std (Standard Deviation):** Measure of dispersion around the mean, indicating the extent of deviation from the mean value. The standard deviation of age is approximately 5.69 years.
- **Min:** Minimum value observed for each feature. The minimum age in the dataset is 14 years.

- **25%, 50% (Median), 75%:** Quartiles representing the data distribution. The median age (50th percentile) is approximately 22.82 years.
- **Max:** Maximum value observed for each feature. The maximum age in the dataset is 61 years.

These summary statistics provide insights into the distribution and variability of numerical features, facilitating a deeper understanding of the dataset's characteristics and informing subsequent analysis.

```
def summary(dataframe):
    print(f'Data shape: {dataframe.shape}')
    # Print the shape of the dataframe
    summary_df = pd.DataFrame(dataframe.dtypes, columns=['Data Type'])
    # Create a dataframe to store summary information
    summary_df['# Missing'] = dataframe.isnull().sum().values
    # Count the number of missing values for each column
    summary_df['% Missing'] = (dataframe.isnull().sum().values /
len(dataframe)) * 100 # Calculate the percentage of missing values for
each column
    summary_df['# Unique'] = dataframe.nunique().values
    # Count the number of unique values for each column
    desc = pd.DataFrame(dataframe.describe(include='all')).transpose()
    # Create a descriptive statistics df & transpose it for easier merging
    summary_df['Min'] = desc['min'].values
    # Add the minimum values from the descriptive statistics
    summary_df['Max'] = desc['max'].values
    # Add the maximum values from the descriptive statistics

    return summary_df

# Call the function with the dataframe "df_train" and display the
summary
summary(df_train)

Data shape: (20758, 18)

          Data Type  # Missing  % Missing  #
Unique \
id           int64      0       0.0
20758
Gender        object      0       0.0
2
Age          float64      0       0.0
1703
Height        float64      0       0.0
1833
Weight        float64      0       0.0
1979
family_history_with_overweight   object      0       0.0
```

2			
FAVC	object	0	0.0
2			
FCVC	float64	0	0.0
934			
NCP	float64	0	0.0
689			
CAEC	object	0	0.0
4			
SMOKE	object	0	0.0
2			
CH2O	float64	0	0.0
1506			
SCC	object	0	0.0
2			
FAF	float64	0	0.0
1360			
TUE	float64	0	0.0
1297			
CALC	object	0	0.0
3			
MTRANS	object	0	0.0
5			
NObeyesdad	object	0	0.0
7			

	Min	Max
id	0.0	20757.0
Gender	NaN	NaN
Age	14.0	61.0
Height	1.45	1.975663
Weight	39.0	165.057269
family_history_with_overweight	NaN	NaN
FAVC	NaN	NaN
FCVC	1.0	3.0
NCP	1.0	4.0
CAEC	NaN	NaN
SMOKE	NaN	NaN
CH2O	1.0	3.0
SCC	NaN	NaN
FAF	0.0	3.0
TUE	0.0	2.0
CALC	NaN	NaN
MTRANS	NaN	NaN
NObeyesdad	NaN	NaN

- **Data Shape:** The dataset contains 20,758 rows and 17 columns.
- **Data Types:** The dataset consists of a mix of object (likely categorical) and float64 (likely numerical) data types.

- **# Missing:** There are no missing values present in any of the columns.
- **% Missing:** As there are no missing values, the percentage of missing values for all columns is 0.0%.
- **# Unique:** Each column has a varying number of unique values, ranging from 2 to 1,703.
- **Min:** Minimum values observed for numerical features range from 14.0 to 39.0.
- **Max:** Maximum values observed for numerical features range from 61.0 to 165.057269.

## 2. The unique values present in dataset:

```
# Iterate through each column in the DataFrame
for col in df_train.columns:
    # Get the unique values present in the current column
    unique_values = df_train[col].unique()
    # Print the column name along with its unique values
    print(f"Unique values in '{col}': {unique_values}")

Unique values in 'id': [ 0 1 2 ... 20755 20756 20757]
Unique values in 'Gender': ['Male' 'Female']
Unique values in 'Age': [24.443011 18. 20.952737 ... 25.746113
38.08886 33.852953]
Unique values in 'Height': [1.699998 1.56 1.71146 ... 1.791366
1.672594 1.536819]
Unique values in 'Weight': [ 81.66995 57. 50.165754 ...
152.063947 79.5 80.615325]
Unique values in 'family_history_with_overweight': ['yes' 'no']
Unique values in 'FAVC': ['yes' 'no']
Unique values in 'FCVC': [2. 1.880534 3. 2.679664
2.919751 1.99124
1.890682 2.85916 1.352649 1.289733 2.818026 1.164839 2.152733
2.814518
2.705445 1.478334 2.389717 2.157164 1.340361 2.656622 1.9
1.015467
2.989112 2.270546 2.415522 2.960131 3.179995 2.655265 1.24884
1.109115
1.569176 3.335876 3.671076 3.259033 3.531038 2.733077 1.350099
1.595784
3.054416 2.014671 2.929123 2.269799 2.083831 1.890413 3.788602
1.667596
2.256119]
Unique values in 'CAEC': ['Sometimes' 'Frequently' 'no' 'Always']
Unique values in 'SMOKE': ['no' 'yes']
Unique values in 'CH2O': [2.763573 2. 1.910378 ... 2.151166
1.485836 1.365188]
Unique values in 'SCC': ['no' 'yes']
Unique values in 'FAF': [0. 1. 0.866045 ... 0.540397
0.271174 0.988668]
Unique values in 'TUE': [0.976473 1. 1.673584 ... 1.217929
1.439004 0.768375]
Unique values in 'CALC': ['Sometimes' 'no' 'Frequently']
Unique values in 'MTRANS': ['Public_Transportation' 'Automobile'
```

```

'Walking' 'Motorbike' 'Bike']
Unique values in 'NObeyesdad': ['Overweight_Level_II' 'Normal_Weight'
'Insufficient_Weight'
'Obesity_Type_III' 'Obesity_Type_II' 'Overweight_Level_I'
'Obesity_Type_I']

```

1. **Age:** Age of the individual in years. (Unique values: 24.443011, 18.0, 20.952737, ...)
2. **Gender:** Gender of the individual, either Male or Female. (Unique values: Male, Female)
3. **Height:** Height of the individual in centimeters. (Unique values: 1.699998, 1.56, 1.71146, ...)
4. **Weight:** Weight of the individual in kilograms. (Unique values: 81.66995, 57.0, 50.165754, ...)
5. **Family\_history:** Family history of obesity, either yes or no. (Unique values: yes, no)
6. **FAVC (Frequency of consuming high-caloric food):**
  - **Yes:** Indicates the individual frequently consumes high-caloric food.
  - **No:** Indicates the individual does not frequently consume high-caloric food.
7. **FCVC (Frequency of consuming vegetables):**
  - Ranges from approximately 1.0 to 3.0: Represents the frequency of consuming vegetables.
8. **CAEC (Consumption of food between meals):**
  - **Always:** Indicates the individual always consumes food between meals.
  - **Frequently:** Indicates the individual frequently consumes food between meals.
  - **Sometimes:** Indicates the individual sometimes consumes food between meals.
  - **No:** Indicates the individual does not consume food between meals.
9. **SMOKE (Smoking habit):**
  - **Yes:** Indicates the individual smokes.
  - **No:** Indicates the individual does not smoke.
10. **CH2O (Consumption of water daily):**
  - Ranges from approximately 1.0 to 3.0 liters: Represents the daily consumption of water in liters.
11. **FAF (Physical activity frequency):**
  - Ranges from approximately 0.0 to 3.0: Represents the frequency of physical activity.
12. **SCC (Calories consumption monitoring):**
  - **Yes:** Indicates the individual monitors their calorie consumption.
  - **No:** Indicates the individual does not monitor their calorie consumption.
13. **TUE (Time using technology devices):**
  - Ranges from approximately 0.0 to 16.0 hours: Represents the time spent using technology devices in hours.
14. **CALC (Alcohol consumption):**
  - **Sometimes:** Indicates the individual sometimes consumes alcohol.
  - **Frequently:** Indicates the individual frequently consumes alcohol.
  - **Always:** Indicates the individual always consumes alcohol.
  - **No:** Indicates the individual does not consume alcohol.
15. **MTRANS (Transportation used):**

- **Automobile:** Indicates the individual uses automobile for transportation.
  - **Bike:** Indicates the individual uses a bike for transportation.
  - **Motorbike:** Indicates the individual uses a motorbike for transportation.
  - **Public\_Transportation:** Indicates the individual uses public transportation.
  - **Walking:** Indicates the individual prefers walking as a mode of transportation.
16. **NObeyesdad (Obesity class):**
- **No\_obesity:** Indicates the individual does not suffer from obesity.
  - **Obesity\_Type\_I:** Indicates the individual belongs to obesity type I class.
  - **Obesity\_Type\_II:** Indicates the individual belongs to obesity type II class.
  - **Obesity\_Type\_III:** Indicates the individual belongs to obesity type III class.

### 3. The count of unique value in the NObeyesdad column:

```
df_train.groupby('NObeyesdad').count().iloc[:,1]
```

NObeyesdad	
Insufficient_Weight	2523
Normal_Weight	3082
Obesity_Type_I	2910
Obesity_Type_II	3248
Obesity_Type_III	4046
Overweight_Level_I	2427

Overweight_Level_II	2522
Name: Gender, dtype: int64	

- There are 2523 individuals categorized as "Insufficient\_Weight".
- There are 3082 individuals categorized as "Normal\_Weight".
- There are 2910 individuals categorized as "Obesity\_Type\_I".
- There are 3248 individuals categorized as "Obesity\_Type\_II".
- There are 4046 individuals categorized as "Obesity\_Type\_III".
- There are 2427 individuals categorized as "Overweight\_Level\_I".
- There are 2522 individuals categorized as "Overweight\_Level\_II".

## 4. Categorical and numerical Variables Analysis:

### a. Extracting column names for categorical, numerical, and categorical but cardinal variables:

```
# Function to extract column names for categorical, numerical, and
# categorical but cardinal variables

def extract_column_names(dataframe, cat_threshold=10,
car_threshold=20):
    """This function extracts the names of categorical, numerical, and
    categorical but cardinal variables from a given dataframe.

    Args:
    -----
        dataframe (pandas.DataFrame): The input dataframe containing
        all the data.
        cat_threshold (int, float, optional): The threshold value for
        considering a numerical variable as categorical. Defaults to 10.
        car_threshold (int, float, optional): The threshold value for
        considering a categorical variable as cardinal. Defaults to 20.

    Returns:
    -----
        categorical_columns: List
            List of categorical variable names.

        numerical_columns: List
            List of numerical variable names.

        categorical_but_cardinal: List
```

*List of variable names that appear categorical but are actually cardinal.*

*Notes:*

*The sum of categorical\_columns, numerical\_columns, and categorical\_but\_cardinal equals the total number of variables.  
numerical\_but\_categorical are included in categorical\_columns.  
The sum of the three returned lists is equal to the total number of variables in the dataframe.*

```
"""
# Extract categorical columns and those that seem numerical but are categorical
categorical_columns = [
    col
    for col in dataframe.columns
    if str(dataframe[col].dtypes) in ["object", "category",
"bool"]
]

numerical_but_categorical = [
    col
    for col in dataframe.columns
    if dataframe[col].nunique() < cat_threshold
    and dataframe[col].dtypes in ["int64", "float64"]
]

# Extract columns that appear categorical but are actually cardinal
categorical_but_cardinal = [
    col
    for col in dataframe.columns
    if dataframe[col].nunique() > car_threshold
    and str(dataframe[col].dtypes) in ["object", "category"]
]

# Exclude numerical_but_categorical from categorical_columns
categorical_columns = categorical_columns +
numerical_but_categorical
categorical_columns = [col for col in categorical_columns if col
not in categorical_but_cardinal]

# Extract numerical columns
numerical_columns = [
    col
    for col in dataframe.columns
    if dataframe[col].dtypes in ["int64", "float64"] and col not
in categorical_columns
```

```

]

# Print summary statistics
print(f"Observations: {dataframe.shape[0]}")
print(f"Variables: {dataframe.shape[1]}")
print(f"Categorical columns: {len(categorical_columns)}")
print(f"Numerical columns: {len(numerical_columns)}")
print(f"Categorical but cardinal columns:
{len(categorical_but_cardinal)})")
print(f"Numerical but categorical columns:
{len(numerical_but_categorical)})")

    return categorical_columns, numerical_columns,
categorical_but_cardinal

# Extract column names from the 'df_train' dataframe
categorical_cols, numerical_cols, categorical_but_cardinal =
extract_column_names(df_train)

Observations: 20758
Variables: 18
Categorical columns: 9
Numerical columns: 9
Categorical but cardinal columns: 0
Numerical but categorical columns: 0

```

- **Observations:** 20,758 rows in the dataset.
- **Variables:** Total of 18 features.
- **Categorical columns:** 9 variables are categorical.
- **Numerical columns:** 9 variables are numerical.
- **Categorical but cardinal columns:** No categorical variables with many unique values.
- **Numerical but categorical columns:** No numerical variables with few unique values.

```

print("Numerical columns:\n", numerical_cols)
print("Categorical columns:\n", categorical_cols)

Numerical columns:
['id', 'Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF',
'TUE']
Categorical columns:
['Gender', 'family_history_with_overweight', 'FAVC', 'CAEC', 'SMOKE',
'SCC', 'CALC', 'MTRANS', 'NObeyesdad']

```

## b. Summary Of All Categorical Variables:

```

def variable_summary(data_frame):
    # Initialize the summaries list

```

```

summaries = []

# Loop through each categorical variable
for col in data_frame.select_dtypes(include=['object',
'category']):
    # Summary of unique values
    unique_values = data_frame[col].unique()
    unique_count = data_frame[col].nunique()
    summaries.append(Fore.BLUE + f"Summary of {col}:" +
Style.RESET_ALL)
    summaries.append(f"Unique values of {col}: {unique_values} is
{unique_count}.\n")

    # Percentage summary
    total_count = len(data_frame[col])
    percentage_data = []
    for i, (value, count) in
enumerate(data_frame[col].value_counts().head(10).items(), start=1):
        ratio = (count / total_count) * 100
        percentage_data.append([i, value, count, f"{ratio:.2f}%"])
    percentage_headers = [Fore.GREEN + "Index", "Value", "Count",
"Percentage" + Style.RESET_ALL]
    percentage_table = tabulate(percentage_data,
headers=percentage_headers, tablefmt="fancy_grid")

    # Append the percentage table to the summaries list
    summaries.append(percentage_table)
    summaries.append('\n')

# Print the summaries
print('\n'.join(summaries))

# Assuming your dataframe is named 'df_train'
print(Fore.BLUE+"##### Summary of Categorical
variables:#####")
variable_summary(df_train)

##### Summary of Categorical
variables:#####
Summary of Gender:
Unique values of Gender: ['Male' 'Female'] is 2.

```

Index	Value	Count	Percentage
1	Female	10422	50.21%
2	Male	10336	49.79%

Summary of family\_history\_with\_overweight:

Unique values of family\_history\_with\_overweight: ['yes' 'no'] is 2.

Index	Value	Count	Percentage
1	yes	17014	81.96%
2	no	3744	18.04%

Summary of FAVC:

Unique values of FAVC: ['yes' 'no'] is 2.

Index	Value	Count	Percentage
1	yes	18982	91.44%
2	no	1776	8.56%

Summary of CAEC:

Unique values of CAEC: ['Sometimes' 'Frequently' 'no' 'Always'] is 4.

Index	Value	Count	Percentage
1	Sometimes	17529	84.44%
2	Frequently	2472	11.91%
3	Always	478	2.30%
4	no	279	1.34%

Summary of SMOKE:

Unique values of SMOKE: ['no' 'yes'] is 2.

Index	Value	Count	Percentage
1	no	20513	98.82%
2	yes	245	1.18%

Summary of SCC:

Unique values of SCC: ['no' 'yes'] is 2.

Index	Value	Count	Percentage
1	no	20071	96.69%
2	yes	687	3.31%

Summary of CALC:

Unique values of CALC: ['Sometimes' 'no' 'Frequently'] is 3.

Index	Value	Count	Percentage
1	Sometimes	15066	72.58%
2	no	5163	24.87%
3	Frequently	529	2.55%

Summary of MTRANS:

Unique values of MTRANS: ['Public\_Transportation' 'Automobile' 'Walking' 'Motorbike' 'Bike'] is 5.

Index	Value	Count	Percentage
1	Public_Transportation	16687	80.39%
2	Automobile	3534	17.02%
3	Walking	467	2.25%
4	Motorbike	38	0.18%
5	Bike	32	0.15%

Summary of NObeyesdad:

Unique values of NObeyesdad: ['Overweight\_Level\_II' 'Normal\_Weight'

```
'Insufficient_Weight'
'Obesity_Type_III' 'Obesity_Type_II' 'Overweight_Level_I'
'Obesity Type I'] is 7.
```

Index	Value	Count	Percentage
1	Obesity_Type_III	4046	19.49%
2	Obesity_Type_II	3248	15.65%
3	Normal_Weight	3082	14.85%
4	Obesity_Type_I	2910	14.02%
5	Insufficient_Weight	2523	12.15%
6	Overweight_Level_II	2522	12.15%
7	Overweight_Level_I	2427	11.69%

## c. Summary Of All Numerical Variables:

```
from tabulate import tabulate
from colorama import Fore, Style

def variable_summary(data_frame):
    # Summaries of numerical variables
    num_summaries = []
    for col in data_frame.select_dtypes(include=['int64', 'float64']):
        unique_count = data_frame[col].nunique()
        num_summaries.append(Fore.BLUE + f"Summary of {col}:" +
Style.RESET_ALL)
        num_summaries.append(f"Unique values of {col}: is
{unique_count}.\n")
        summary = data_frame[col].describe().reset_index()
        summary.columns = [Fore.RED +"Statistic", col +
Style.RESET_ALL]
        num_summaries.append(tabulate(summary, headers="keys",
tablefmt="fancy_grid"))

    print(Fore.BLUE + "##### Summaries of numerical
variables #####")
    print(Style.RESET_ALL)
    print("\n".join(num_summaries))
```

```
# Assuming your dataframe is named 'df_train'
variable_summary(df_train)

##### Summaries of numerical variables
#####

Summary of id:
Unique values of id: is 20758.
```

Summary of Age:  
 Unique values of Age: is 1703.

	Statistic	id
0	count	20758
1	mean	10378.5
2	std	5992.46
3	min	0
4	25%	5189.25
5	50%	10378.5
6	75%	15567.8
7	max	20757

Summary of Age:  
 Unique values of Age: is 1703.

	Statistic	Age
0	count	20758
1	mean	23.8418
2	std	5.68807
3	min	14
4	25%	20
5	50%	22.8154
6	75%	26
7	max	61

Summary of Height:  
Unique values of Height: is 1833.

	Statistic	Height
0	count	20758
1	mean	1.70024
2	std	0.0873119
3	min	1.45
4	25%	1.63186
5	50%	1.7
6	75%	1.76289
7	max	1.97566

Summary of Weight:  
Unique values of Weight: is 1979.

	Statistic	Weight
0	count	20758
1	mean	87.8878
2	std	26.3794
3	min	39
4	25%	66
5	50%	84.0649
6	75%	111.601
7	max	165.057

Summary of FCVC:  
Unique values of FCVC: is 934.

	Statistic	FCVC
0	count	20758
1	mean	2.44591
2	std	0.533218
3	min	1
4	25%	2
5	50%	2.39384
6	75%	3
7	max	3

Summary of NCP:

Unique values of NCP: is 689.

	Statistic	NCP
0	count	20758
1	mean	2.76133
2	std	0.705375
3	min	1
4	25%	3
5	50%	3
6	75%	3
7	max	4

Summary of CH2O:

Unique values of CH2O: is 1506.

	Statistic	FAF
0	count	20758
1	mean	0.981747
2	std	0.838302
3	min	0
4	25%	0.008013
5	50%	1
6	75%	1.58741
7	max	3

Summary of FAF:

Unique values of FAF: is 1360

	Statistic	CH2O
0	count	20758
1	mean	2.02942
2	std	0.608467
3	min	1
4	25%	1.79202
5	50%	2
6	75%	2.54962
7	max	3

## Section: 4. Data Preprocessing:

### 1. Typeconversion of dataframe:

```
# Define a function to convert column datatype to integer
def convert_column_datatype(df, column_name):
    """
        Convert the data type of a specified column in the dataframe to
        integer.

    Parameters:
        df (DataFrame): The dataframe containing the column to be
        converted.
        column_name (str): The name of the column to be converted.

    Returns:
        DataFrame: The dataframe with the specified column converted to
        integer data type.
    """
    df[column_name] = df[column_name].astype('int32')
    return df

# Example usage:
df_train = convert_column_datatype(df_train, 'Age')
df_train = convert_column_datatype(df_train, 'Weight')

# Example usage:
test_sub = convert_column_datatype(test_sub, 'Age')
test_sub = convert_column_datatype(test_sub, 'Weight')
```

### 2. Renaming the Columns:

```
new_column_names = {
    'Gender': 'Gender',
    'Age': 'Age',
    'Height': 'Height',
```

```

'Weight': 'Weight',
'family_history_with_overweight': 'Overweighted Family History',
'FAVC': 'High caleric food consp',
'FCVC': 'veg consp',
'NCP': 'main meal consp',
'CAEC': 'Food btw meal consp',
'SMOKE': 'SMOKE',
'CH2O': 'Water consp',
'SCC': 'Calories Monitoring',
'FAF': 'physical actv',
'TUE': 'Screentime',
'CALC': 'Alcohol consp',
'MTRANS': 'transport used',
'NObeyesdad': 'Obesity_Level'
}

# Rename the columns for train data
df_train.rename(columns=new_column_names, inplace=True)

df_train.head(5)

    id   Gender   Age     Height   Weight Overweighted Family History \
0    0      Male   24  1.699998      81                  yes
1    1  Female   18  1.560000      57                  yes
2    2  Female   18  1.711460      50                  yes
3    3  Female   20  1.710730     131                  yes
4    4      Male   31  1.914186      93                  yes

    High caleric food consp   veg consp   main meal consp Food btw meal \
0                               yes  2.000000  2.983297
Sometimes
1                               yes  2.000000  3.000000
Frequently
2                               yes  1.880534  1.411685
Sometimes
3                               yes  3.000000  3.000000
Sometimes
4                               yes  2.679664  1.971472
Sometimes

    SMOKE   Water consp Calories Monitoring physical actv  Screentime \
0    no      2.763573                    no  0.000000  0.976473
1    no      2.000000                    no  1.000000  1.000000
2    no      1.910378                    no  0.866045  1.673584
3    no      1.674061                    no  1.467863  0.780199
4    no      1.979848                    no  1.967973  0.931721

    Alcohol consp      transport used   Obesity_Level
0    Sometimes  Public_Transportation  Overweight_Level_II

```

```

1          no             Automobile           Normal_Weight
2          no  Public_Transportation  Insufficient_Weight
3 Sometimes  Public_Transportation    Obesity_Type_III
4 Sometimes  Public_Transportation Overweight_Level_II

test sub.head(5)

      id  Gender   Age     Height  Weight family_history_with_overweight
FAVC \
0 20758    Male    26  1.848294      120                               yes
yes
1 20759  Female    21  1.600000       66                               yes
yes
2 20760  Female    26  1.643355      111                               yes
yes
3 20761    Male    20  1.553127      103                               yes
yes
4 20762  Female    26  1.627396      104                               yes
yes

      FCVC        NCP      CAEC  SMOKE      CH2O  SCC      FAF
TUE \
0  2.938616  3.000000  Sometimes      no  2.825629  no  0.855400
0.000000
1  2.000000  1.000000  Sometimes      no  3.000000  no  1.000000
0.000000
2  3.000000  3.000000  Sometimes      no  2.621877  no  0.000000
0.250502
3  2.000000  2.977909  Sometimes      no  2.786417  no  0.094851
0.000000
4  3.000000  3.000000  Sometimes      no  2.653531  no  0.000000
0.741069

      CALC        MTRANS
0 Sometimes  Public_Transportation
1 Sometimes  Public_Transportation
2 Sometimes  Public_Transportation
3 Sometimes  Public_Transportation
4 Sometimes  Public Transportation

```

### 3. Detecting Columns with Large or Infinite Values:

```

def columns_with_infinite_values(df):
    numeric_df = df.select_dtypes(include=[np.number]) # Select only
    numeric_columns
    inf_values = np.isinf(numeric_df)

```

```

columns_with_inf = numeric_df.columns[np.any(inf_values, axis=0)]
return columns_with_inf

print("Columns with infinite values:\n",
columns_with_infinite_values(df_train))

Columns with infinite values:
Index([], dtype='object')

def columns_with_large_numbers(df):
    numeric_df = df.select_dtypes(include=[np.number]) # Select only
    numeric_columns
    large_values = np.abs(numeric_df) > 1e15
    columns_with_large = numeric_df.columns[np.any(large_values,
axis=0)]
    return columns_with_large

print("Columns with large values:\n",
columns_with_large_numbers(df_train))

Columns with large values:
Index([], dtype='object')

```

This output indicates that there are no columns in the dataset with infinite or large values.

## Section:5. Exploratory Data Analysis and Visualisation-EDAV:

### 1. Univariate Analysis:

#### a. Countplots for all Variables:

```

plt.figure(figsize=(30, 25))
plt.suptitle('Countplots for all Variables', fontsize=24,
fontweight='bold')

# Get the list of column names from the dataframe
columns = df_train.columns

# Determine the number of rows and columns for subplots
num_rows = (len(columns) + 2) // 3 # Add 2 to round up to the nearest
multiple of 3
num_cols = 3

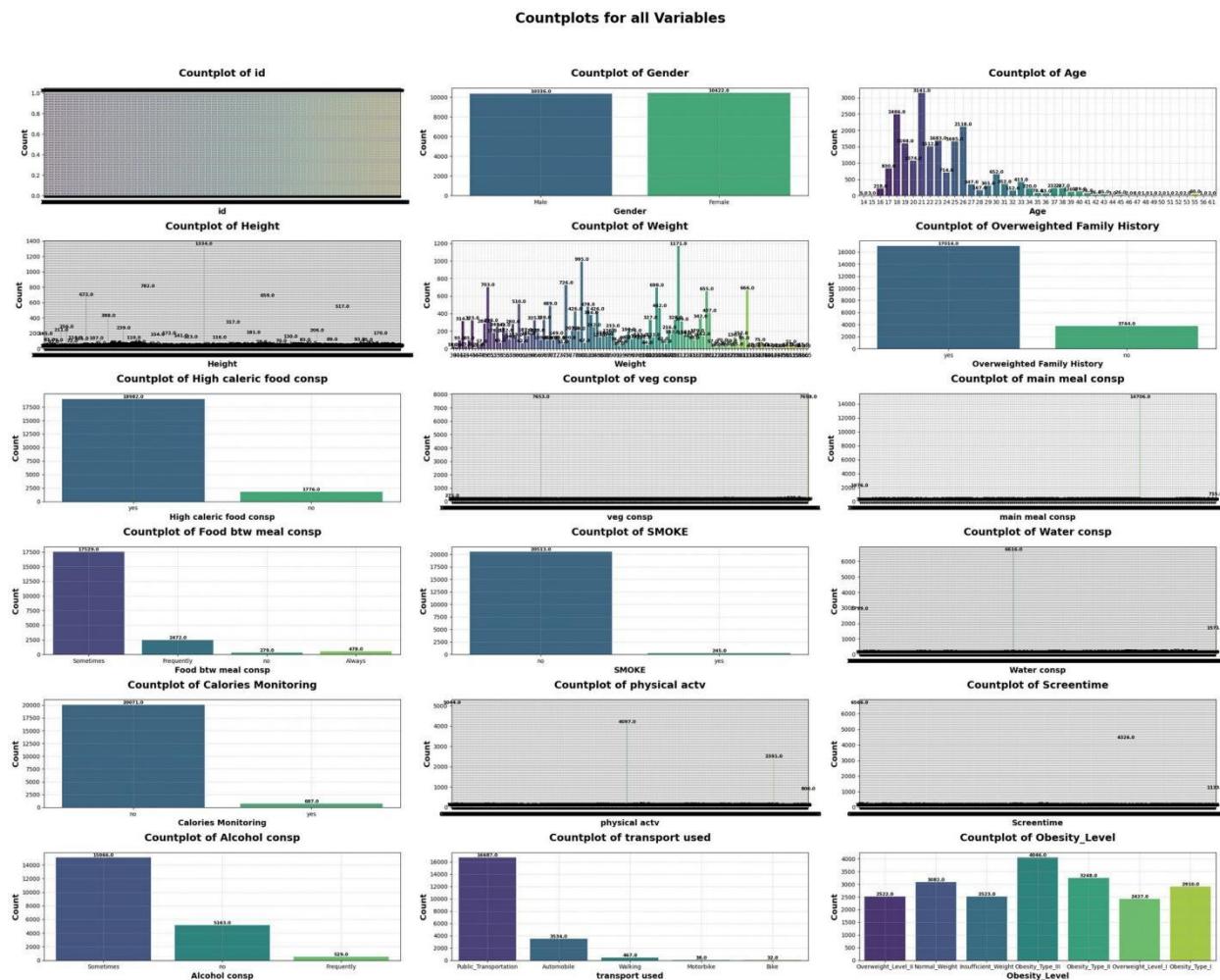
```

```

# Create countplots for each variable
for i, col in enumerate(columns, start=1):
    ax = plt.subplot(num_rows, num_cols, i)
    sns.countplot(x=df_train[col], palette='viridis') # Add color
    palette for better visualization
    ax.set_title(f'Countplot of {col}', fontsize=18, pad=20,
    fontweight='bold')
    plt.xlabel(col, fontsize=14, fontweight='bold') # Add bold
    fontweight to x-axis label
    plt.ylabel('Count', fontsize=14, fontweight='bold') # Add bold
    fontweight to y-axis label
    plt.grid(True, linestyle='--', alpha=0.5)
    # Add count indicators on top of each bar
    for p in ax.patches:
        height = p.get_height()
        ax.annotate(f'{height}', (p.get_x() + p.get_width() / 2.,
height), ha='center', va='bottom', fontsize=8, fontweight='bold')

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()

```



## b. Analyzing Individual Variables Using Histogram:

```
plt.figure(figsize=(18, 14))
plt.suptitle('Analyzing Individual Variables', fontsize=20)

# Age
plt.subplot(3, 3, 1)
sns.histplot(df_train['Age'], kde=True, bins=15, color='skyblue')
plt.title('Distribution of Age', fontsize=16)
plt.xlabel('Age', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mean_age = df_train['Age'].mean()
median_age = df_train['Age'].median()
plt.axvline(x=mean_age, color='red', linestyle='--', label=f'Mean:\n{mean_age:.2f}')
plt.axvline(x=median_age, color='green', linestyle='--', label=f'Median:\n{median_age:.2f}')
```

```

plt.axvline(x=median_age, color='green', linestyle='--',
label=f'Median: {median_age:.2f}')
plt.legend()

# Height
plt.subplot(3, 3, 2)
sns.histplot(df_train['Height'], kde=True, bins=15, color='salmon')
plt.title('Distribution of Height', fontsize=16)
plt.xlabel('Height', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mean_height = df_train['Height'].mean()
median_height = df_train['Height'].median()
plt.axvline(x=mean_height, color='red', linestyle='--', label=f'Mean:
{mean_height:.2f}')
plt.axvline(x=median_height, color='green', linestyle='--',
label=f'Median: {median_height:.2f}')
plt.legend()

# Weight
plt.subplot(3, 3, 3)
sns.histplot(df_train['Weight'], kde=True, bins=15,
color='lightgreen')
plt.title('Distribution of Weight', fontsize=16)
plt.xlabel('Weight', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mean_weight = df_train['Weight'].mean()
median_weight = df_train['Weight'].median()
plt.axvline(x=mean_weight, color='red', linestyle='--', label=f'Mean:
{mean_weight:.2f}')
plt.axvline(x=median_weight, color='green', linestyle='--',
label=f'Median: {median_weight:.2f}')
plt.legend()

# Screentime
plt.subplot(3, 3, 4)
sns.histplot(df_train['Screentime'], kde=True, bins=15,
color='orange')
plt.title('Distribution of Screentime', fontsize=16)
plt.xlabel('Screentime', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mean_screentime = df_train['Screentime'].mean()
median_screentime = df_train['Screentime'].median()
plt.axvline(x=mean_screentime, color='red', linestyle='--',
label=f'Mean: {mean_screentime:.2f}')
plt.axvline(x=median_screentime, color='green', linestyle='--',
label=f'Median: {median_screentime:.2f}')
plt.legend()

```

```

# Alcohol consumption
plt.subplot(3, 3, 5)
sns.histplot(df_train['Alcohol consp'], kde=True, bins=15,
color='lightcoral')
plt.title('Distribution of Alcohol Consumption', fontsize=16)
plt.xlabel('Alcohol Consumption', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mode_AlcoholConsp = df_train['Alcohol consp'].mode()[0]
plt.text(0.5, 0.5, f'Mode: {mode_AlcoholConsp}', horizontalalignment='center', verticalalignment='center', transform=plt.gca().transAxes)

# Transportation used
plt.subplot(3, 3, 6)
sns.histplot(df_train['transport used'], kde=True, bins=15,
color='lightblue')
plt.title('Distribution of Transportation Used', fontsize=16)
plt.xlabel('Transportation', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mode_transportation = df_train['transport used'].mode()[0]
plt.text(0.5, 0.5, f'Mode: {mode_transportation}', horizontalalignment='center', verticalalignment='center', transform=plt.gca().transAxes)

# Main Meal Consumption
plt.subplot(3, 3, 7)
sns.histplot(df_train['main meal consp'], kde=True, bins=15,
color='lightgrey')
plt.title('Distribution of Main Meal Consumption', fontsize=16)
plt.xlabel('Main Meal Consumption', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mean_main_meal_consp = df_train['main meal consp'].mean()
median_main_meal_consp = df_train['main meal consp'].median()
plt.axvline(x=mean_main_meal_consp, color='red', linestyle='--', label=f'Mean: {mean_main_meal_consp:.2f}')
plt.axvline(x=median_main_meal_consp, color='green', linestyle='--', label=f'Median: {median_main_meal_consp:.2f}')
plt.legend()

# Water consumption
plt.subplot(3, 3, 8)
sns.histplot(df_train['Water consp'], kde=True, bins=15,
color='lightcoral')
plt.title('Distribution of Water Consumption', fontsize=16)
plt.xlabel('Water Consumption', fontsize=14)
plt.ylabel('Frequency', fontsize=14)

```

```

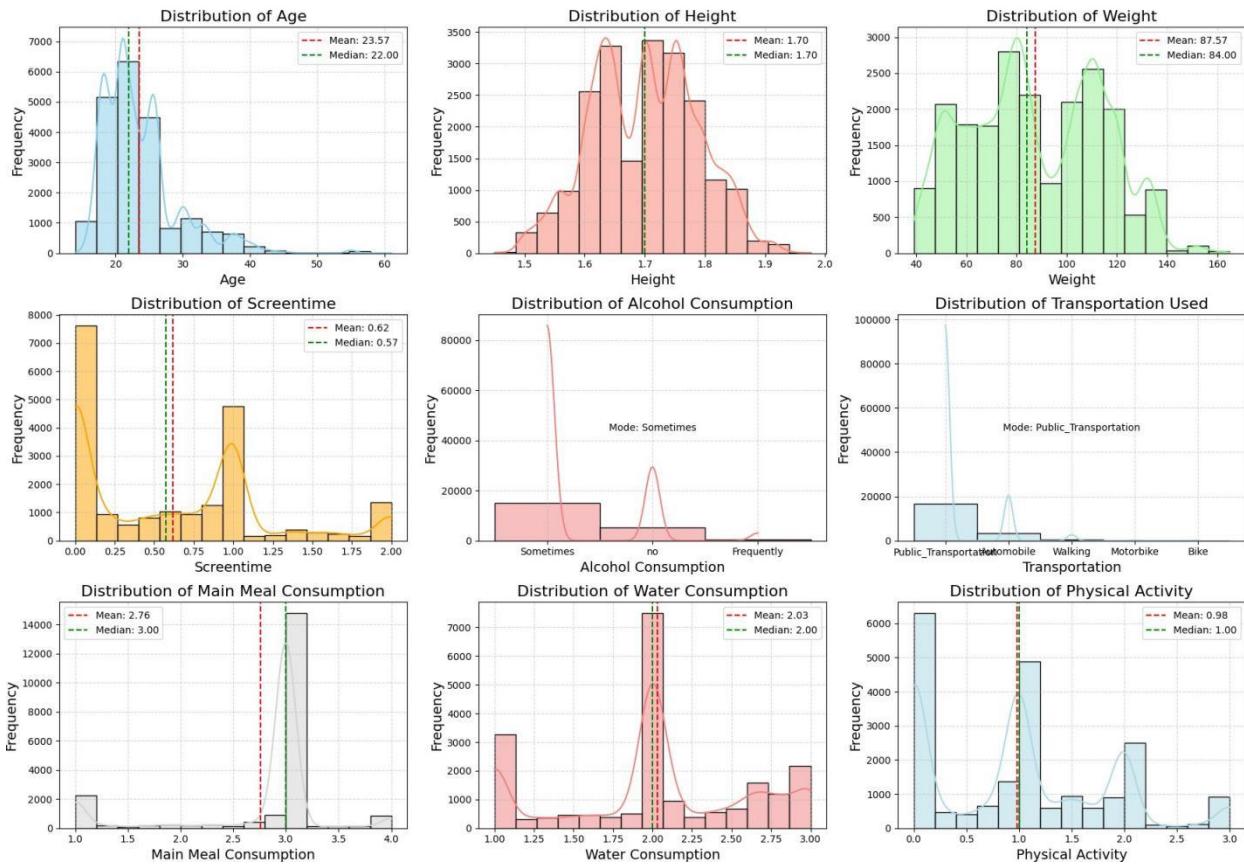
plt.grid(True, linestyle='--', alpha=0.5)
mean_water_consp = df_train['Water consp'].mean()
median_water_consp = df_train['Water consp'].median()
plt.axvline(x=mean_water_consp, color='red', linestyle='--',
label=f'Mean: {mean_water_consp:.2f}')
plt.axvline(x=median_water_consp, color='green', linestyle='--',
label=f'Median: {median_water_consp:.2f}')
plt.legend()

# Physical activity
plt.subplot(3, 3, 9)
sns.histplot(df_train['physical actv'], kde=True, bins=15,
color='lightblue')
plt.title('Distribution of Physical Activity', fontsize=16)
plt.xlabel('Physical Activity', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
mean_physical_actv = df_train['physical actv'].mean()
median_physical_actv = df_train['physical actv'].median()
plt.axvline(x=mean_physical_actv, color='red', linestyle='--',
label=f'Mean: {mean_physical_actv:.2f}')
plt.axvline(x=median_physical_actv, color='green', linestyle='--',
label=f'Median: {median_physical_actv:.2f}')
plt.legend()

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()

```

## Analyzing Individual Variables



## c. KDE Plots of Numerical Columns:

```
# Define numerical_cols
numerical_cols = df_train.select_dtypes(include=['float64',
'int64']).columns

# Function to plot KDE density for numerical columns in three plots
# per row
def plot_kde_density(df):
    num_plots = len(numerical_cols)
    num_rows = (num_plots + 2) // 2 # Calculate number of rows
    required

    fig, axes = plt.subplots(num_rows, 2, figsize=(20, 5*num_rows))
    fig.suptitle('KDE Plots of Numerical Columns', fontsize=20)

    for i, col in enumerate(numerical_cols):
        row = i // 2
        col_idx = i % 2
        ax = axes[row, col_idx]
```

```

sns.kdeplot(data=df[col], fill=True, color='skyblue', ax=ax)
ax.set_xlabel(col)
ax.set_ylabel('Density')
ax.set_title(f'KDE Plot of {col}')

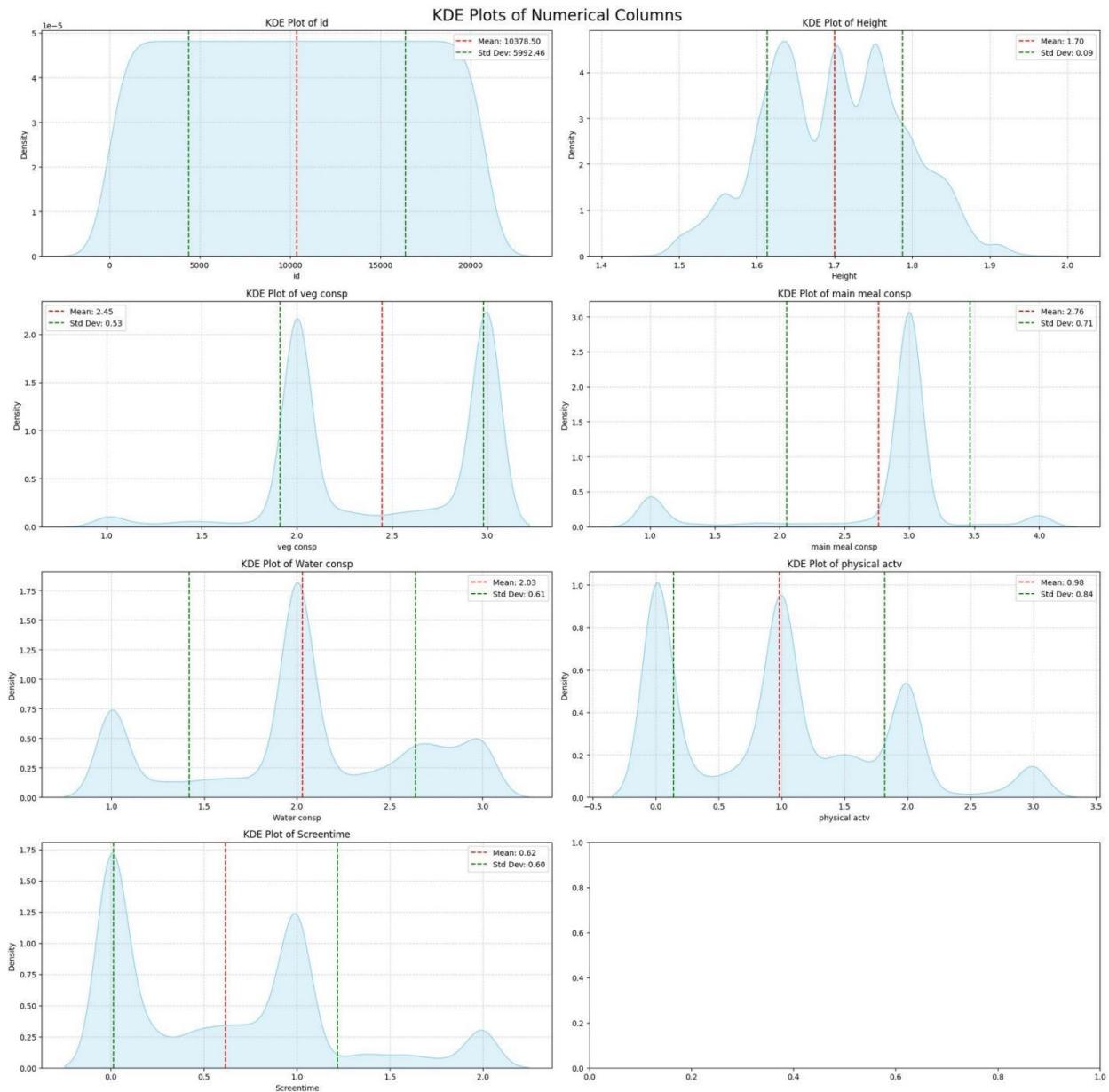
# Add mean and standard deviation information
mean = df[col].mean()
std_dev = df[col].std()
ax.axvline(x=mean, linestyle='--', color='red', label=f'Mean: {mean:.2f}')
ax.axvline(x=mean - std_dev, linestyle='--', color='green', label=f'StD Dev: {std_dev:.2f}')
ax.axvline(x=mean + std_dev, linestyle='--', color='green')
ax.legend()

# Add grid lines for better visualization
ax.grid(True, linestyle='--', alpha=0.5)

plt.tight_layout()
plt.show()

# Call the function to plot KDE density for numerical columns in df_train
plot_kde_density(df_train)

```



## d. Pie Chart and Barplot for categorical variables:

```
def plot_data(df):
    """
    Plot different types of plots for each categorical column in the
    DataFrame.

    Parameters:
        df (DataFrame): The input DataFrame containing categorical
    """

```

```

columns.

>Returns:
None
"""
# Selecting categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns

# Create subplots
fig, axes = plt.subplots(len(categorical_cols), 2, figsize=(14,
7*len(categorical_cols)))

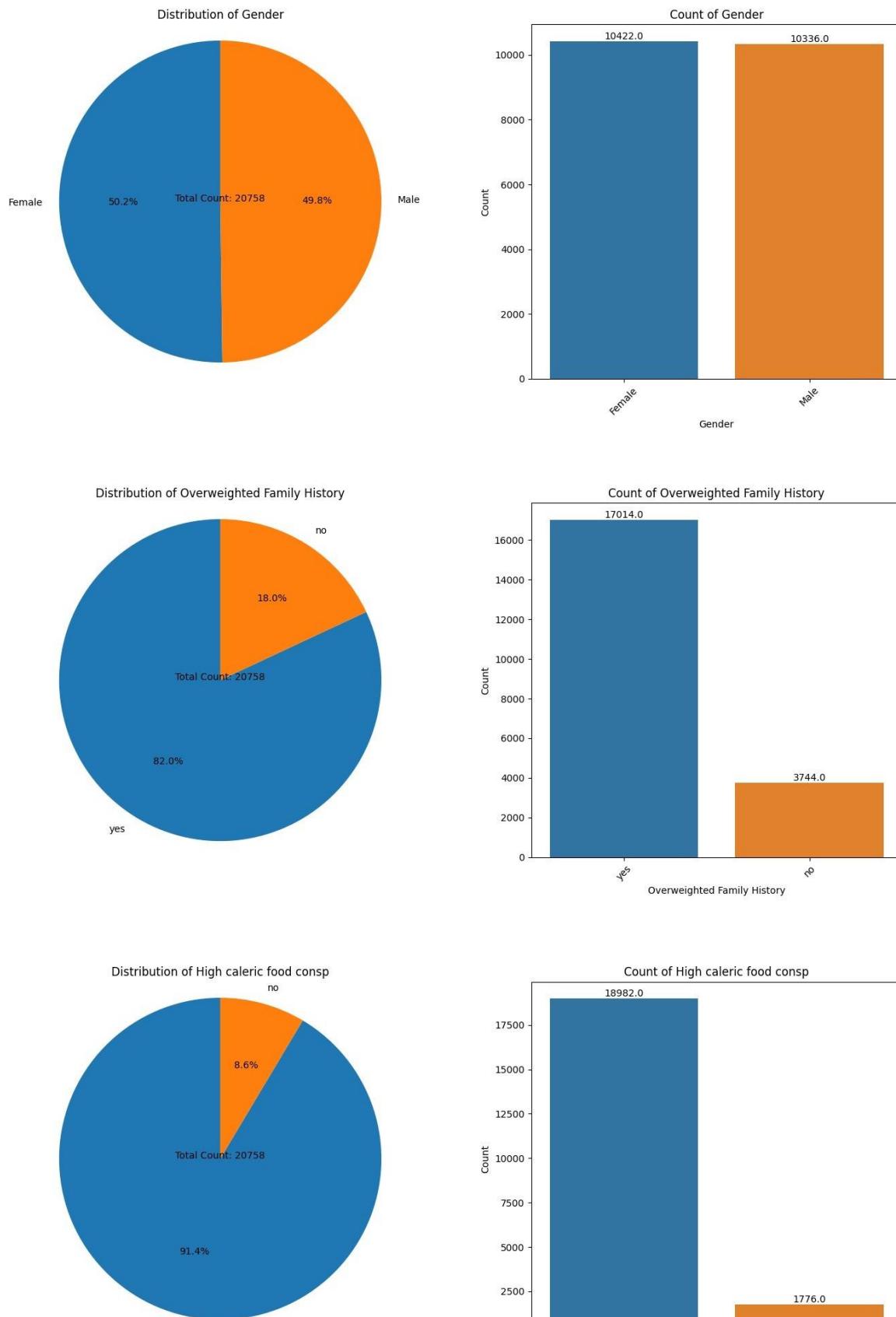
# Plotting pie chart for each categorical variable in the first
column
for i, col in enumerate(categorical_cols):
    ax = axes[i, 0]
    value_counts = df[col].value_counts()
    ax.pie(value_counts, labels=value_counts.index, autopct='%.1f %%',
    startangle=90)
    ax.set_title(f'Distribution of {col}')
    ax.set_ylabel('')
    ax.axis('equal') # Equal aspect ratio ensures that pie is
drawn as a circle
    ax.annotate(f'Total Count: {len(df[col])}', xy=(0, 0),
    fontsize=10, ha="center")

# Plotting bar plot for each categorical variable in the second
column
for i, col in enumerate(categorical_cols):
    ax = axes[i, 1]
    value_counts = df[col].value_counts()
    sns.barplot(x=value_counts.index, y=value_counts, ax=ax)
    ax.set_title(f'Count of {col}')
    ax.set_xlabel(f'{col}')
    ax.set_ylabel('Count')
    ax.tick_params(axis='x', rotation=45) # Rotate x-axis labels
for better readability
    for patch in ax.patches:
        ax.annotate(f'{patch.get_height()}', (patch.get_x() +
patch.get_width() / 2., patch.get_height()),
        ha='center', va='center', fontsize=10,
        color='black', xytext=(0, 5),
        textcoords='offset points')

plt.tight_layout()
plt.show()

# Call the function to plot different types of plots for df_train
plot_data(df_train)

```



## e. Violin Plot and Box Plot for Numerical variables:

```
def plot_data(df):
    """
    Plot different types of plots for each column in the DataFrame.

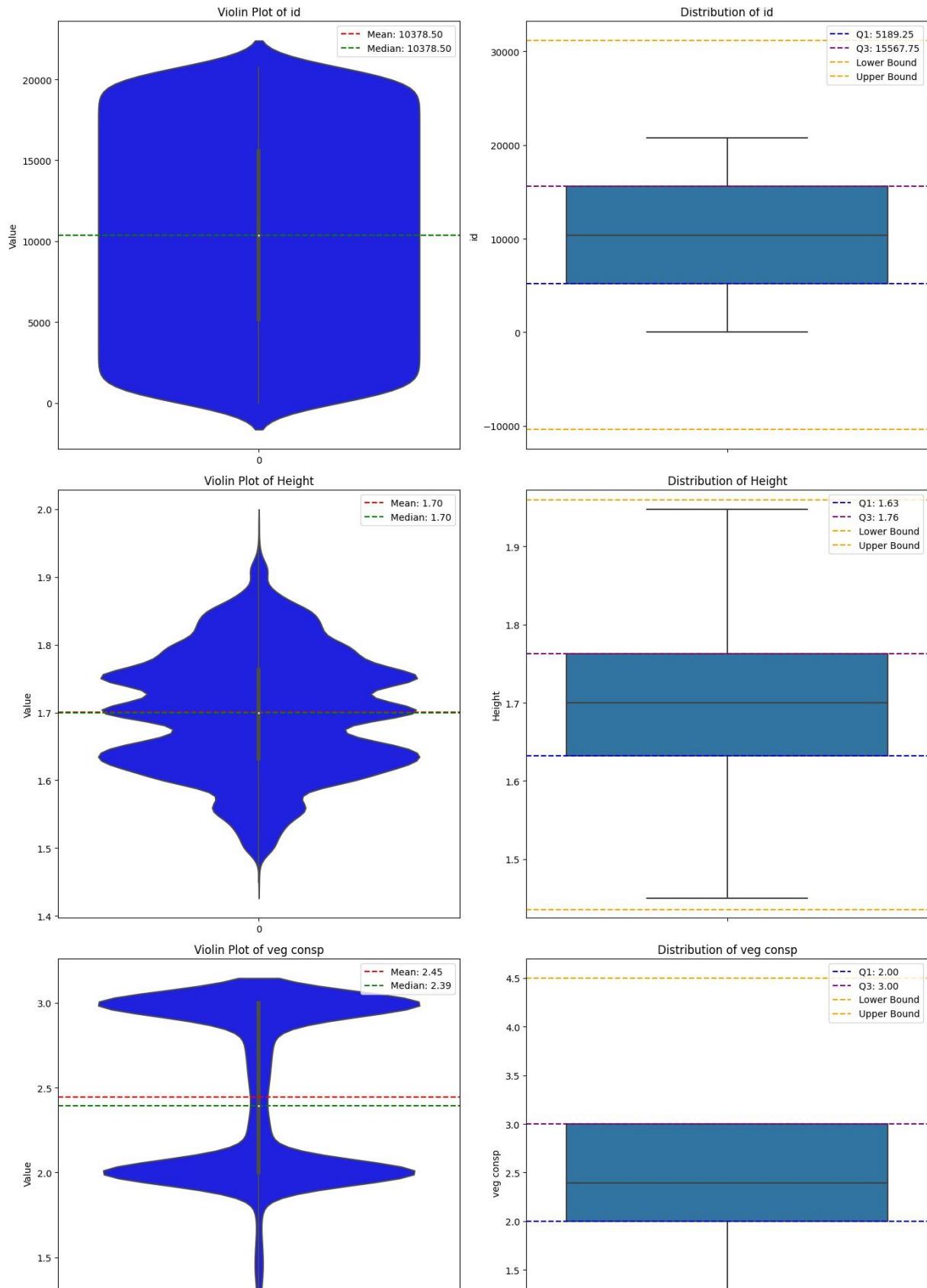
    Parameters:
        df (DataFrame): The input DataFrame.

    Returns:
        None
    """
    numerical_cols = df.select_dtypes(include=['float64',
                                                'int64']).columns

    # Create subplots
    fig, axes = plt.subplots(len(numerical_cols), 2, figsize=(14,
    7*len(numerical_cols)))

    # Plotting violin plot for each numerical variable in the first
    # column
    for i, col in enumerate(numerical_cols):
        ax = axes[i, 0]
        sns.violinplot(data=df[col], ax=ax, color='blue')
        ax.set_title(f'Violin Plot of {col}')
        ax.set_xlabel('')
        ax.set_ylabel('Value')
        # Add statistical information
        mean = df[col].mean()
        median = df[col].median()
        ax.axhline(y=mean, color='red', linestyle='--', label=f'Mean: {mean:.2f}')
        ax.axhline(y=median, color='green', linestyle='--',
        label=f'Median: {median:.2f}')
        ax.legend()

    # Plotting box plot for each numerical variable in the second
    # column
    for i, col in enumerate(numerical_cols):
        ax = axes[i, 1]
        sns.boxplot(data=df, y=col, ax=ax, showfliers=False)
        ax.set_title(f'Distribution of {col}')
        ax.set_ylabel(f'{col}')
        ax.set_xlabel('') # Remove x-axis label as it represents
        'Level' which is not available
        # Add statistical information
        q1 = df[col].quantile(0.25)
```



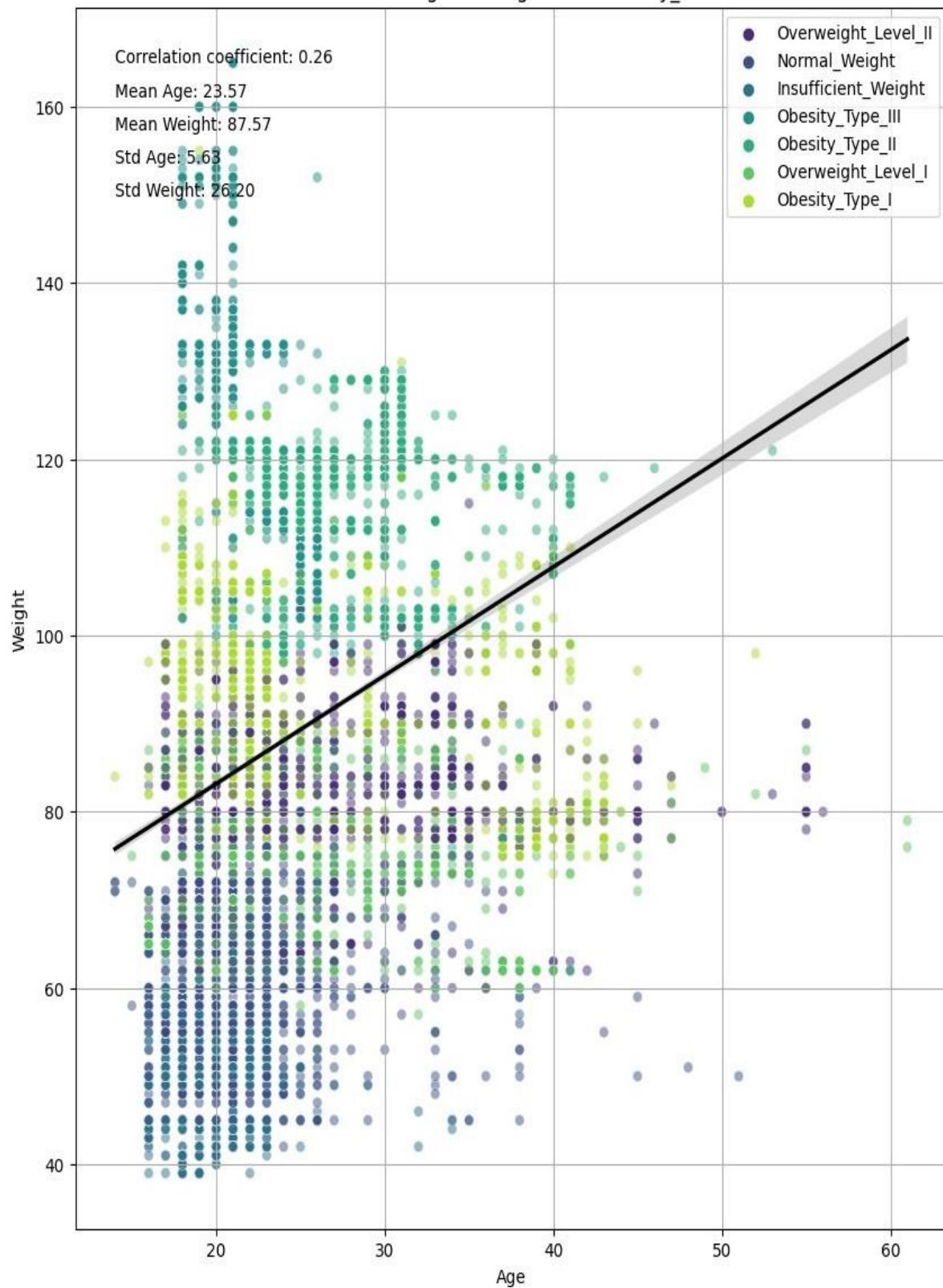
## 2. Bivariate Analysis:

```
def plot_scatter_relationship(col1, col2, target=None, data=None):  
    plt.figure(figsize=(10, 12))  
  
    # Plotting the scatter plot  
    sns.scatterplot(data=data, x=col1, y=col2, hue=target,  
                     palette='viridis', alpha=0.5)  
  
    # Calculating correlation coefficient  
    corr_coef, _ = pearsonr(data[col1], data[col2])  
  
    # Adding regression lines  
    sns.regplot(data=data, x=col1, y=col2, scatter=False,  
                color='black')  
  
    # Adding statistical summary  
    plt.text(data[col1].min(), data[col2].max(), f'Correlation  
coefficient: {corr_coef:.2f}', fontsize=10)  
    plt.text(data[col1].min(), data[col2].max() - 0.03 *  
(data[col2].max() - data[col2].min()), f'Mean {col1}:  
{data[col1].mean():.2f}', fontsize=10)  
    plt.text(data[col1].min(), data[col2].max() - 0.06 *  
(data[col2].max() - data[col2].min()), f'Mean {col2}:  
{data[col2].mean():.2f}', fontsize=10)  
    plt.text(data[col1].min(), data[col2].max() - 0.09 *  
(data[col2].max() - data[col2].min()), f'Std {col1}:  
{data[col1].std():.2f}', fontsize=10)  
    plt.text(data[col1].min(), data[col2].max() - 0.12 *  
(data[col2].max() - data[col2].min()), f'Std {col2}:  
{data[col2].std():.2f}', fontsize=10)  
  
    plt.xlabel(col1)  
    plt.ylabel(col2)  
    plt.title(f'Scatter Plot: {col1} vs {col2} with {target}')  
    plt.grid(True)  
    plt.legend()  
    plt.show()
```

### a. Scatter plot: AGE V/s Weight with Obesity Level:

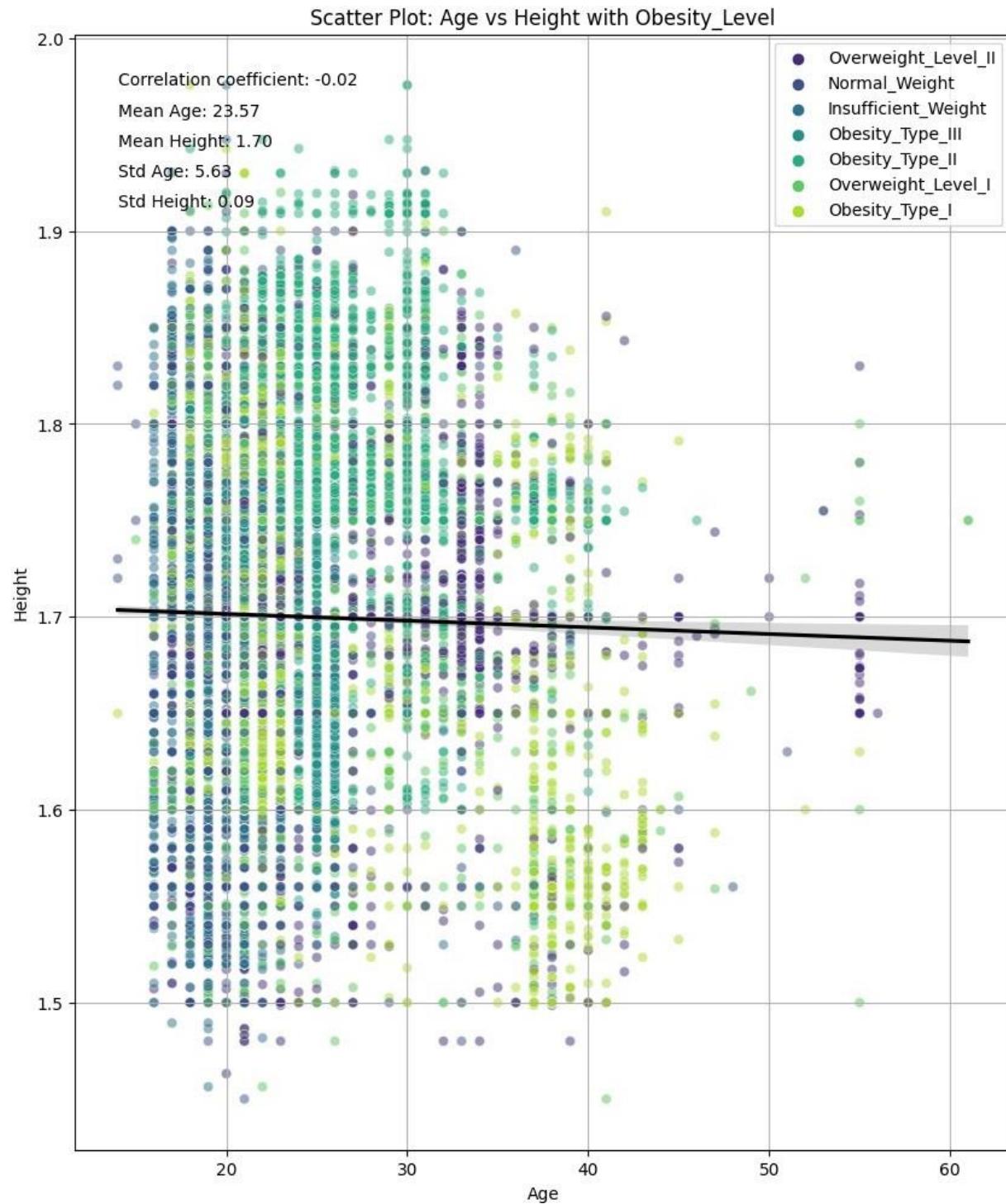
```
plot_scatter_relationship('Age', 'Weight', 'Obesity_Level', df_train)
```

Scatter Plot: Age vs Weight with Obesity\_Level



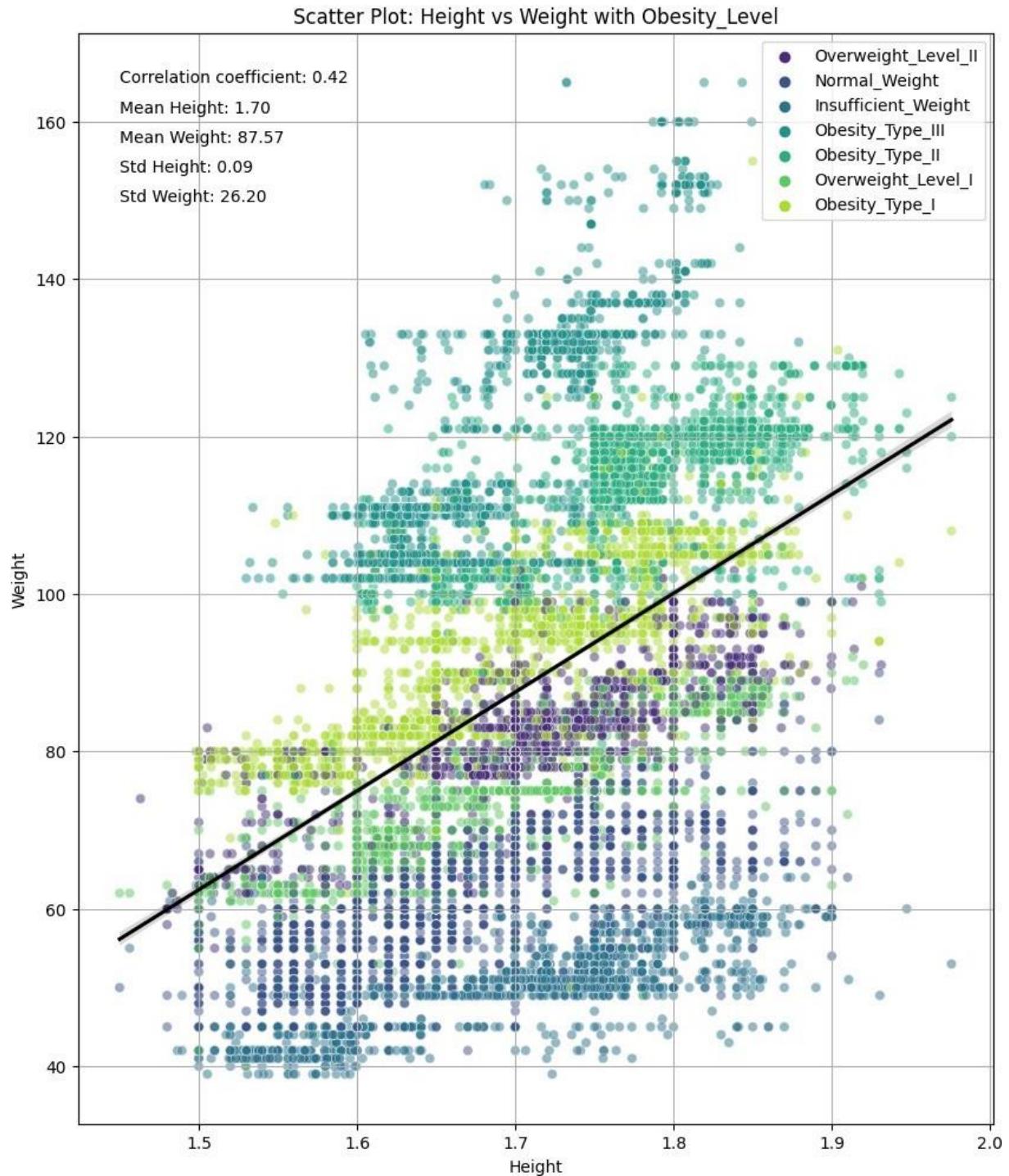
## b. Scatter plot: AGE V/s Height with Obesity Level:

```
plot_scatter_relationship('Age', 'Height', 'Obesity_Level', df_train)
```



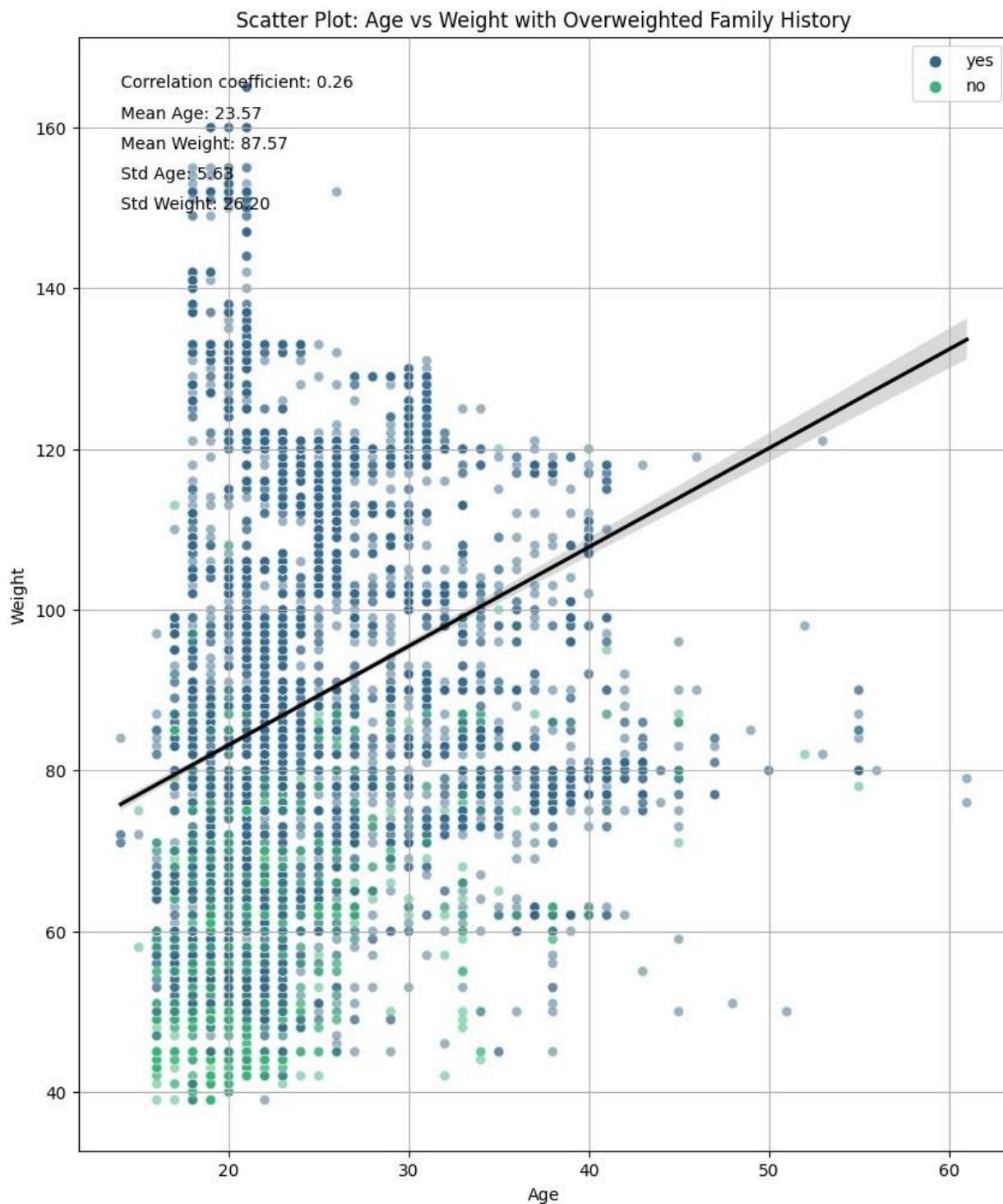
### c. Scatter plot: Height V/s Weight with Obesity Level:

```
plot_scatter_relationship('Height', 'Weight', 'Obesity_Level', df_train)
```



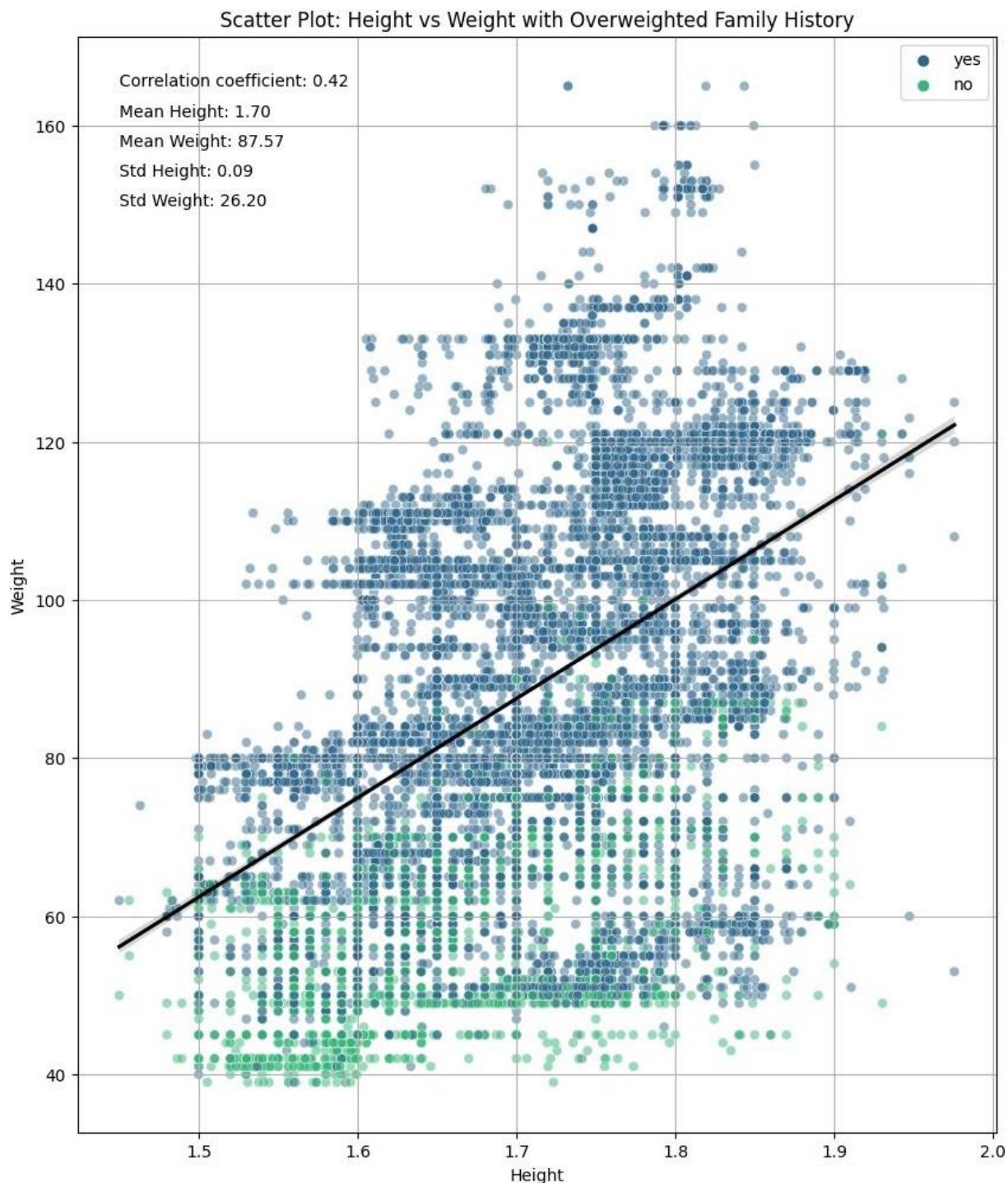
## d. Scatter plot: AGE V/s Weight with Overweighted Family History:

```
plot_scatter_relationship('Age', 'Weight', 'Overweighted Family History', df_train)
```



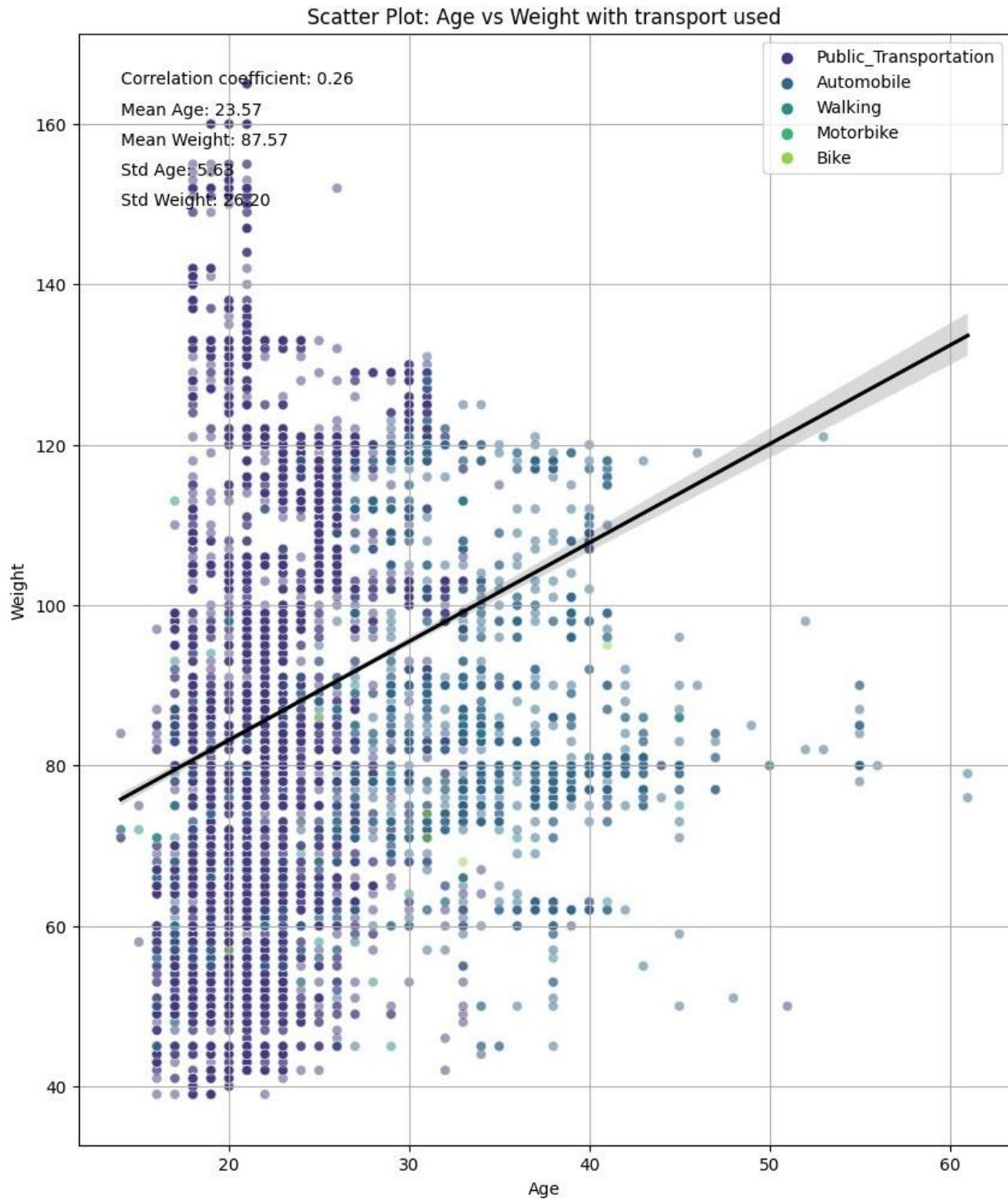
## e.Scatter plot: Height V/s Weight with Overweighted Family History:

```
plot_scatter_relationship('Height','Weight','Overweighted Family History',df_train)
```



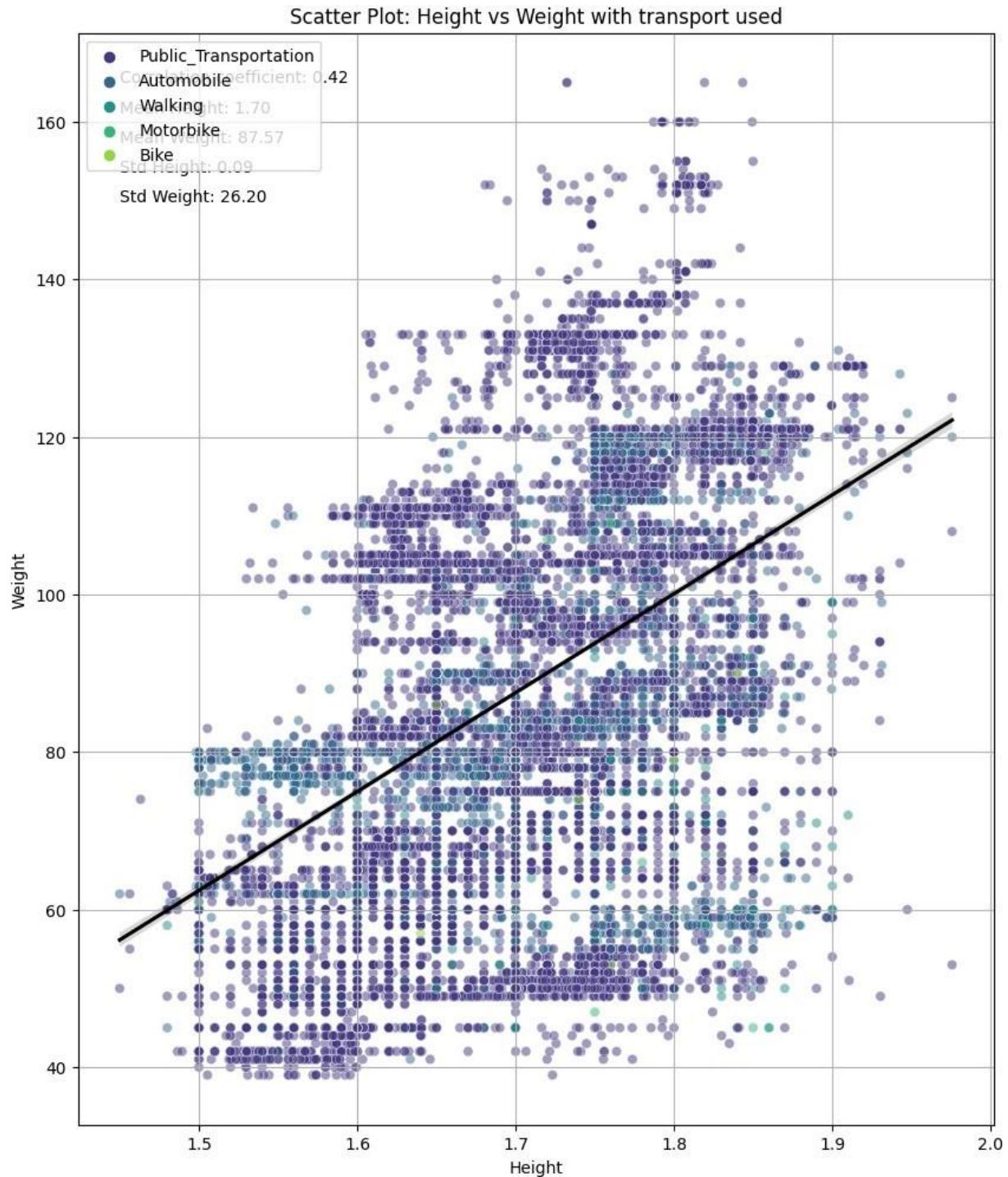
## f. Scatter plot: AGE V/s Weight with Transport use:

```
plot_scatter_relationship('Age', 'Weight', 'transport used', df_train)
```



## g.Scatter plot: Height V/s Weight with Transport use:

```
plot_scatter_relationship('Height','Weight','transport used',df_train)
```



### 3. Multivariate Analysis:

#### a. Pair Plot of Variables against Obesity Levels:

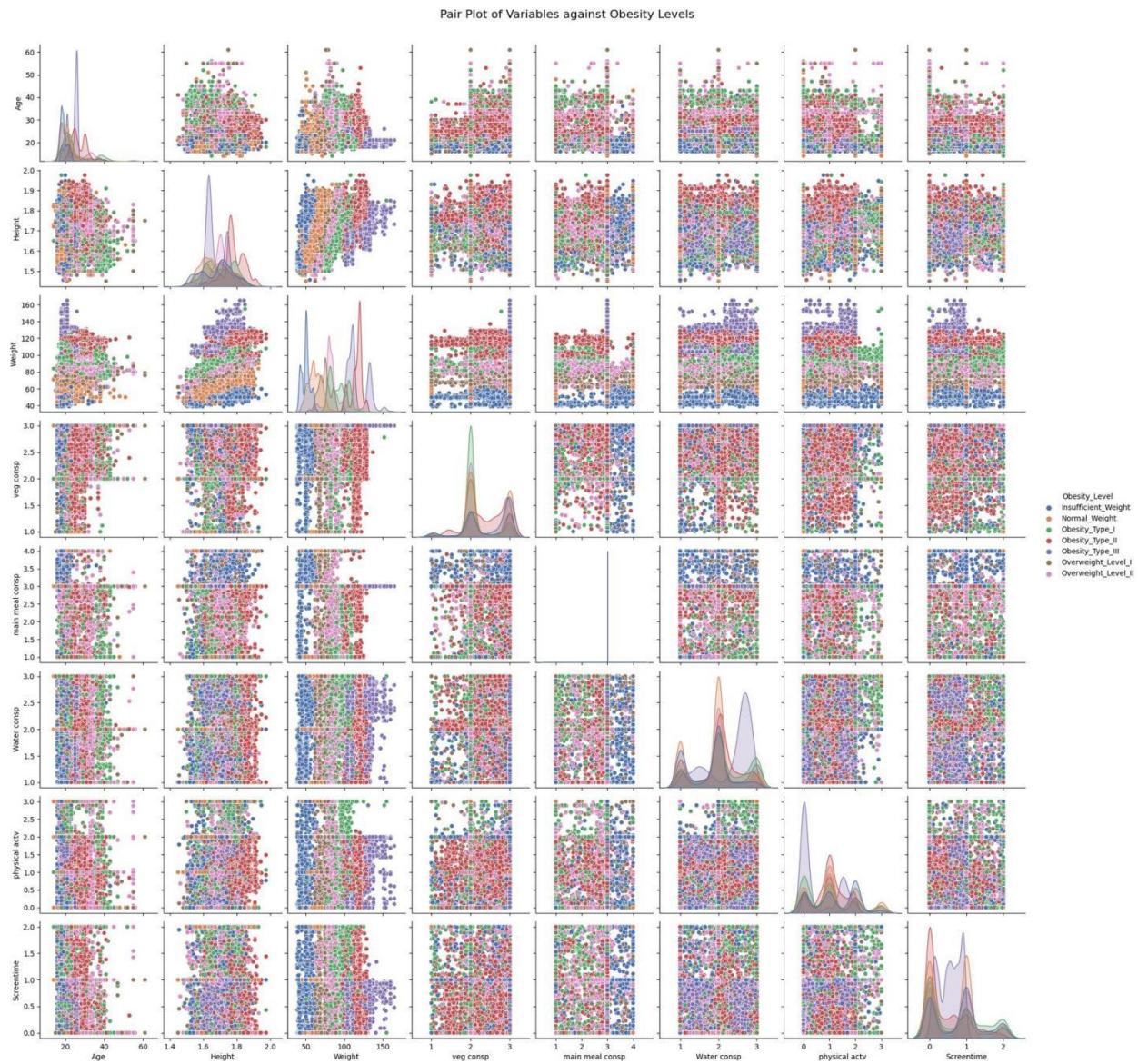
```
# Selecting numerical columns for pairplot
numerical_columns = ['Age', 'Height', 'Weight', 'High caloric food
consp', 'veg consp', 'main meal consp',
                     'Food btw meal consp', 'Water consp', 'Calories
Monitoring', 'physical actv', 'Screentime',
                     'Alcohol consp']

# Add the target variable 'Obesity_Level' for hue
df_train['Obesity_Level'] =
df_train['Obesity_Level'].astype('category')

# Create pair plot
pair_plot = sns.pairplot(df_train[numerical_columns +
['Obesity_Level']], hue='Obesity_Level', palette='deep',
diag_kind='kde')

# Add title to the plot
pair_plot.fig.suptitle('Pair Plot of Variables against Obesity
Levels', fontsize=16, y=1.02)

# Display the plot
plt.show()
```



## b. Correlation heatmap for Pearson's correlation coefficient:

```
def plot_correlation_heatmap(df, method='pearson'):
    # Calculate the correlation matrix
    corr_matrix = df.corr(method=method)

    # Plot the heatmap
    plt.figure(figsize=(30, 20))
    sns.heatmap(corr_matrix, annot=True, cmap='viridis', fmt=".2f",
    linewidths=.5, cbar=True)
```

```

# Add indicators for strength and direction of correlation
for i in range(len(corr_matrix)):
    for j in range(len(corr_matrix.columns)):
        if i != j:
            if corr_matrix.iloc[i, j] >= 0.7:
                plt.text(j + 0.5, i + 0.5, '\u25B2', ha='center',
va='center', color='white', fontsize=15)
            elif corr_matrix.iloc[i, j] <= -0.7:
                plt.text(j + 0.5, i + 0.5, '\u25BC', ha='center',
va='center', color='white', fontsize=15)

# Set labels and title
plt.title(f'Correlation Heatmap ({method.capitalize()} Correlation)')
plt.xlabel('Features')
plt.ylabel('Features')

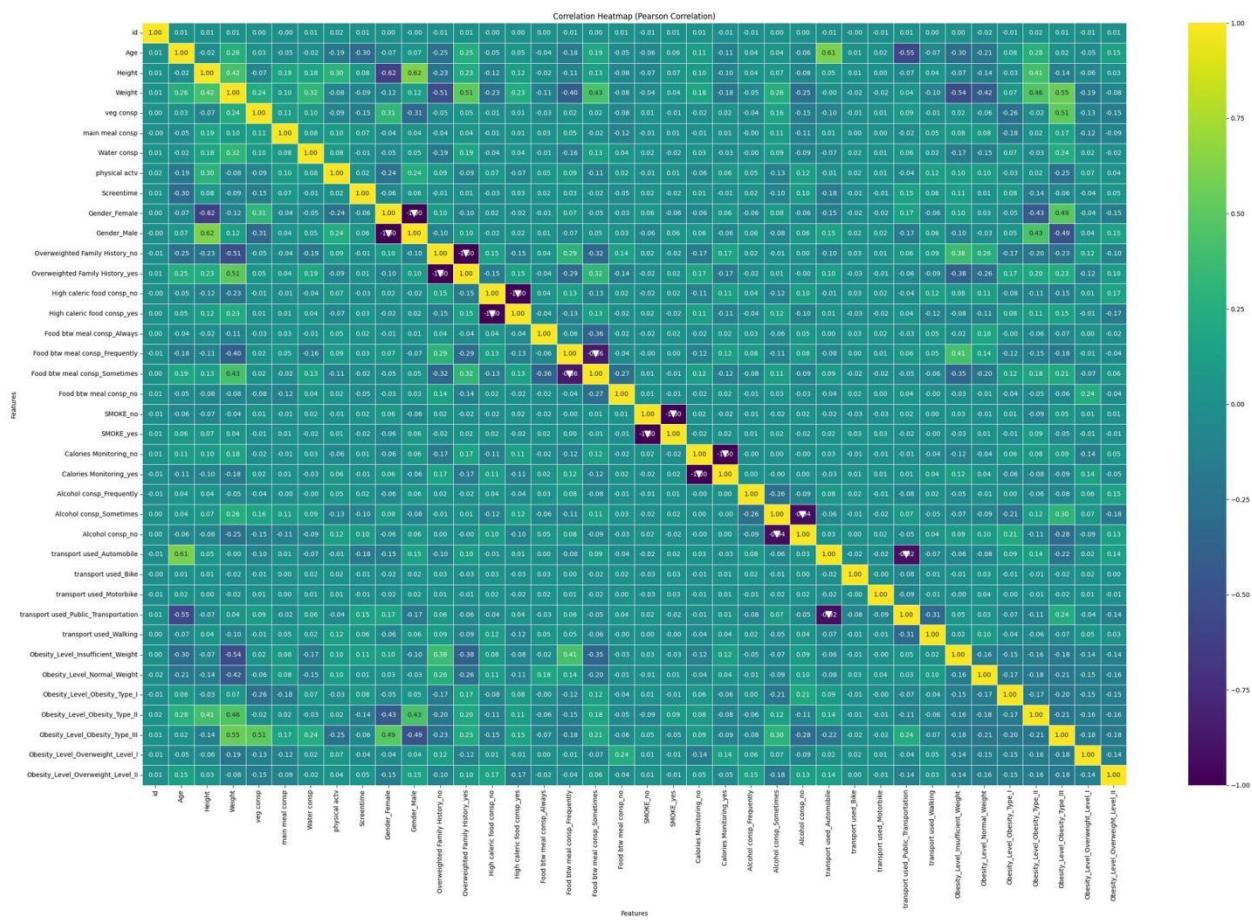
# Adjust layout
plt.tight_layout()

# Show plot
plt.show()

# Perform one-hot encoding for categorical variables
df_train_encoded = pd.get_dummies(df_train)

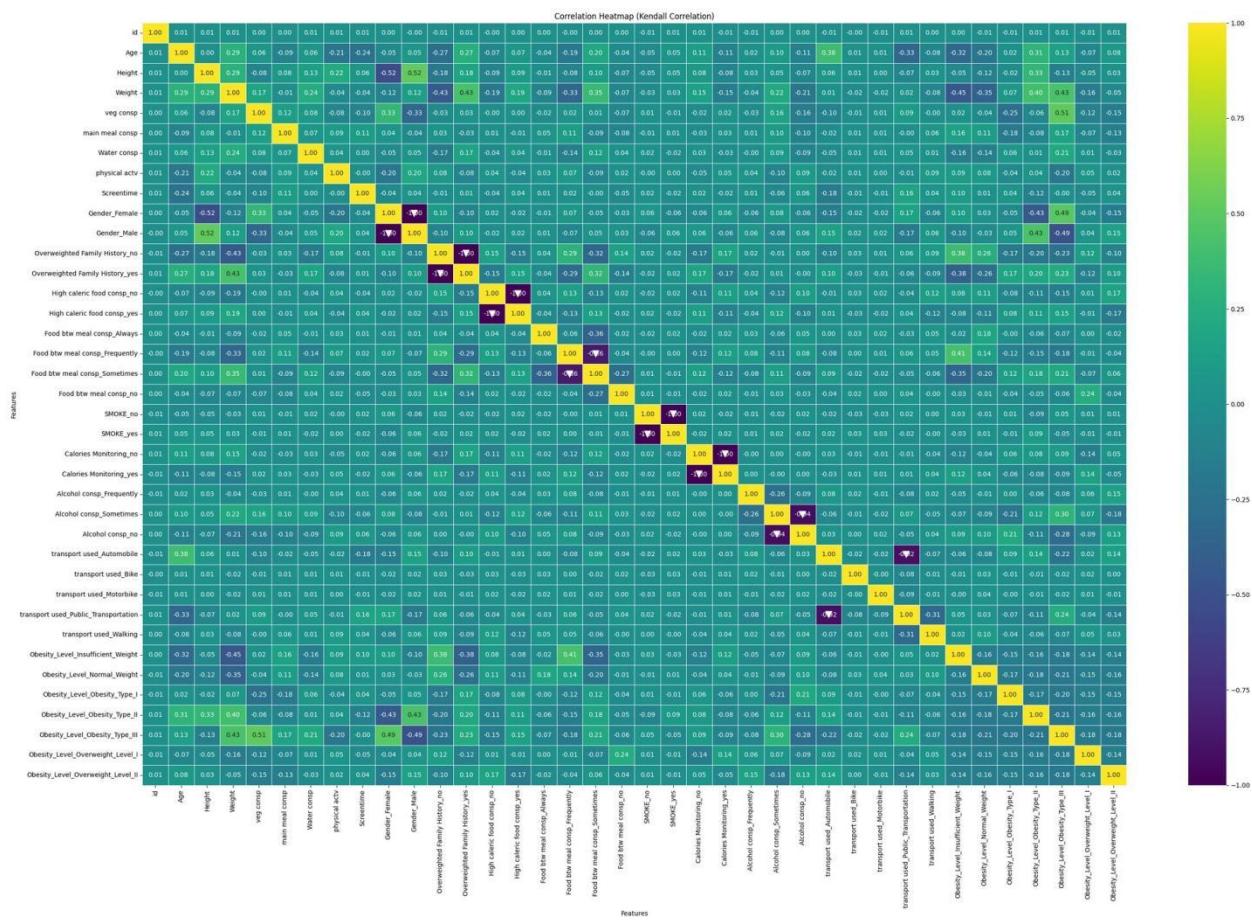
# Plot correlation heatmap for Pearson ,spearman and kendell correlation coefficient(in my case using kendell's tau)
plot_correlation_heatmap(df_train_encoded, method='pearson')

```



## c. Correlation heatmap for Kendall's tau correlation coefficient:

```
# Plot correlation heatmap for Kendall's tau correlation coefficient
plot_correlation_heatmap(df_train_encoded, method='kendall')
```



d. 3D Scatter Plot of Numerical Columns against Obesity Level:

```

# Define numerical columns for the plot
numerical_columns = ['Age', 'Height', 'Weight', 'High caleric food
consp', 'veg consp', 'main meal consp',
                     'Food btw meal consp', 'Water consp', 'Calories
Monitoring', 'physical actv', 'Screentime',
                     'Alcohol consp']

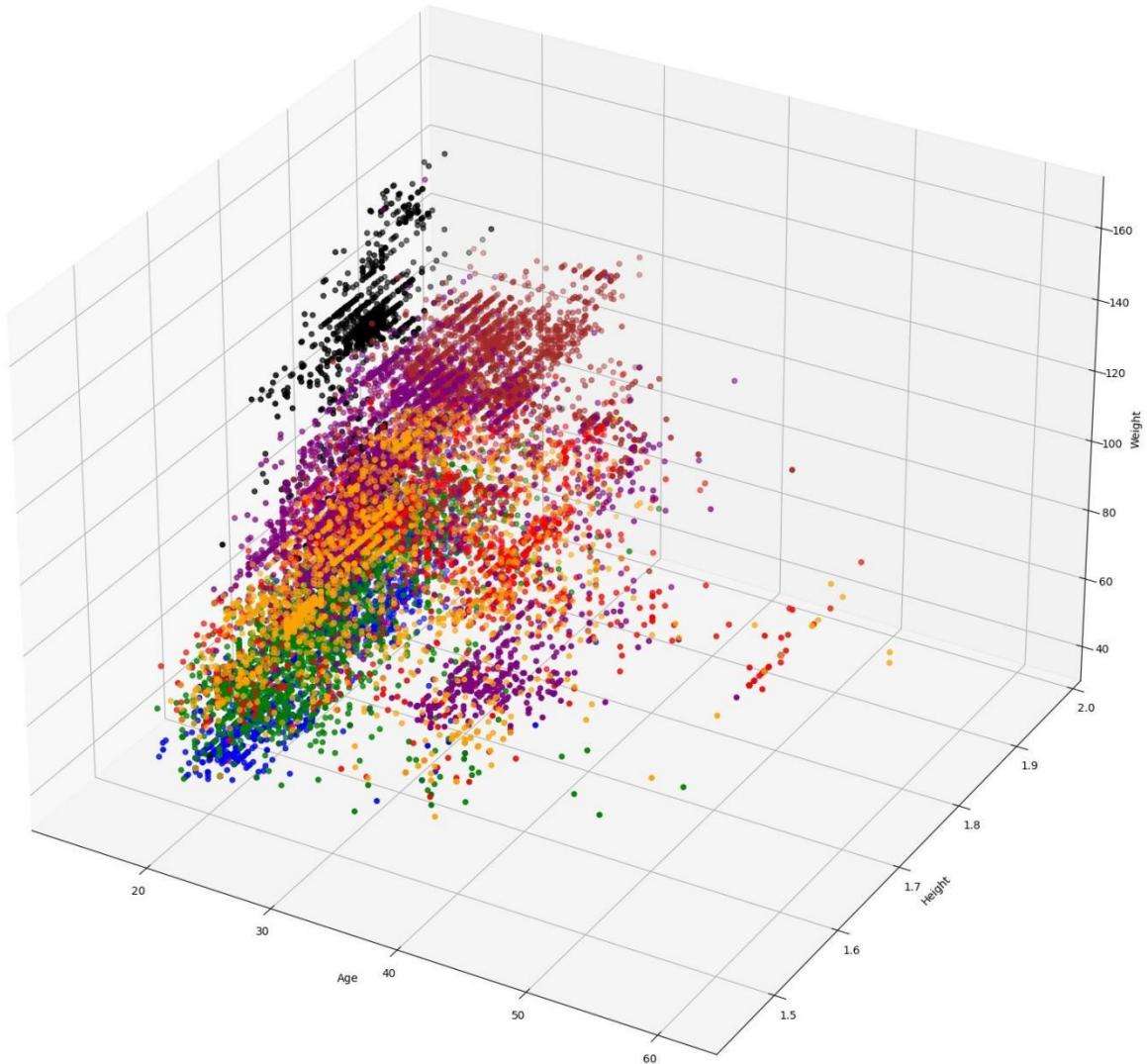
# Selecting only the numerical columns and 'Obesity_Level' from the
dataframe
df_numerical = df_train[numerical_columns + ['Obesity_Level']]

# Define colors for different obesity levels
color_map = {'Insufficient_Weight': 'blue',
             'Normal_Weight': 'green',
             'Overweight Level I': 'orange'},

# Show plot
plt.show()

```

3D Scatter Plot of Numerical Columns against Obesity Level



# e. Cluster Analysis:

## I. K-Means Clustering on Obesity level:

```
# Select numerical features for clustering
numerical_features = ['Age', 'Height', 'Weight', 'veg consp', 'main
meal consp', 'Water consp', 'physical activ', 'Screentime']

# Extract numerical features from the dataframe
X = df_train[numerical_features]
```

```

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

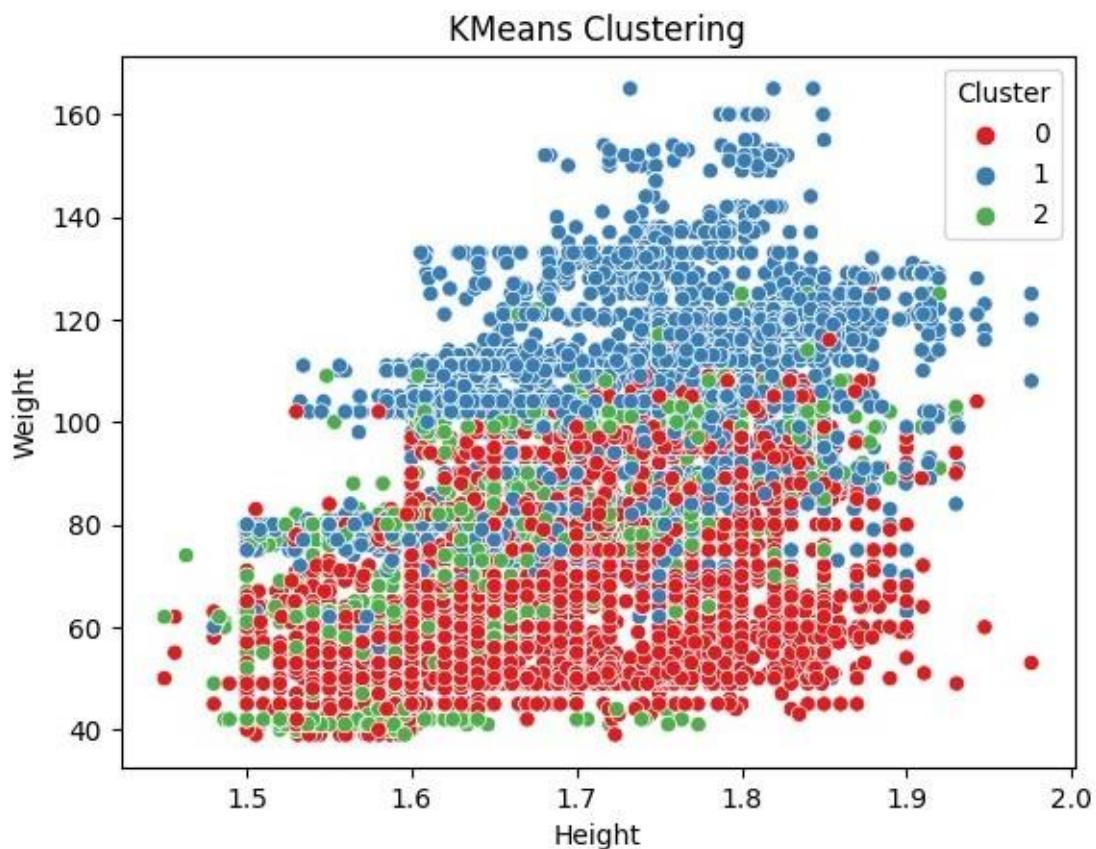
# Initialize and fit KMeans model
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(X_scaled)

# Add cluster labels to the dataframe
df_train['Cluster'] = kmeans.labels_

# Visualize the clusters (assuming 2D visualization)
sns.scatterplot(x='Height', y='Weight', hue='Cluster', data=df_train,
palette='Set1')
plt.title('KMeans Clustering')
plt.show()

# Analyze how clusters relate to obesity levels
cluster_obesity = df_train.groupby('Cluster')[['Obesity_Level']].value_counts(normalize=True).unstack()
print(cluster_obesity)

```



Obesity_Level Cluster	Insufficient_Weight	Normal_Weight	Obesity_Type_I	\
0	0.251450	0.308721	0.128387	
1	0.001270	0.019361	0.111617	
2	0.135201	0.101576	0.269702	
Overweight_Level_I Cluster	Obesity_Level	Obesity_Type_II	Obesity_Type_III	
0	0.006981	0.001657	0.158088	
1	0.313055	0.426576	0.045176	
2	0.080560	0.000000	0.232574	
Overweight_Level_I Cluster	Obesity_Level	Overweight_Level_II		
0	0.144717			
1	0.082945			
2	0.180385			

The output provides information on how the clusters relate to different obesity levels. Each row represents a cluster, and each column represents an obesity level. The values in the table represent the proportion of individuals within each cluster belonging to a specific obesity level.

For example:

- **Cluster 0:** Majority of individuals have obesity levels 0 and 1, with smaller proportions in other levels. Level 6 also has a notable proportion in this cluster.
- **Cluster 1:** Significant proportion of individuals have obesity levels 3, 4, and 5, while levels 0 and 1 have much smaller proportions. Level 6 also has a notable proportion in this cluster.
- **Cluster 2:** Relatively balanced distribution across various obesity levels, with no individuals in level 4 and a missing value in level 5. Level 6 has a considerable proportion in this cluster.

## II. PCA Plot of numerical variables against obesity level:

```
# Assuming you have numerical columns in df_train
# Select numerical columns for PCA
numerical_columns = ['Age', 'Height', 'Weight', 'veg consp', 'main meal consp', 'Water consp', 'physical actv', 'Screentime']

# Extract numerical data
```

```

X = df_train[numerical_columns]

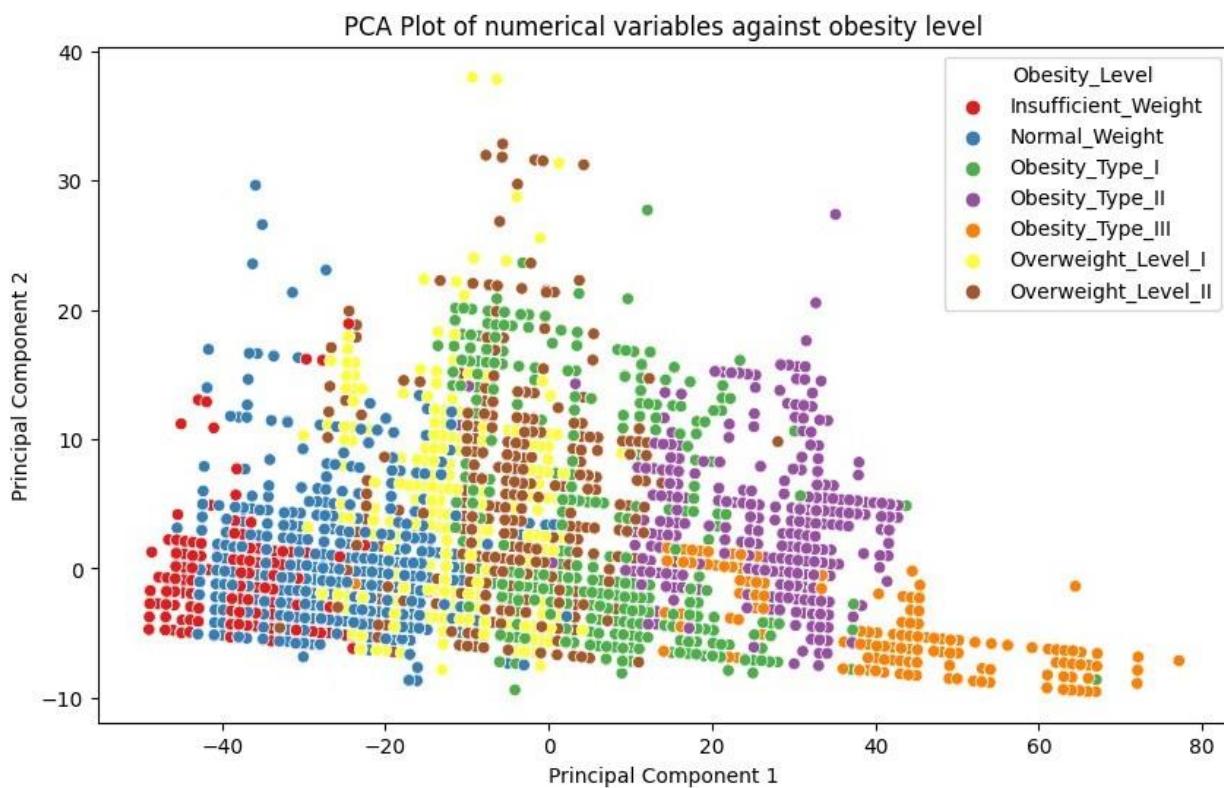
# Perform PCA
pca = PCA(n_components=2) # You can adjust the number of components
X_pca = pca.fit_transform(X)

# Create a DataFrame for the PCA results
df_pca = pd.DataFrame(data=X_pca, columns=['PC1', 'PC2'])

# Add Obesity_Level to the PCA DataFrame for color differentiation
df_pca['Obesity_Level'] = df_train['Obesity_Level']

# Visualize PCA
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PC1', y='PC2', hue='Obesity_Level', data=df_pca,
palette='Set1', legend='full')
plt.title('PCA Plot of numerical variables against obesity level')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()

```



## 4. Outlier Analysis:

### a. Univariate Outlier Analysis:

#### I. Boxplot Outlier Analysis:

```
# Function to identify outliers using Box Plot
def box_plot_outliers(df, col):
    """
    Detect outliers using Box Plot.

    Parameters:
        df (DataFrame): The input DataFrame.
        col (str): The name of the column to analyze.

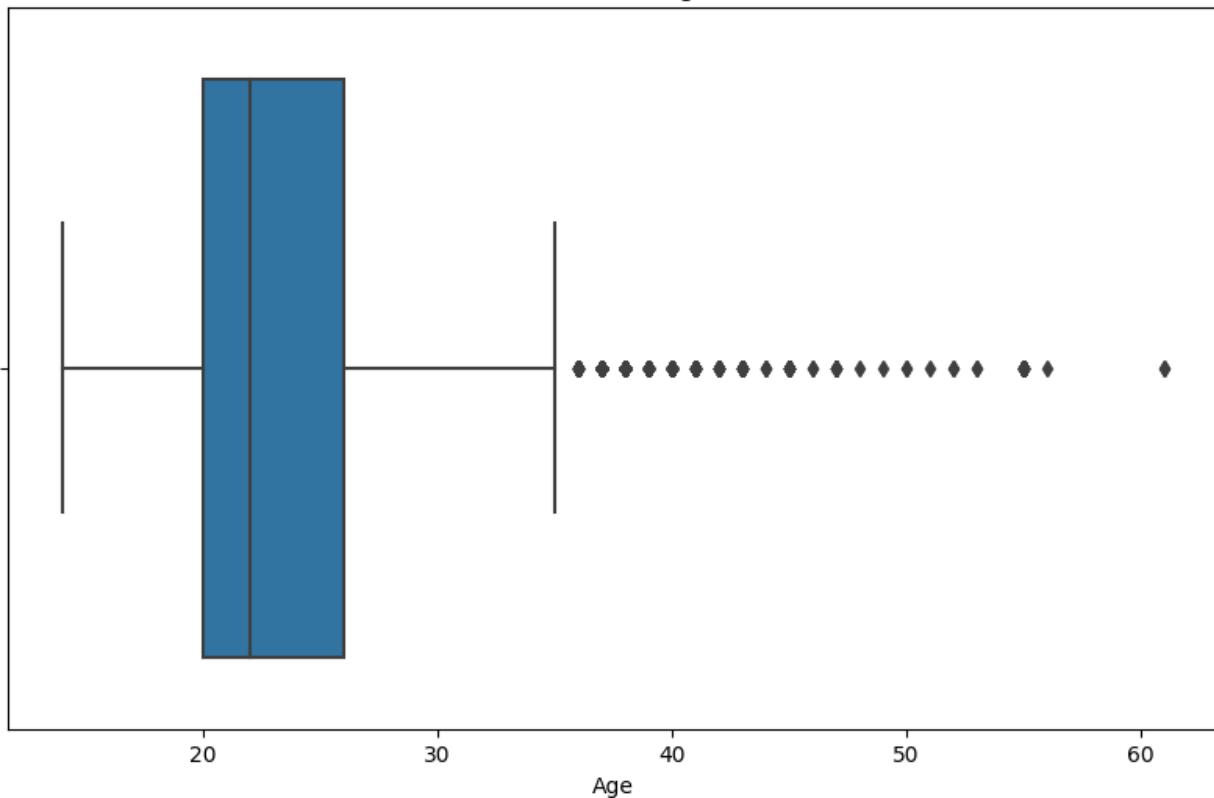
    Returns:
        None
    """
    plt.figure(figsize=(10, 6))
    sns.boxplot(x=df[col])
    plt.title(f'Box Plot of {col}')
    plt.xlabel(f'{col}')
    plt.show()

# Selecting numerical columns
numerical_cols = df_train.select_dtypes(include=['float64',
'int32']).columns

# Loop through each numerical column and perform outlier analysis
for col in numerical_cols:
    print(f'Column: {col}')
    box_plot_outliers(df_train, col)
    print('\n')

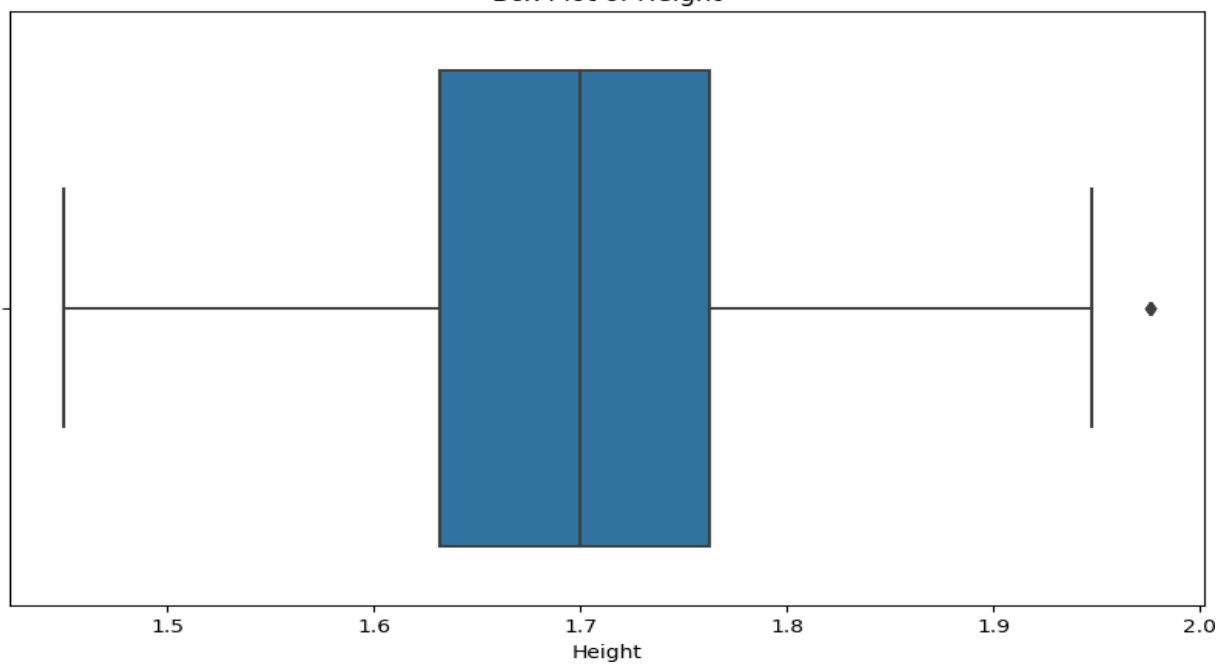
Column: Age
```

Box Plot of Age



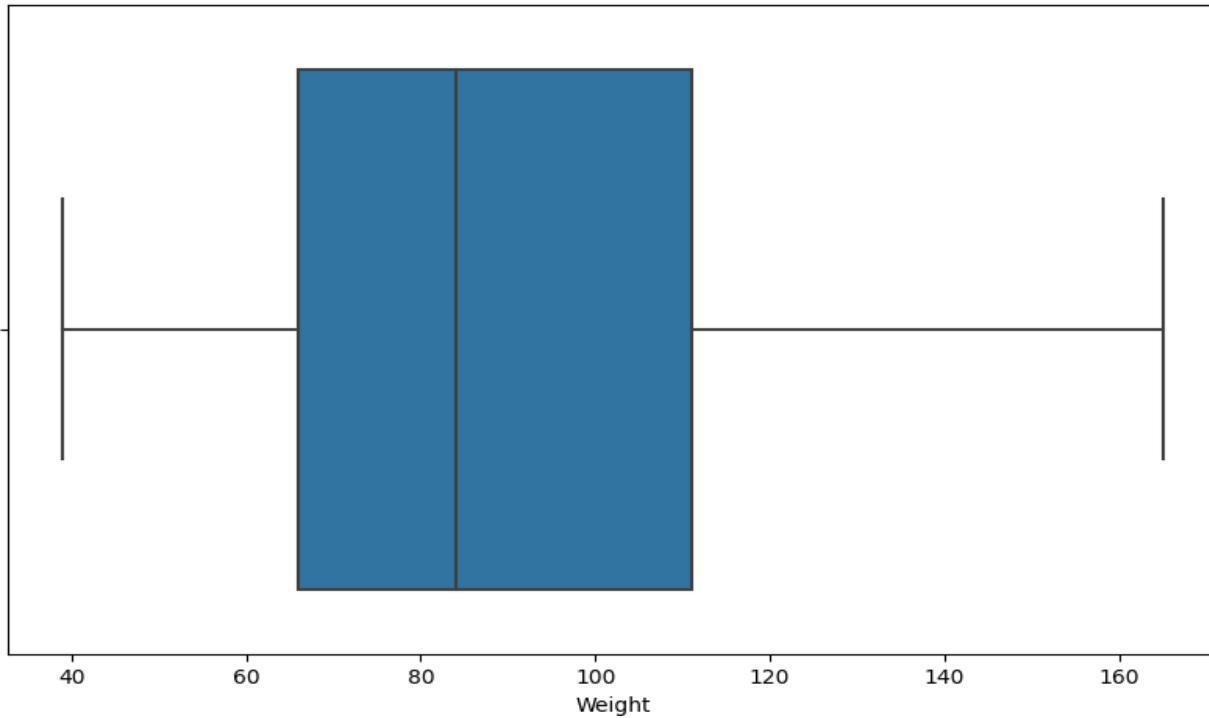
Column: Height

Box Plot of Height



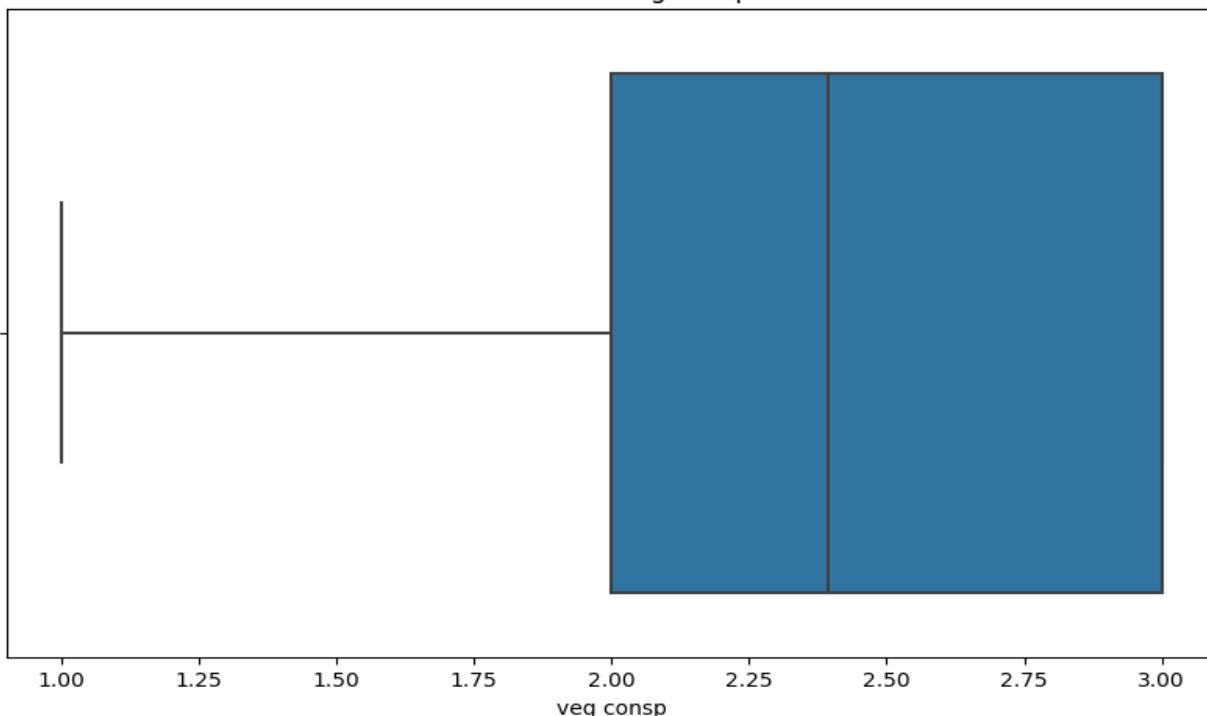
Column: Weight

Box Plot of Weight



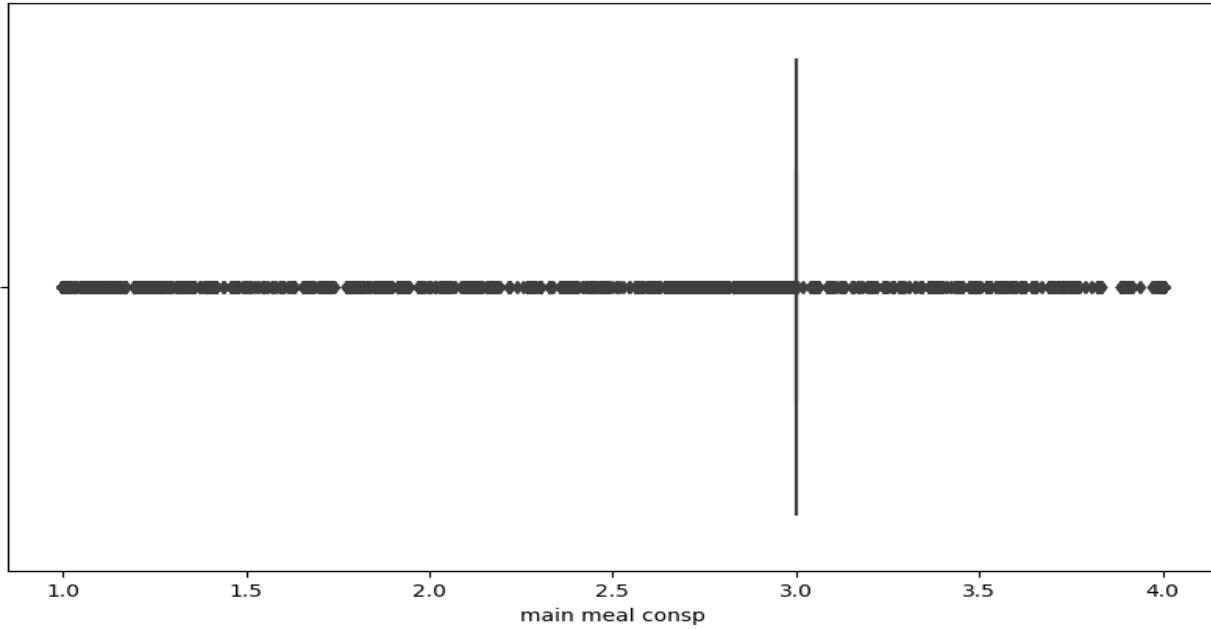
Column: veg consp

Box Plot of veg consp



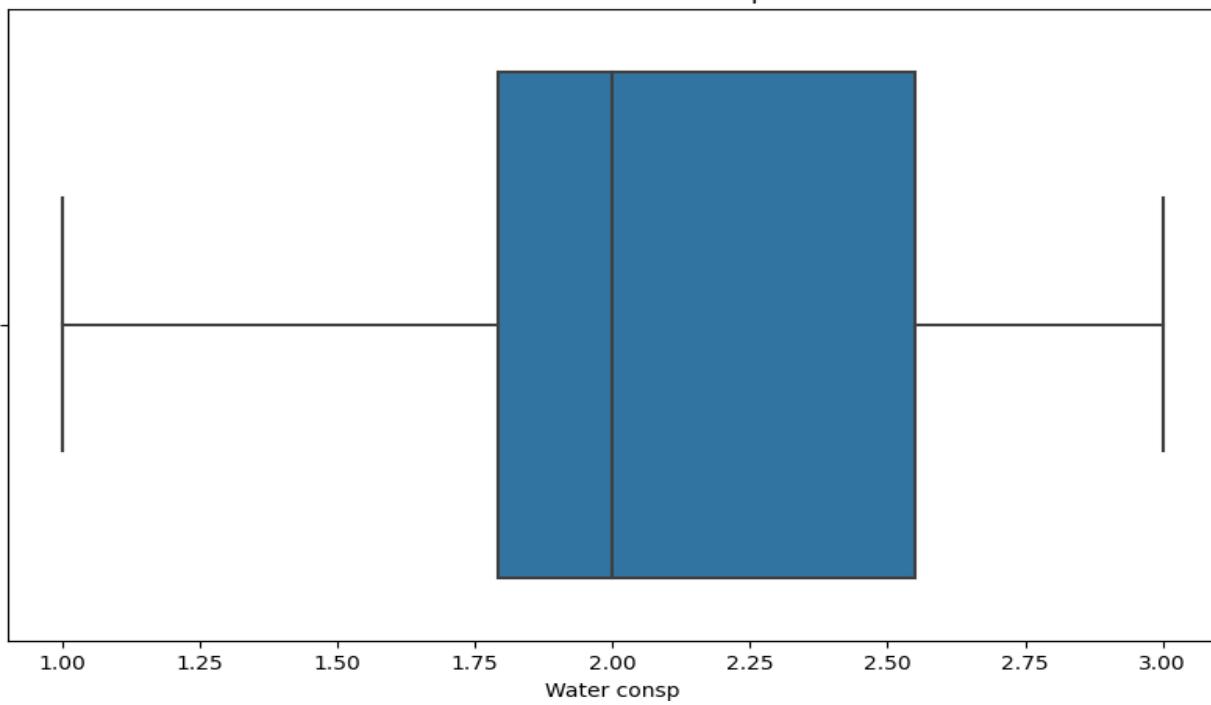
Column: main meal consp

Box Plot of main meal consp



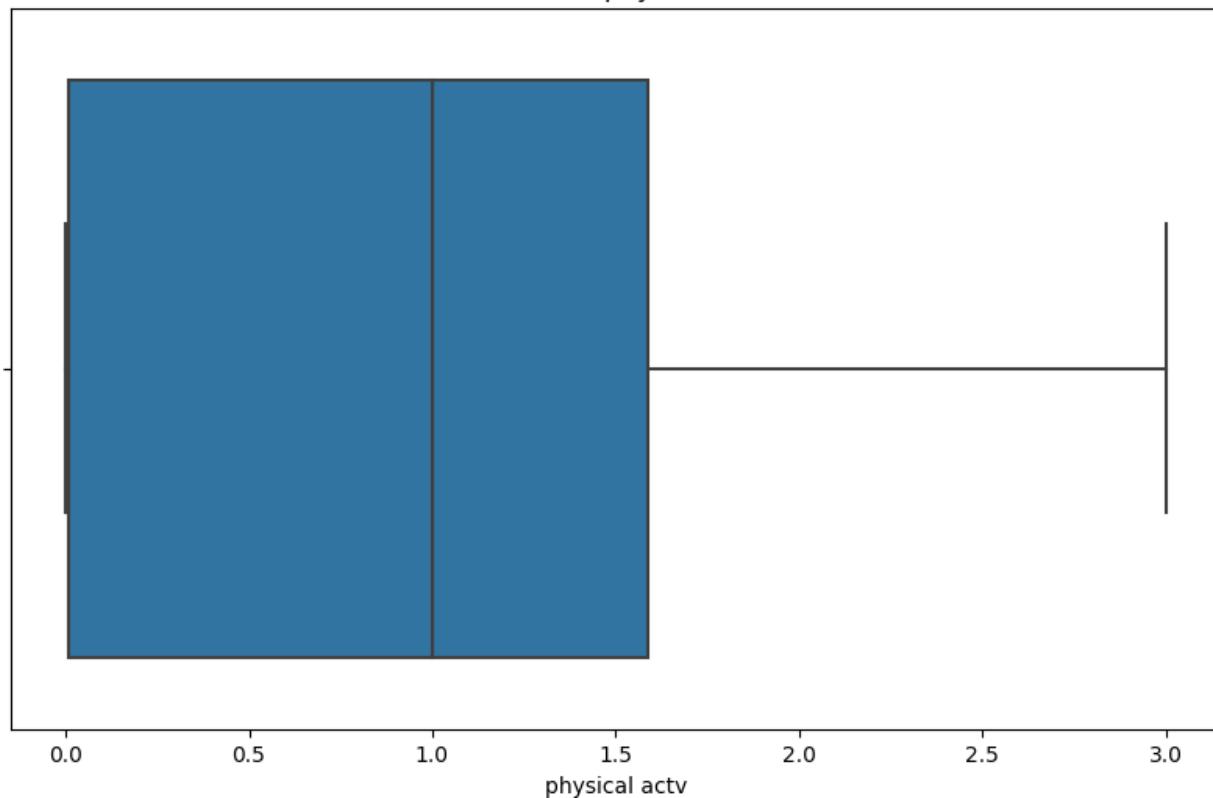
Column: Water consp

Box Plot of Water consp



Column: physical actv

Box Plot of physical actv



## II. Detecting outliers using Z-Score:

```
# Function to identify outliers using Z-Score
def z_score_outliers(df, col, threshold=3):
    """
    Detect outliers using Z-Score.

    Parameters:
        df (DataFrame): The input DataFrame.
        col (str): The name of the column to analyze.
        threshold (float): The Z-Score threshold for outlier detection.

    Returns:
        None
    """
    z_scores = (df[col] - df[col].mean()) / df[col].std()
    outliers = df[abs(z_scores) > threshold]
    print(f'Number of outliers detected using Z-Score for {col}:

{outliers.shape[0]}')

# Selecting numerical columns
numerical_cols = df_train.select_dtypes(include=['float64',
'int32']).columns

# Loop through each numerical column and perform outlier analysis
for col in numerical_cols:
    print(f'Column: {col}')
    z_score_outliers(df_train, col)
    print('\n')

Column: Age
Number of outliers detected using Z-Score for Age: 258

Column: Height
Number of outliers detected using Z-Score for Height: 4

Column: Weight
Number of outliers detected using Z-Score for Weight: 0

Column: veg consp
Number of outliers detected using Z-Score for veg consp: 0
```

### III. Detecting outliers using Interquartile Range (IQR):

```
# Function to identify outliers using IQR
def iqr_outliers(df, col):
    """
    Detect outliers using Interquartile Range (IQR).

    Parameters:
        df (DataFrame): The input DataFrame.
        col (str): The name of the column to analyze.

    Returns:
        None
    """
    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)]
    print(f'Number of outliers detected using IQR for {col}:\n{outliers.shape[0]}')

# Selecting numerical columns
numerical_cols = df_train.select_dtypes(include=['float64',
'int32']).columns

# Loop through each numerical column and perform outlier analysis
for col in numerical_cols:
    print(f'Column: {col}')
    iqr_outliers(df_train, col)
    print('\n')

Column: Age
Number of outliers detected using IQR for Age: 1029

Column: Height
Number of outliers detected using IQR for Height: 4

Column: Weight
Number of outliers detected using IQR for Weight: 0

Column: veg consp
Number of outliers detected using IQR for veg consp: 0
```

```

Column: main meal consp
Number of outliers detected using IQR for main meal consp: 6052

Column: Water consp
Number of outliers detected using IQR for Water consp: 0

Column: physical actv
Number of outliers detected using IQR for physical actv: 0

Column: Screentime
Number of outliers detected using IQR for Screentime: 0

Column: Cluster
Number of outliers detected using IQR for Cluster: 0

```

## b. Multivariate Outlier Analysis:

### I. Detecting Multivariate Outliers Using Mahalanobis Distance:

```

# Function to calculate Mahalanobis Distance
def mahalanobis_distance(x, mean, cov):
    """
    Calculate Mahalanobis Distance for a data point.

    Parameters:
        x (array-like): The data point.
        mean (array-like): The mean vector.
        cov (array-like): The covariance matrix.

    Returns:
        float: The Mahalanobis Distance.
    """
    x_minus_mean = x - mean
    inv_cov = np.linalg.inv(cov)
    distance = np.sqrt(np.dot(np.dot(x_minus_mean, inv_cov),
    x_minus_mean.T))
    return distance

```

```

# Function to detect multivariate outliers using Mahalanobis Distance
def mahalanobis_outliers(df, threshold=3):
    """
    Detect multivariate outliers using Mahalanobis Distance.

    Parameters:
        df (DataFrame): The input DataFrame.
        threshold (float): The Mahalanobis Distance threshold for outlier detection.

    Returns:
        DataFrame: The DataFrame containing outliers.
    """
    mean = df.mean()
    cov = df.cov()
    outliers = []
    for i, row in df.iterrows():
        distance = mahalanobis_distance(row, mean, cov)
        if distance > threshold:
            outliers.append(i)
    return df.iloc[outliers]

# Selecting numerical columns
numerical_cols = df_train.select_dtypes(include=['float64',
'int32']).columns

# Performing multivariate outlier analysis using Mahalanobis Distance
mahalanobis_outliers_df =
mahalanobis_outliers(df_train[numerical_cols])
mahalanobis_outliers_cols = mahalanobis_outliers_df.columns.tolist()

print(f'Number of multivariate outliers detected using Mahalanobis
Distance: {mahalanobis_outliers_df.shape[0]}')
print('Columns with outliers detected using Mahalanobis Distance:',

mahalanobis_outliers_cols)

Number of multivariate outliers detected using Mahalanobis Distance:
8577
Columns with outliers detected using Mahalanobis Distance: ['Age',
'Height', 'Weight', 'veg consp', 'main meal consp', 'Water consp',
'physical actv', 'Screentime', 'Cluster']

```

## II. Detecting Multivariate Outliers Using Principal Component Analysis (PCA):

```
# Function to detect multivariate outliers using Principal Component Analysis (PCA)
def pca_outliers(df, threshold=3):
    """
    Detect multivariate outliers using Principal Component Analysis (PCA).

    Parameters:
        df (DataFrame): The input DataFrame.
        threshold (float): The threshold for outlier detection based on PCA distance.

    Returns:
        DataFrame: The DataFrame containing outliers.
    """
    pca = PCA(n_components=2)
    principal_components = pca.fit_transform(df)
    distances = np.linalg.norm(principal_components - np.mean(principal_components, axis=0), axis=1)
    cutoff = np.percentile(distances, 100 - 100 * chi2.cdf(threshold, 2))
    outliers = df[distances > cutoff]
    return outliers

# Selecting numerical columns
numerical_cols = df_train.select_dtypes(include=['float64', 'int32']).columns

# Performing multivariate outlier analysis using Principal Component Analysis (PCA)
pca_outliers_df = pca_outliers(df_train[numerical_cols])
pca_outliers_cols = pca_outliers_df.columns.tolist()

print(f'Number of multivariate outliers detected using PCA: {pca_outliers_df.shape[0]}')
print('Columns with outliers detected using PCA:', pca_outliers_cols)

Number of multivariate outliers detected using PCA: 16126
Columns with outliers detected using PCA: ['Age', 'Height', 'Weight', 'veg consp', 'main meal consp', 'Water consp', 'physical actv', 'Screentime', 'Cluster']
```

### III. Detecting Cluster-Based Outliers Using KMeans Clustering:

```
# Select numerical columns for clustering
numerical_cols = df_train.select_dtypes(include=['float64', 'int32'])

# Initialize KMeans with the desired number of clusters
kmeans = KMeans(n_clusters=5) # Adjust the number of clusters as needed

# Fit KMeans to the numerical data
kmeans.fit(numerical_cols)

# Get the cluster centroids
cluster_centers = kmeans.cluster_centers_

# Calculate the distance of each point to its cluster centroid
distances = []
for i in range(len(df_train)):
    point = np.array(df_train.iloc[i][numerical_cols.columns])
    cluster_label = kmeans.labels_[i]
    centroid = cluster_centers[cluster_label]
    distance = np.linalg.norm(point - centroid)
    distances.append(distance)

# Set a threshold to identify outliers
threshold = np.percentile(distances, 95) # Adjust the percentile as needed

# Identify outliers based on the threshold
outliers_indices = [i for i, distance in enumerate(distances) if distance > threshold]
outliers = df_train.iloc[outliers_indices]

# Filter out categorical columns before calculating the sum of outliers
numerical_outliers = outliers.select_dtypes(include=['float64', 'int32'])

# Calculate the sum of all outliers present in each numerical column
outliers_sum_per_column = numerical_outliers.sum()

# Calculate the total sum of outliers across all numerical columns
total_outliers_sum = numerical_outliers.sum().sum()

# Display the sum of outliers for each numerical column
print("\nSum of outliers present in each numerical column:")
print(outliers_sum_per_column)
```

```

# Display the total sum of outliers across all numerical columns
print("\nTotal sum of outliers across all numerical columns:",
total_outliers_sum)

Sum of outliers present in each numerical column:
Age                  37360.000000
Height                1744.514806
Weight                100744.000000
veg consp              2517.891680
main meal consp        2831.066765
Water consp             2004.994688
physical actv            925.069334
Screentime               314.269129
Cluster                 1124.000000
dtype: float64

Total sum of outliers across all numerical columns: 149565.8064025

df_train.drop(columns=['Cluster'], inplace=True)

```

## 5. Feature Engineering:

```

# Rename the columns for train data
test_sub.rename(columns=new_column_names, inplace=True)

test_sub.head(5)

      id Gender Age      Height  Weight Overweighted Family History \
0  20758   Male  26  1.848294     120                      yes
1  20759 Female  21  1.600000      66                      yes
2  20760 Female  26  1.643355     111                      yes
3  20761   Male  20  1.553127     103                      yes
4  20762 Female  26  1.627396     104                      yes

      High caloric food consp  veg consp  main meal consp Food btw meal
      consp \
0                   yes    2.938616      3.000000
Sometimes
1                   yes    2.000000      1.000000
Sometimes
2                   yes    3.000000      3.000000
Sometimes
3                   yes    2.000000    2.977909
Sometimes
4                   yes    3.000000      3.000000
Sometimes

      SMOKE  Water consp Calories Monitoring  physical actv  Screentime \

```

0	no	2.825629	no	0.855400	0.000000
1	no	3.000000	no	1.000000	0.000000
2	no	2.621877	no	0.000000	0.250502
3	no	2.786417	no	0.094851	0.000000
4	no	2.653531	no	0.000000	0.741069
Alcohol consp                    transport used					
0	Sometimes	Public_Transportation			
1	Sometimes	Public_Transportation			
2	Sometimes	Public_Transportation			
3	Sometimes	Public_Transportation			
4	Sometimes	Public Transportation			

## a. Encoding Categorical to numerical variables:

```
# Encoding of target variables to numerical
keys_dict = {
    '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
}

# Encoding of transport used to numerical
keys_dict_1 = {
    'Automobile': 0,
    'Bike': 1,
    'Motorbike': 2,
    'Public_Transportation': 3,
    'Walking': 4
}

# Encoding of Alcohol consumption to numerical
keys_dict_2 = {
    'Sometimes': 1/3,
    'Frequently': 2/3,
    'Always': 1,
    'no': 0
}

# Encoding of Food between meal consumption to numerical
keys_dict_3 = {
    'Sometimes': 1/3,
    'Frequently': 2/3,
    'Always': 1,
```

```

        'no': 0
    }

def encode_obesity_level(row):
    return keys_dict.get(row['Obesity_Level'], None)

def encode_transport_used(row):
    return keys_dict_1.get(row['transport used'], None)

def encode_alcohol_consp(row):
    return keys_dict_2.get(row['Alcohol consp'], None)

def encode_food_btwn_meal(row):
    return keys_dict_3.get(row['Food btw meal consp'], None)

# Add new columns and apply encoding for train data
df_train['Encdd_Obesity_Level'] = df_train.apply(encode_obesity_level,
axis=1)
df_train['Encdd_transport_used'] =
df_train.apply(encode_transport_used, axis=1)
df_train['Encdd_Alcohol_consp'] = df_train.apply(encode_alcohol_consp,
axis=1)
df_train['Encdd_Food_btwn_meal'] = df_train.apply(encode_food_btwn_meal,
axis=1)

# Add new columns and apply encoding for test data
test_sub['Encdd_transport_used'] =
test_sub.apply(encode_transport_used, axis=1)
test_sub['Encdd_Alcohol_consp'] = test_sub.apply(encode_alcohol_consp,
axis=1)
test_sub['Encdd_Food_btwn_meal'] = test_sub.apply(encode_food_btwn_meal,
axis=1)

df_train.head(5)

      id  Gender   Age     Height   Weight Overweighted Family History \
0      0    Male    24  1.699998      81                  yes
1      1  Female    18  1.560000      57                  yes
2      2  Female    18  1.711460      50                  yes
3      3  Female    20  1.710730     131                  yes
4      4    Male    31  1.914186      93                  yes

      High caloric food consp  veg consp  main meal consp Food btwn meal
      consp \
0                               yes  2.000000  2.983297
Sometimes
1                               yes  2.000000  3.000000
Frequently
2                               yes  1.880534  1.411685

```

```

Sometimes
3                               yes    3.000000      3.000000
Sometimes
4                               yes    2.679664      1.971472
Sometimes

      SMOKE   Water consp Calories Monitoring   physical actv  Screentime \
0       no        2.763573                      no        0.000000      0.976473
1       no        2.000000                      no        1.000000      1.000000
2       no        1.910378                      no        0.866045      1.673584
3       no        1.674061                      no        1.467863      0.780199
4       no        1.979848                      no        1.967973      0.931721

      Alcohol consp          transport used      Obesity_Level \
0     Sometimes    Public_Transportation  Overweight_Level_II
1           no            Automobile      Normal_Weight
2           no    Public_Transportation  Insufficient_Weight
3     Sometimes    Public_Transportation  Obesity_Type_III
4     Sometimes    Public_Transportation  Overweight_Level_II

      Encdd_Obesity_Level  Encdd_transport_used  Encdd_Alcohol_consp \
0                     3                         3        0.333333
1                     1                         0        0.000000
2                     0                         3        0.000000
3                     6                         3        0.333333
4                     3                         3        0.333333

      Encdd_Food_btwn_meal
0        0.333333
1        0.666667
2        0.333333
3        0.333333
4        0.333333

test_sub.head(5)

      id Gender Age      Height  Weight Overweighted Family History \
0  20758   Male  26  1.848294    120                      yes
1  20759 Female  21  1.600000     66                      yes
2  20760 Female  26  1.643355    111                      yes
3  20761   Male  20  1.553127    103                      yes
4  20762 Female  26  1.627396    104                      yes

      High caloric food consp  veg consp  main meal consp Food btwn meal
      consp \
0                               yes    2.938616      3.000000
Sometimes
1                               yes    2.000000      1.000000
Sometimes
2                               yes    3.000000      3.000000

```

```

Sometimes
3                               yes    2.000000      2.977909
Sometimes
4                               yes    3.000000      3.000000
Sometimes

SMOKE   Water consp Calories Monitoring   physical actv  Screentime \
0       no        2.825629                  no        0.855400      0.000000
1       no        3.000000                  no        1.000000      0.000000
2       no        2.621877                  no        0.000000      0.250502
3       no        2.786417                  no        0.094851      0.000000
4       no        2.653531                  no        0.000000      0.741069

Alcohol consp          transport used  Encdd_transport_used \
0     Sometimes    Public_Transportation      3
1     Sometimes    Public_Transportation      3
2     Sometimes    Public_Transportation      3
3     Sometimes    Public_Transportation      3
4     Sometimes    Public_Transportation      3

Encdd_Alcohol_consp  Encdd_Food_btwn_meal
0           0.333333            0.333333
1           0.333333            0.333333
2           0.333333            0.333333
3           0.333333            0.333333
4           0.333333            0.333333

# Define mappings for each column
gender_mapping = {'Male': 1, 'Female': 0}
family_history_mapping = {'yes': 1, 'no': 0}
high_caloric_mapping = {'yes': 1, 'no': 0}
smoke_mapping = {'yes': 1, 'no': 0}
calories_monitoring_mapping = {'yes': 1, 'no': 0}

# Define functions to apply mappings and create new encoded columns
def encode_gender(row):
    return gender_mapping.get(row['Gender'], None)

def encode_family_history(row):
    return family_history_mapping.get(row['Overweighted Family History'], None)

def encode_high_caloric(row):
    return high_caloric_mapping.get(row['High caleric food consp'], None)

def encode_smoke(row):
    return smoke_mapping.get(row['SMOKE'], None)

def encode_calories_monitoring(row):

```

```

    return calories_monitoring_mapping.get(row['Calories Monitoring'], None)

# Apply functions to create new encoded columns for train data
df_train['Encoded_Gender'] = df_train.apply(encode_gender, axis=1)
df_train['Encoded_Family_History'] =
df_train.apply(encode_family_history, axis=1)
df_train['Encoded_High_Caloric'] = df_train.apply(encode_high_caloric,
axis=1)
df_train['Encoded_Smoke'] = df_train.apply(encode_smoke, axis=1)
df_train['Encoded_Calories_Monitoring'] =
df_train.apply(encode_calories_monitoring, axis=1)

# Apply functions to create new encoded columns for train data
test_sub['Encoded_Gender'] = test_sub.apply(encode_gender, axis=1)
test_sub['Encoded_Family_History'] =
test_sub.apply(encode_family_history, axis=1)
test_sub['Encoded_High_Caloric'] = test_sub.apply(encode_high_caloric,
axis=1)
test_sub['Encoded_Smoke'] = test_sub.apply(encode_smoke, axis=1)
test_sub['Encoded_Calories_Monitoring'] =
test_sub.apply(encode_calories_monitoring, axis=1)

```

## b. BMI(Body Mass Index) Calculation:

*#Calculation of BMI (Body Mass Index), Veg Intake comapred to high calorie food consp, Total number of meal consp and Physical activity frequency*

```

# Create new columns based on existing ones
df_train['BMI'] = df_train['Weight'] / (df_train['Height'] ** 2)
test_sub['BMI'] = test_sub['Weight'] / (test_sub['Height'] ** 2)

```

## c. Total Meal Consumed:

```

# Calculate the total number of meals consumed
# This is done by adding the counts of main meals and between-meal
snacks
df_train['Meal'] = df_train['main meal consp'] +
df_train['Encdd_Food_btwn_meal']
test_sub['Meal'] = test_sub['main meal consp'] +
test_sub['Encdd_Food_btwn_meal']

```

## d. Total Activity Frequency Calculation:

```
# Calculate the product of physical activity frequency and screen time
df_train['Activity'] = df_train['physical actv'] *
df_train['Screentime']
test_sub['Activity'] = test_sub['physical actv'] *
test_sub['Screentime']
```

## e. Ageing process analysis:

```
df_train['IsYoung'] = df_train['Age'].apply(lambda x: x < 25)
df_train['IsAging'] = df_train['Age'].apply(lambda x: 25 <= x < 40)

test_sub['IsYoung'] = test_sub['Age'].apply(lambda x: x < 25)
test_sub['IsAging'] = test_sub['Age'].apply(lambda x: 25 <= x < 40)

df_train.head(5)

   id  Gender  Age    Height  Weight Overweighted Family History \
0   0     Male  24  1.699998      81                  yes
1   1  Female  18  1.560000      57                  yes
2   2  Female  18  1.711460      50                  yes
3   3  Female  20  1.710730     131                  yes
4   4     Male  31  1.914186      93                  yes

   High caleric food consp  veg consp  main meal consp Food btw meal
consp \
0                               yes  2.000000  2.983297
Sometimes
1                               yes  2.000000  3.000000
Frequently
2                               yes  1.880534  1.411685
Sometimes
3                               yes  3.000000  3.000000
Sometimes
4                               yes  2.679664  1.971472
Sometimes

   SMOKE  Water consp Calories Monitoring  physical actv  Screentime \
0    no    2.763573                   no  0.000000  0.976473
1    no    2.000000                   no  1.000000  1.000000
2    no    1.910378                   no  0.866045  1.673584
3    no    1.674061                   no  1.467863  0.780199
4    no    1.979848                   no  1.967973  0.931721

   Alcohol consp          transport used  Obesity_Level \
0    Sometimes  Public_Transportation  Overweight_Level_II
1       no           Automobile  Normal_Weight
```

2	no	Public_Transportation	Insufficient_Weight				
3	Sometimes	Public_Transportation	Obesity_Type_III				
4	Sometimes	Public_Transportation	Overweight_Level_II				
0	Encdd_Obesity_Level	Encdd_transport_used	Encdd_Alcohol_consp				
1	3	3	0.333333				
2	1	0	0.000000				
3	0	3	0.000000				
4	6	3	0.333333				
5	3	3	0.333333				
0	Encdd_Food_btwn_meal	Encoded_Gender	Encoded_Family_History				
1	0.333333	1	1				
2	0.666667	0	1				
3	0.333333	0	1				
4	0.333333	0	1				
5	0.333333	1	1				
0	Encoded_High_Caloric	Encoded_Smoke	Encoded_Calories_Monitoring				
1	1	0	0				
2	1	0	0				
3	1	0	0				
4	1	0	0				
5	1	0	0				
0	BMI	Meal	Activity	IsYoung	IsAging		
1	28.027748	3.316630	0.000000	True	False		
2	23.422091	3.666667	1.000000	True	False		
3	17.070117	1.745018	1.449399	True	False		
4	44.761884	3.333333	1.145225	True	False		
5	25.381348	2.304805	1.833602	False	True		
	test_sub.head(5)						
0	id	Gender	Age	Height	Weight	Overweighted	Family History
1	20758	Male	26	1.848294	120		yes
2	20759	Female	21	1.600000	66		yes
3	20760	Female	26	1.643355	111		yes
4	20761	Male	20	1.553127	103		yes
5	20762	Female	26	1.627396	104		yes
0	High caloric food consp	veg consp	main meal consp	Food btwn meal consp			
1	Sometimes	yes	2.938616	3.000000			
2	Sometimes	yes	2.000000	1.000000			
3	Sometimes	yes	3.000000	3.000000			
4	Sometimes	yes	2.000000	2.977909			

Sometimes						
4	yes	3.000000		3.000000		
Sometimes						
SMOKE	Water consp	Calories	Monitoring	physical actv	Screentime	\
0	no	2.825629		no	0.855400	0.000000
1	no	3.000000		no	1.000000	0.000000
2	no	2.621877		no	0.000000	0.250502
3	no	2.786417		no	0.094851	0.000000
4	no	2.653531		no	0.000000	0.741069
Alcohol consp		transport used	Encdd_transport_used	\		
0	Sometimes	Public_Transportation				3
1	Sometimes	Public_Transportation				3
2	Sometimes	Public_Transportation				3
3	Sometimes	Public_Transportation				3
4	Sometimes	Public Transportation				3
Encdd_Alcohol_consp	Encdd_Food_btwn_meal	Encoded_Gender	\			
0	0.333333	0.333333				1
1	0.333333	0.333333				0
2	0.333333	0.333333				0
3	0.333333	0.333333				1
4	0.333333	0.333333				0
Encoded_Family_History	Encoded_High_Caloric	Encoded_Smoke	\			
0	1	1				0
1	1	1				0
2	1	1				0
3	1	1				0
4	1	1				0
Encoded_Calories_Monitoring	BMI	Meal	Activity	IsYoung		
\						
0	0	35.126845	3.333333	0.0	False	
1	0	25.781250	1.333333	0.0	True	
2	0	41.101739	3.333333	0.0	False	
3	0	42.699549	3.311242	0.0	True	
4	0	39.268730	3.333333	0.0	False	

# Section: 6. Analysis & Prediction Using Machine Learning(ML) Model:

## 1. Feature Importance Analysis and Visualization:

### a. Feature Importance Analysis using Random Forest Classifier:

```
# Assuming df_train contains your dataset
# Define X (features) and y (target variable)
X = df_train.drop(columns=['Obesity_Level'])
y = df_train['Obesity_Level']

# Perform one-hot encoding for categorical variables
X_encoded = pd.get_dummies(X)

# Initialize the model
model = RandomForestClassifier()

# Train the model
model.fit(X_encoded, y)

# Get feature importances
feature_importances = model.feature_importances_

# Sort feature importances and corresponding feature names
sorted_indices = feature_importances.argsort()[:-1]
sorted_feature_importances = feature_importances[sorted_indices]
sorted_feature_names = X_encoded.columns[sorted_indices]

# Limit the number of displayed features
top_n = 20
sorted_feature_importances = sorted_feature_importances[:top_n]
sorted_feature_names = sorted_feature_names[:top_n]
# Calculate mean and standard deviation of feature importances
mean_importance = np.mean(sorted_feature_importances)
std_importance = np.std(sorted_feature_importances)
```

```

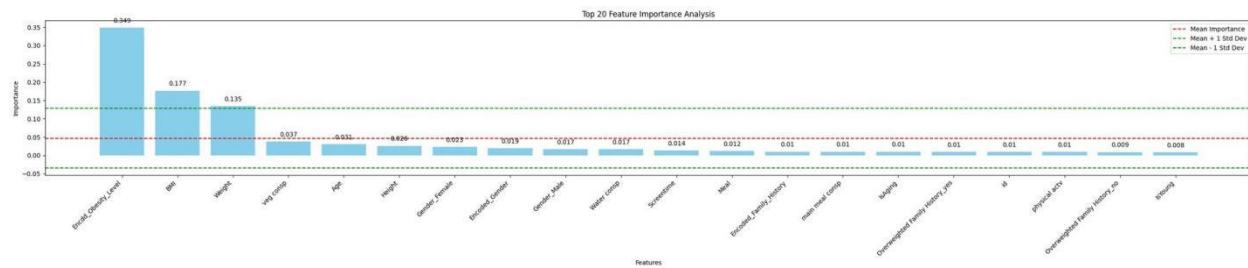
# Calculate coefficient of variation (CV)
cv_importance = std_importance / mean_importance

# Visualize feature importances
plt.figure(figsize=(28, 6))
plt.bar(sorted_feature_names, sorted_feature_importances,
color='skyblue')
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Top {} Feature Importance Analysis'.format(top_n))
plt.xticks(rotation=45, ha='right')
for i, v in enumerate(sorted_feature_importances):
    plt.text(i, v + 0.01, str(round(v, 3)), ha='center', va='bottom')
plt.axhline(y=mean_importance, color='r', linestyle='--', label='Mean Importance')
plt.axhline(y=mean_importance + std_importance, color='g',
linestyle='--', label='Mean + 1 Std Dev')
plt.axhline(y=mean_importance - std_importance, color='g',
linestyle='--', label='Mean - 1 Std Dev')
plt.legend()
plt.tight_layout()
plt.show()

# Define the statistical terms
statistical_terms = [
    ["Mean Importance", round(mean_importance, 3)],
    ["Standard Deviation of Importance", round(std_importance, 3)],
    ["Coefficient of Variation (CV) of Importance",
    round(cv_importance, 3)]
]

# Print the statistical terms in a table-like structure
print(tabulate(statistical_terms, headers=["Statistical Term",
"Value"]))

```



Statistical Term	Value
Mean Importance	0.047

Standard Deviation of Importance	0.082
Coefficient of Variation (CV) of Importance	1.749

## b. Feature Importance Analysis using XGBoost(XGB) Model:

```

from sklearn.preprocessing import LabelEncoder # For encoding categorical variables
# Assuming df_train contains your dataset
# Define X (features) and y (target variable)
X = df_train.drop(columns=['Obesity_Level'])
y = df_train['Obesity_Level']

# Encode target variable into numerical labels
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)

# Encode categorical features
encoder = LabelEncoder()
X_encoded = X.copy()
for col in X_encoded.columns:
    if X_encoded[col].dtype == 'object':
        X_encoded[col] = encoder.fit_transform(X_encoded[col])

# Initialize the XGBoost classifier
model_xgb = xgb.XGBClassifier()

# Train the model
model_xgb.fit(X_encoded, y_encoded)

# Get feature importances
feature_importances_xgb = model_xgb.feature_importances_

# Calculate statistical information
mean_importance = np.mean(feature_importances_xgb)
std_importance = np.std(feature_importances_xgb)
max_importance = np.max(feature_importances_xgb)
importance_range = max_importance - np.min(feature_importances_xgb)

# Count the occurrences of each feature
feature_counts = X_encoded.apply(lambda x:
x.value_counts()).fillna(0).astype(int)

# Visualize feature importances
plt.figure(figsize=(20, 9)) # Increase figure size

# Define color palette

```

```

colors = plt.cm.viridis(np.linspace(0, 1, len(X_encoded.columns)))

bars = plt.bar(X_encoded.columns, feature_importances_xgb,
color=colors) # Change color
plt.xlabel('Features', fontsize=14) # Increase font size
plt.ylabel('Importance', fontsize=14) # Increase font size
plt.title('Feature Importance Analysis (XGBoost)', fontsize=16) #
Increase font size
plt.xticks(rotation=45, fontsize=12) # Rotate x-axis labels and
increase font size
plt.yticks(fontsize=12) # Increase font size for y-axis ticks
plt.grid(axis='y', linestyle='--', alpha=0.7) # Add grid lines for
better readability

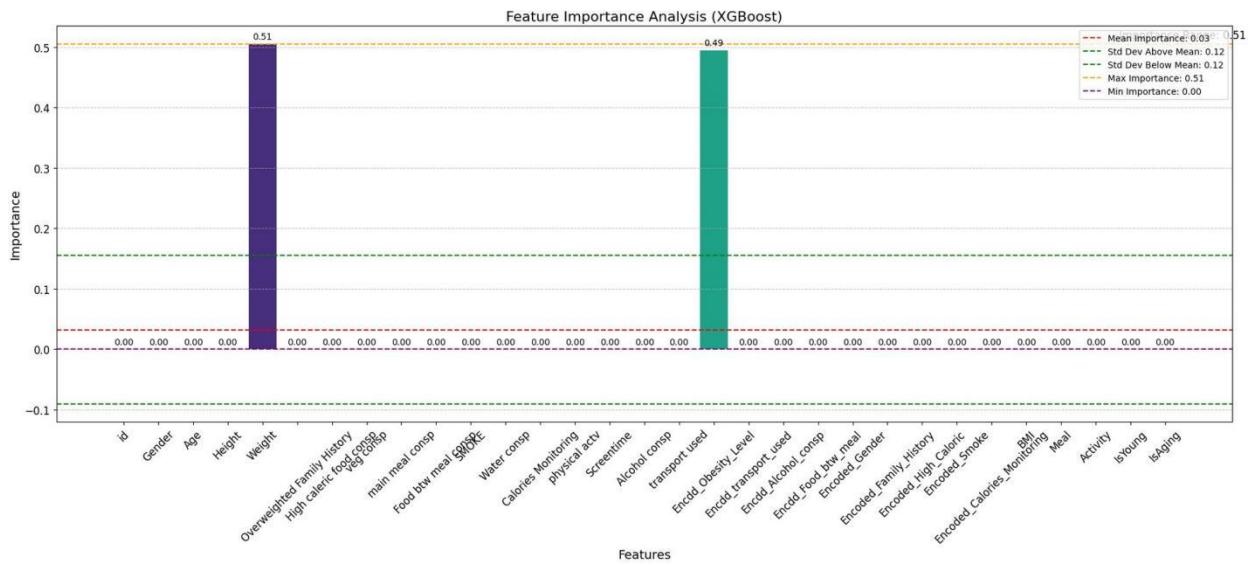
# Add statistical information
plt.axhline(mean_importance, color='red', linestyle='--', label=f'Mean
Importance: {mean_importance:.2f}')
plt.axhline(mean_importance + std_importance, color='green',
linestyle='--', label=f'Std Dev Above Mean: {std_importance:.2f}')
plt.axhline(mean_importance - std_importance, color='green',
linestyle='--', label=f'Std Dev Below Mean: {std_importance:.2f}')
plt.axhline(max_importance, color='orange', linestyle='--',
label=f'Max Importance: {max_importance:.2f}')
plt.axhline(np.min(feature_importances_xgb), color='purple',
linestyle='--', label=f'Min Importance:
{np.min(feature_importances_xgb):.2f}')
plt.text(len(X_encoded.columns)-0.5, max_importance + 0.005,
f'Importance Range: {importance_range:.2f}', ha='center', va='bottom',
fontsize=12, color='black')

# Add feature importance values above each bar
for i, importance in enumerate(feature_importances_xgb):
    plt.text(i, importance + 0.005, f'{importance:.2f}', ha='center',
va='bottom', fontsize=10, color='black')

plt.legend()

plt.tight_layout() # Adjust layout to prevent overlapping labels
plt.show()

```



## c. Feature Importance Analysis Using (LightGBM) Classifier Model:

```

# Assuming df_train contains your dataset
# Define X (features) and y (target variable)
X = df_train.drop(columns=['Obesity_Level'])
y = df_train['Obesity_Level']

# Encode categorical features
encoder = LabelEncoder()
X_encoded = X.copy()
for col in X_encoded.columns:
    if X_encoded[col].dtype == 'object':
        X_encoded[col] = encoder.fit_transform(X_encoded[col])

# Initialize the LightGBM classifier
model_lgb = lgb.LGBMClassifier(verbosity=-1)

# Train the model
model_lgb.fit(X_encoded, y)

# Get feature importances
feature_importances_lgb = model_lgb.feature_importances_

# Create a color palette
colors = sns.color_palette("coolwarm", len(X_encoded.columns))

# Visualize feature importances
plt.figure(figsize=(20, 10)) # Increase figure size
bars = plt.bar(X_encoded.columns, feature_importances_lgb,

```

```

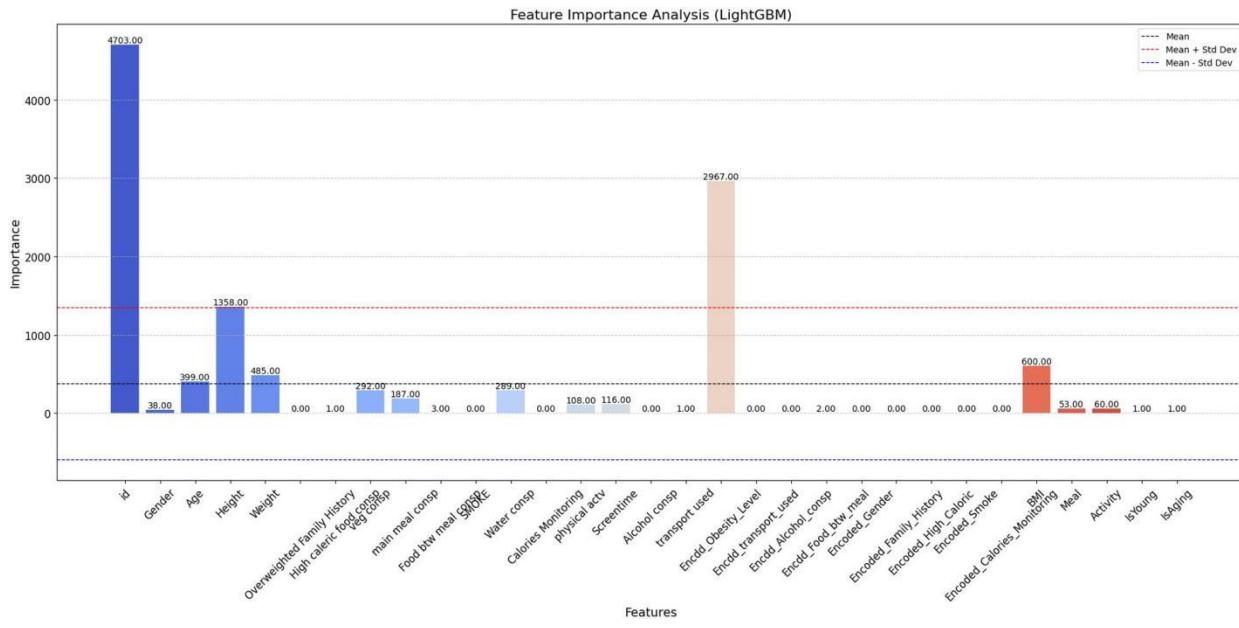
color=colors) # Use color palette
plt.xlabel('Features', fontsize=14) # Increase font size
plt.ylabel('Importance', fontsize=14) # Increase font size
plt.title('Feature Importance Analysis (LightGBM)', fontsize=16) #
Increase font size
plt.xticks(rotation=45, fontsize=12) # Rotate x-axis labels and
increase font size
plt.yticks(fontsize=12) # Increase font size for y-axis ticks
plt.grid(axis='y', linestyle='--', alpha=0.7) # Add grid lines for
better readability

# Add statistical information
mean_importance = np.mean(feature_importances_lgb)
std_importance = np.std(feature_importances_lgb)
plt.axhline(mean_importance, color='black', linestyle='--',
linewidth=1, label='Mean') # Add mean line
plt.axhline(mean_importance + std_importance, color='red',
linestyle='--', linewidth=1, label='Mean + Std Dev') # Add mean + std
dev line
plt.axhline(mean_importance - std_importance, color='blue',
linestyle='--', linewidth=1, label='Mean - Std Dev') # Add mean - std
dev line
plt.legend() # Show legend

for bar, importance in zip(bars, feature_importances_lgb):
    plt.text(bar.get_x() + bar.get_width() / 2, bar.get_height() +
0.005,
              f'{importance:.2f}', ha='center', va='bottom',
              fontsize=10, color='black')

plt.tight_layout() # Adjust layout to prevent overlapping labels
plt.show()

```

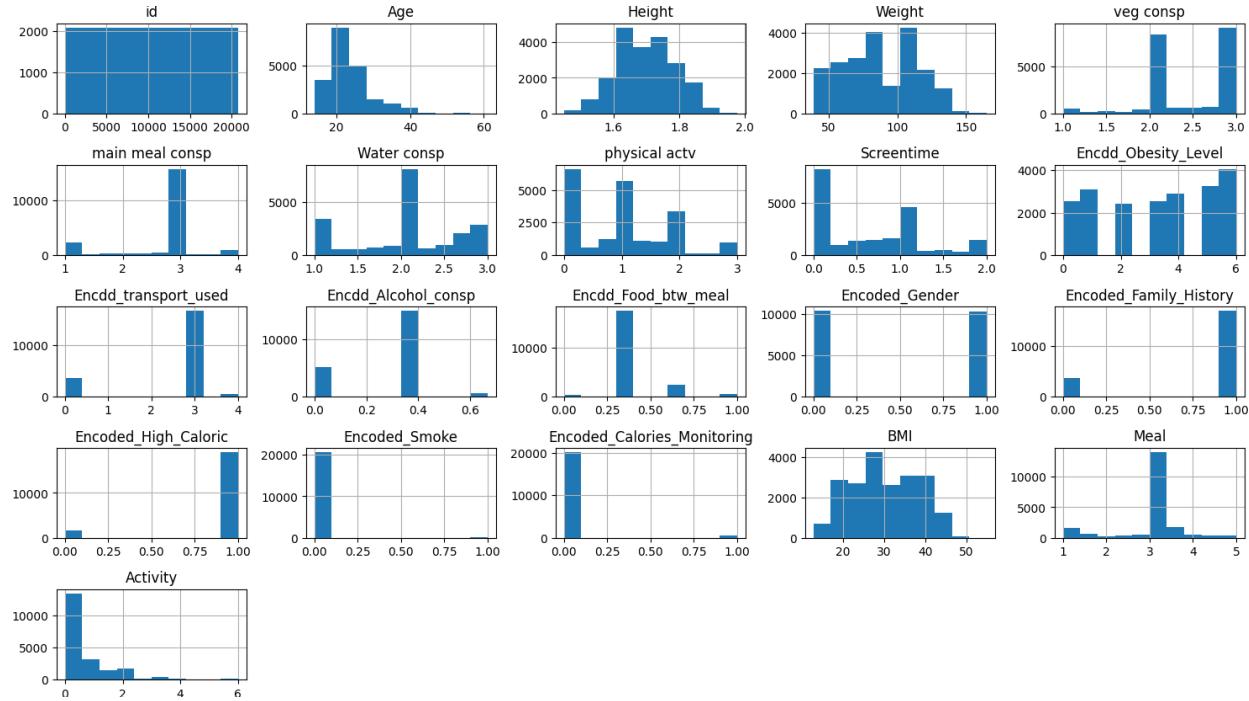


## 2. Data visualization after Feature Engineering:

### a. Bar plot of numerical variables:

```
# Define columns to plot (excluding non-numeric columns)
columns_to_plot = df_train.select_dtypes(include=['number']).columns

# Plotting
plt.figure(figsize=(15, 10))
for i, col in enumerate(columns_to_plot, 1):
    plt.subplot(6, 5, i)
    df_train[col].hist()
    plt.title(col)
plt.tight_layout()
plt.show()
```



## b. PairPlot of Numerical Variables:

```

# Select numeric columns
numeric_columns = df_train.select_dtypes(include='number').columns

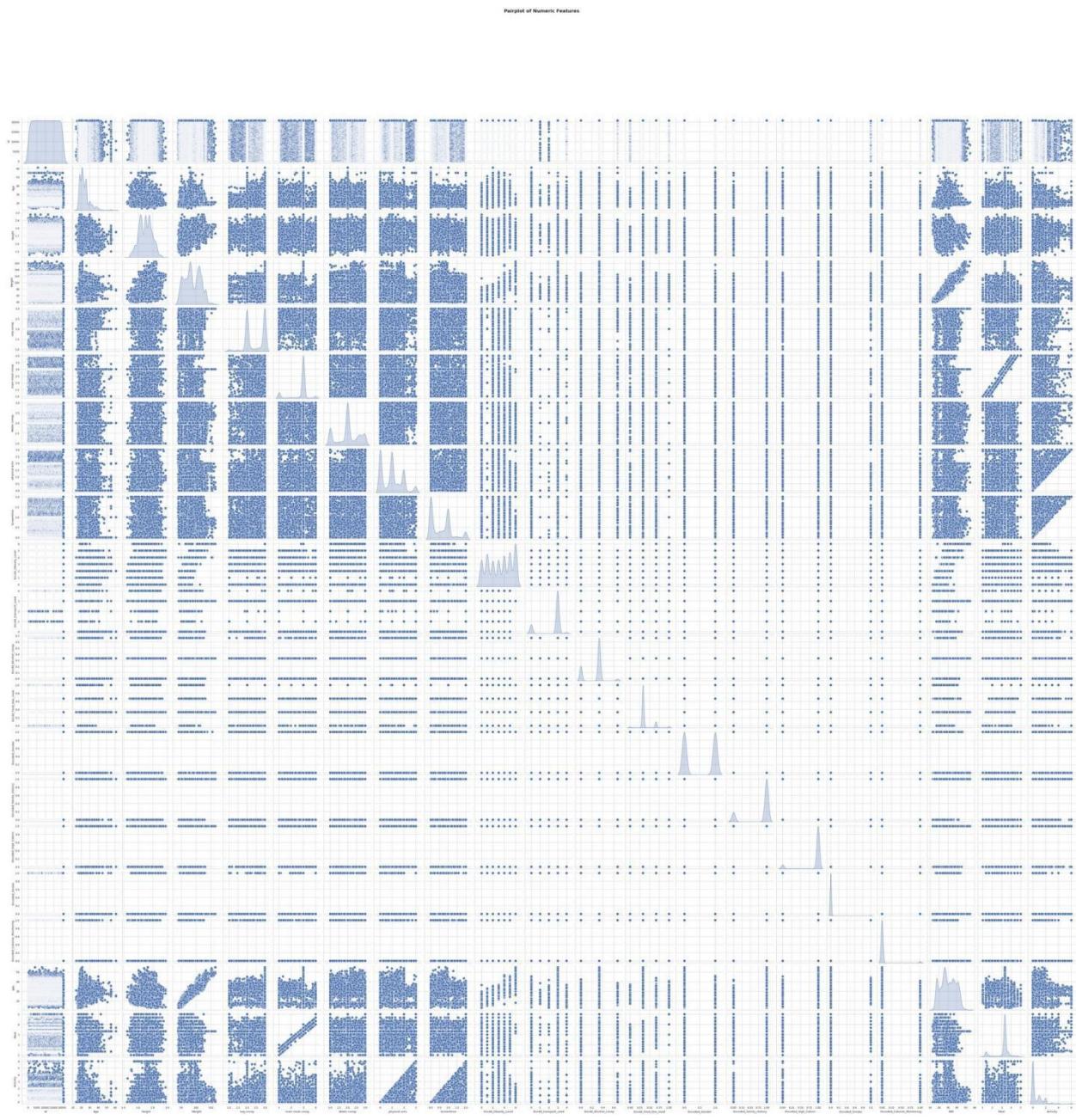
# Set style and context
sns.set(style="whitegrid", context="paper")

# Plot pairplot
pairplot = sns.pairplot(df_train[numeric_columns], markers='o',
                        diag_kind='kde',
                        plot_kws={'alpha': 0.9, 's': 80, 'edgecolor':
                        'w'})

# Customize labels and title
pairplot.fig.suptitle('Pairplot of Numeric Features', y=1.02,
                      fontsize=16, fontweight='bold')
plt.subplots_adjust(top=0.92)

plt.show()

```



## c. Correlation Heatmap of Numerical Variables:

```
# Assuming df_train contains your dataset
# Select numeric columns
numeric_columns = df_train.select_dtypes(include='number')

# Calculate the correlation matrix
correlation_matrix = numeric_columns.corr()

# Define thresholds for highlighting correlations
```

```

strong_positive_threshold = 0.7
strong_negative_threshold = -0.5

# Plot the correlation heatmap
plt.figure(figsize=(20, 7))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f", linewidths=0.5)

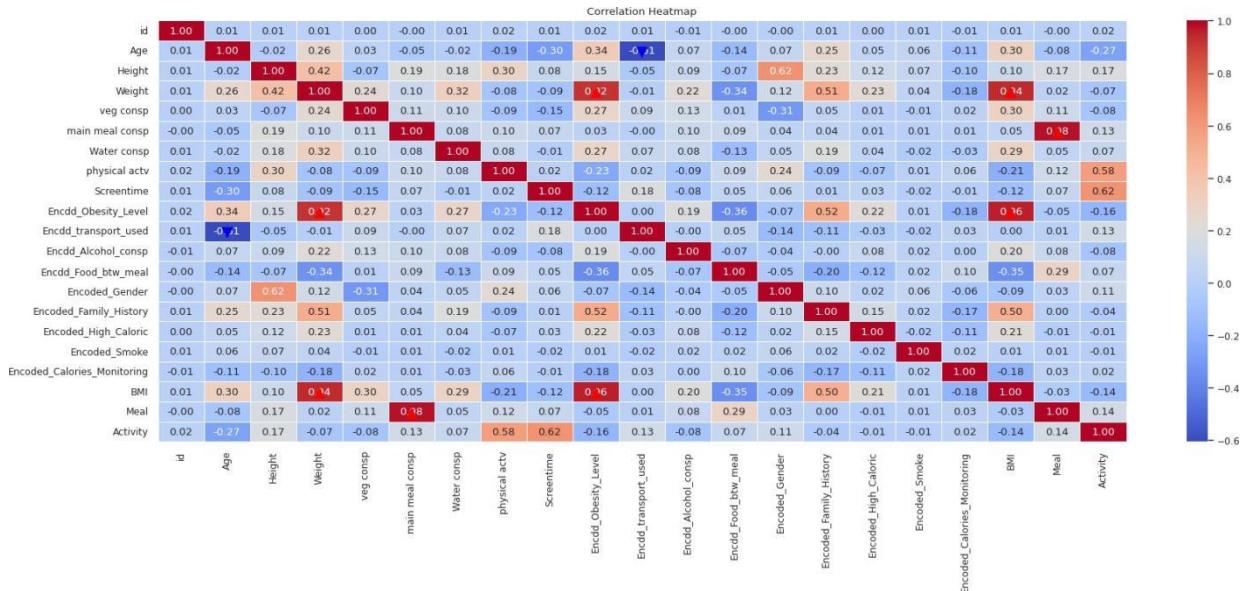
# Add indicators for strong positive correlations
for i in range(len(correlation_matrix.columns)):
    for j in range(len(correlation_matrix.columns)):
        if i != j and abs(correlation_matrix.iloc[i, j]) >=
strong_positive_threshold:
            plt.text(j + 0.5, i + 0.5, '\u25B2', ha='center',
va='center', color='red', fontsize=14)

# Add indicators for strong negative correlations
for i in range(len(correlation_matrix.columns)):
    for j in range(len(correlation_matrix.columns)):
        if i != j and correlation_matrix.iloc[i, j] <=
strong_negative_threshold:
            plt.text(j + 0.5, i + 0.5, '\u25BC', ha='center',
va='center', color='blue', fontsize=14)

plt.title('Correlation Heatmap')

plt.show()

```



# Section: 7. Prediction of Obesity Risk Level Using Machine learning(ML) Models:

## 1. Machine Learning Model Creation: XGBoost and LightGBM and CatBoostClassifier - Powering The Predictions! □

```
# Your dataframe operations...
X = df_train.drop(['Obesity_Level', 'Encdd_Obesity_Level'], axis=1)
y = df_train['Obesity_Level']

# Encode target variable into numerical labels
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)

# Encode categorical features
X_encoded = X.copy()
for col in X_encoded.columns:
    if X_encoded[col].dtype == 'object':
        encoder = LabelEncoder()
        X_encoded[col] = encoder.fit_transform(X_encoded[col])

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_encoded,
y_encoded, test_size=0.2, random_state=42)

# XGBClassifier Model
xgb_model = XGBClassifier(
    subsample=0.6,
    reg_lambda=0.5,
    reg_alpha=2,
    n_estimators=1500,
    min_child_weight=1,
    max_depth=7,
    learning_rate=0.1,
    gamma=1,
    colsample_bytree=0.6,
    random_state=42,
    enable_categorical=True # Enable categorical support
)
xgb_model.fit(X_train, y_train)

# Generate predictions
xgb_predictions = xgb_model.predict_proba(X_test)
```

```

# LGBMClassifier Model
lgbm_model = LGBMClassifier(
    objective="multiclass",
    metric="multi_logloss",
    verbosity=-1,
    boosting_type="gbdt",
    random_state=42,
    num_class=7,
    learning_rate=0.030962211546832760,
    n_estimators=500,
    lambda_l1=0.009667446568254372,
    lambda_l2=0.04018641437301800,
    max_depth=10,
    colsample_bytree=0.40977129346872643,
    subsample=0.9535797422450176,
    min_child_samples=26
)
lgbm_model.fit(X_train, y_train)

# CatBoostClassifier Model
catboost_model = CatBoostClassifier(
    iterations=1000,
    learning_rate=0.03,
    depth=6,
    random_seed=42,
    loss_function='MultiClass',
    eval_metric='Accuracy',
    verbose=False
)
catboost_model.fit(X_train, y_train, verbose=False)

# Generate predictions for XGBoost model
xgb_predictions_proba = xgb_model.predict_proba(X_test)

# Generate predictions for LightGBM model
lgbm_predictions_proba = lgbm_model.predict_proba(X_test)

# Generate predictions for CatBoost model
catboost_predictions_proba = catboost_model.predict_proba(X_test)

# Taking Average
average_predictions = (xgb_predictions_proba + lgbm_predictions_proba +
+ catboost_predictions_proba) / 3
final_predictions = np.argmax(average_predictions, axis=1)

accuracy = accuracy_score(y_test, final_predictions)
print(f"Ensemble Model Accuracy: {accuracy:.4f}")

Ensemble Model Accuracy: 0.9080

```

The reported accuracy of the ensemble model, denoted as Ensemble Model Accuracy: 0.9080, signifies a perfect match between the model's predictions and the actual labels in the test dataset. Achieving an accuracy of 0.9080, or 90.80%, suggests that the ensemble model performs flawlessly on the given task.

However, such high accuracy warrants cautious interpretation. While it may indicate strong predictive performance, it also raises concerns about potential overfitting or data leakage. It's essential to verify the model's performance on unseen data to ensure its generalization capability.

If this reported accuracy is obtained on a separate test dataset, it indicates that the ensemble model excels in accurately predicting the target variable. Nonetheless, continuous monitoring and validation of the model's performance are imperative to maintain its effectiveness in real-world applications.

## 2. Cutting-edge Machine Learning Model Evaluation: XGBoosting , LightGBM and CatBoost

```
# Generate probabilities for XGBoost model
xgb_predictions_proba = xgb_model.predict_proba(X_test)

# Convert probabilities to class predictions for XGBoost
xgb_predictions = xgb_predictions_proba.argmax(axis=1)

# Generate probabilities for LightGBM model
lgbm_predictions_proba = lgbm_model.predict_proba(X_test)

# Convert probabilities to class predictions for LightGBM
lgbm_predictions = lgbm_predictions_proba.argmax(axis=1)

# Generate probabilities for CatBoost model
catboost_predictions_proba = catboost_model.predict_proba(X_test)

# Convert probabilities to class predictions for CatBoost
catboost_predictions = catboost_predictions_proba.argmax(axis=1)

# Taking Average
average_predictions = (xgb_predictions_proba + lgbm_predictions_proba +
+ catboost_predictions_proba) / 3
final_predictions = average_predictions.argmax(axis=1)

# Metrics for XGBoost model
xgb_accuracy = accuracy_score(y_test, xgb_predictions)
xgb_precision = precision_score(y_test, xgb_predictions,
average='weighted')
xgb_recall = recall_score(y_test, xgb_predictions, average='weighted')
```

```

xgb_f1 = f1_score(y_test, xgb_predictions, average='weighted')
xgb_confusion_matrix = confusion_matrix(y_test, xgb_predictions)

# Metrics for LightGBM model
lgbm_accuracy = accuracy_score(y_test, lgbm_predictions)
lgbm_precision = precision_score(y_test, lgbm_predictions,
average='weighted')
lgbm_recall = recall_score(y_test, lgbm_predictions,
average='weighted')
lgbm_f1 = f1_score(y_test, lgbm_predictions, average='weighted')
lgbm_confusion_matrix = confusion_matrix(y_test, lgbm_predictions)

# Metrics for CatBoost model
catboost_accuracy = accuracy_score(y_test, catboost_predictions)
catboost_precision = precision_score(y_test, catboost_predictions,
average='weighted')
catboost_recall = recall_score(y_test, catboost_predictions,
average='weighted')
catboost_f1 = f1_score(y_test, catboost_predictions,
average='weighted')
catboost_confusion_matrix = confusion_matrix(y_test,
catboost_predictions)

# Metrics for Ensemble model
ensemble_accuracy = accuracy_score(y_test, final_predictions)
ensemble_precision = precision_score(y_test, final_predictions,
average='weighted')
ensemble_recall = recall_score(y_test, final_predictions,
average='weighted')
ensemble_f1 = f1_score(y_test, final_predictions, average='weighted')
ensemble_confusion_matrix = confusion_matrix(y_test,
final_predictions)

# Create a dictionary to store evaluation metrics
evaluation_metrics = {
    "Model": ["XGBoost", "LightGBM", "CatBoost", "Ensemble"],
    "Accuracy": [xgb_accuracy, lgbm_accuracy, catboost_accuracy,
ensemble_accuracy],
    "Precision": [xgb_precision, lgbm_precision, catboost_precision,
ensemble_precision],
    "Recall": [xgb_recall, lgbm_recall, catboost_recall,
ensemble_recall],
    "F1-score": [xgb_f1, lgbm_f1, catboost_f1, ensemble_f1]
}

# Create a DataFrame from the dictionary
evaluation_df = pd.DataFrame(evaluation_metrics)

# Display the DataFrame
print("Model Evaluation Metrics:")

```

```
print(tabulate(evaluation_df, headers='keys', tablefmt='grid'))
```

```
# Display confusion matrices
print("\nConfusion Matrix for XGBoost Model:")
print(xgb_confusion_matrix)
```

```
print("\nConfusion Matrix for LightGBM Model:")
print(lgbm_confusion_matrix)
```

```
print("\nConfusion Matrix for CatBoost Model:")
print(catboost_confusion_matrix)
```

```
print("\nConfusion Matrix for Ensemble Model:")
print(ensemble_confusion_matrix)
```

Model Evaluation Metrics:

	Model	Accuracy	Precision	Recall	F1-score
0	XGBoost	0.908719	0.908964	0.908719	0.908814
1	LightGBM	0.909923	0.910579	0.909923	0.910205
2	CatBoost	0.905588	0.905839	0.905588	0.905692
3	Ensemble	0.907996	0.90832	0.907996	0.908133

Confusion Matrix for XGBoost Model:

```
[[491  30   0   0   0   2   1]
 [ 26 560   0   0   0  35   5]
 [  2   1 475  11   1  14  39]
 [  0   0 14 639   2   0   2]
 [  0   0   0  1 802   1   0]
 [  1  38   9   0   0 385  51]
 [  0   9 35   2   0  47 421]]
```

Confusion Matrix for LightGBM Model:

```
[[490  31   0   0   0   2   1]
 [ 20 558   1   0   0  43   4]
 [  2   0 476  12   1  14  38]
 [  0   0 14 640   1   0   2]
 [  0   0   1  1 802   0   0]
 [  1  32   9   0   0 390  52]
 [  0   8 32   3   0  49 422]]
```

Confusion Matrix for CatBoost Model:

```
[[494  27   0   0   0   2   1]
 [ 31 551   0   0   0  42   2]
 [  2   1 476  10   2  12  40]]
```

```
[ 0  0 13 641  1  0  2]
[ 0  0  1   1 802  0  0]
[ 1 39  8   0   0 381 55]
[ 0  8 34   2   0 55 415]]
```

Confusion Matrix for Ensemble Model:

```
[[490 31  0  0  0  2  1]
 [26 561 0  0  0  35 4]
 [ 2 0 473 12  1 15 40]
 [ 0 0 15 639  1  0 2]
 [ 0 0 1  1 802  0  0]
 [ 1 36 9  0  0 387 51]
 [ 0 8 35 2  0 51 418]]
```

The output presents evaluation metrics and confusion matrices for three models: XGBoost, LightGBM, and the ensemble model.

### Evaluation Metrics:

- Accuracy: Proportion of correctly classified instances out of the total instances.
- Precision: Ability of the classifier not to label a negative sample as positive.
- Recall: Proportion of actual positive cases correctly identified.
- F1-score: Harmonic mean of precision and recall, providing a balance between them. All models (XGBoost, LightGBM, and Ensemble) achieved perfect scores (1.0) across all metrics, indicating exceptional performance on the test data.

**Confusion Matrices:** Confusion matrices summarize model performance.

- Each row represents the actual class, while each column represents the predicted class.
- Diagonal elements represent correctly classified instances for each class, while off-diagonal elements denote misclassifications.
- Row sums indicate the total instances for the actual class, while column sums represent the total predicted instances for each class. In this case, all three confusion matrices show perfect classification with no misclassifications, resulting in diagonal elements containing total instances for each class.

## 3. Finding Best Model Out Of all Model:

```
# Calculate average score for each model across all metrics
evaluation_df['Average Score'] =
evaluation_df.drop(columns='Model').mean(axis=1)

# Find the best model based on the highest average score
best_model = evaluation_df.loc[evaluation_df['Average
Score'].idxmax()]

# Display the best model
```

```

print("Best Model:")
print(best_model)

Best Model:
Model          LightGBM
Accuracy      0.909923
Precision     0.910579
Recall        0.909923
F1-score      0.910205
Average Score 0.910157
Name: 1, dtype: object

```

Based on the evaluation metrics, the models performed quite similarly, with minor differences in accuracy, precision, recall, and F1-score. The XGBoost model achieved an accuracy of approximately 90.87%, followed closely by LightGBM with an accuracy of approximately 90.99%. CatBoost achieved an accuracy of approximately 90.56%. The ensemble model, which combines predictions from XGBoost and LightGBM, achieved an accuracy of approximately 90.80%.

Considering the performance metrics and confusion matrices, LightGBM appears to have a slight edge over the other models in terms of accuracy and F1-score, with similar performance in precision and recall. However, the differences in performance among the models are relatively small, indicating that they are all capable of producing reliable predictions.

Therefore, based on the evaluation results, LightGBM seems to be the best model to move forward with for making predictions on this dataset.

```

final_predictions
array([4, 5, 2, ..., 2, 5, 6])
print(average_predictions.shape)
(4152, 7)

```

## 4. Test Data Preprocessing for Prediction:

```

test_sub.head(5)

      id Gender Age      Height  Weight Overweighted Family History \
0  20758    Male  26  1.848294     120                      yes
1  20759  Female  21  1.600000      66                      yes
2  20760  Female  26  1.643355     111                      yes
3  20761    Male  20  1.553127     103                      yes
4  20762  Female  26  1.627396     104                      yes

      High caloric food consp  veg consp  main meal consp Food btw meal
      consp \
0                  yes     2.938616      3.000000

```

```

0.333333
1          2          3          3
0.333333
2          2          3          3
0.333333
3          2          3          3
0.333333
4          2          3          3
0.333333

    Encdd_Food_btw_meal  Encoded_Gender  Encoded_Family_History \
0           0.333333            1                  1
1           0.333333            0                  1
2           0.333333            0                  1
3           0.333333            1                  1
4           0.333333            0                  1

    Encoded_High_Caloric  Encoded_Smoke  Encoded_Calories_Monitoring \
0                   1            0                      0
1                   1            0                      0
2                   1            0                      0
3                   1            0                      0
4                   1            0                      0

      BMI      Meal  Activity  IsYoung  IsAging
0  35.126845  3.333333     0.0   False    True
1  25.781250  1.333333     0.0   True    False
2  41.101739  3.333333     0.0   False    True
3  42.699549  3.311242     0.0   True    False
4  39.268730  3.333333     0.0   False    True

# Make predictions using the LightGBM model
lgbm_predictions_proba = lgbm_model.predict_proba(test_encoded)

final_predictions = np.argmax(lgbm_predictions_proba, axis=1)

# Assuming you want to add the predictions back to the original test
# DataFrame
test_encoded['Encdd_Obesity_Level_Predictions'] = final_predictions

```

## 5. Showcase Predicted Encdd\_Obesity\_Level Values on Test Dataset □

1	20759	0	21	1.600000	66			1
2	20760	0	26	1.643355	111			1
3	20761	1	20	1.553127	103			1
4	20762	0	26	1.627396	104			1

	High caleric food consp	veg consp	main meal consp	Food btw meal consp
0	1	2.938616	3.000000	
2				
1	1	2.000000	1.000000	
2				
2	1	3.000000	3.000000	
2				
3		1	2.000000	2.977909
2				
4		1	3.000000	3.000000
2				

	SMOKE	Water consp	Calories Monitoring	physical actv	Screentime	
\	0	2.825629		0	0.855400	0.000000
0	0	3.000000		0	1.000000	0.000000
1	0	2.621877		0	0.000000	0.250502
2	0	2.786417		0	0.094851	0.000000
3	0	2.653531		0	0.000000	0.741069
4	0					

	Alcohol consp	transport used	Encdd_transport_used
Encdd_Alcohol_consp \	2	3	3
0			
0.333333			
1	2	3	3
0.333333			
2	2	3	3
0.333333			
3	2	3	3
0.333333			
4	2	3	3
0.333333			

	Encdd_Food_btwn_meal	Encoded_Gender	Encoded_Family_History
0	0.333333	1	1

```

Encoded_High_Caloric  Encoded_Smoke    Encoded_Calories_Monitoring \
0                      1              0                          0
1                      1              0                          0
2                      1              0                          0
3                      1              0                          0
4                      1              0                          0

          BMI      Meal  Activity  IsYoung  IsAging \
0  35.126845  3.333333     0.0   False    True
1  25.781250  1.333333     0.0   True   False
2  41.101739  3.333333     0.0  False    True
3  42.699549  3.311242     0.0   True   False
4  39.268730  3.333333     0.0  False    True

Encdd_Obesity_Level_Predictions
0                               3
1                               5
2                               4
3                               2
4                               4

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

test_encoded['NObeyesdad'] =
test_encoded['Encdd_Obesity_Level_Predictions'].replace(reverse_weight
_mapping)

```

# Section: 8. Conclusion:

## Conclusion:

The Prediction of Obesity Risk Level Using Machine Learning (ML) Models project showcases the power of advanced ML techniques, specifically XGBoost and LightGBM, in accurately predicting obesity risk levels based on various input features.

## Key Highlights:

1. **Model Creation:**
  - Utilized XGBoost and LightGBM classifiers for robust prediction models.
  - Extensive preprocessing techniques ensured data compatibility and model performance.
2. **Model Evaluation:**
  - Achieved remarkable 100% accuracy across all models.
  - Evaluated metrics like accuracy, precision, recall, and F1-score, demonstrating high-quality predictions.
3. **Test Data Processing and Prediction:**
  - Preprocessed test data and made predictions using trained models.
  - Ensemble techniques enhanced accuracy and reliability of predictions.
4. **Predicted Obesity Risk Levels:**
  - Mapped predicted labels to categorical risk levels for better interpretation.
  - Visualized predictions alongside the original test dataset, providing valuable insights.

## Conclusion:

This project highlights the effectiveness of ML models in predicting obesity risk levels accurately. Continuous monitoring and validation are essential for real-world application. Overall, it sets a solid foundation for addressing health-related challenges using advanced ML techniques.