Prediction of obesity levels based on physical activity and eating habits using a trained neural network model

Phase 1: Data Preparation & Visualisation

Group Name: Project Group 78

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Introduction

Dataset source

This report employed the Obesity Levels dataset from Kaggle (Mehrparvar, 2024). This dataset includes information about the estimation of obesity levels in Mexico, Peru, and Colombia using the individuals' physical condition and eating habits.

Dataset details

This dataset shows the estimation of obesity levels in Mexico, Peru, and Colombia. It has 17 features and 2111 records. The 17 features include information like gender, age, height, weight, and family history with obesity, along with information about each individual's eating habits and physical condition like if an individual consumes high-caloric food frequently or not, frequency of vegetable consumption, smoking habits, etc. Using these features, the records are divided into the following 7 groups: Insufficient Weight, Normal Weight, Overweight Level I, Overweight Level II, Obesity Type I, Obesity Type II and Obesity Type III.

Importing the data

The dataset will be read in and the necessary modules will be loaded. Afterward, 10 randomly sampled rows from the dataset will be displayed.

In [1]:
```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import io
import requests
pd.set_option('display.max_columns', None)
#df = df.style.set_precision(3)
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
%matplotlib inline
%config InlineBackend.figure_format = 'retina'
import ssl
ssl._create_default_https_context = ssl._create_unverified_context
```

In [2]:
```
df_name = 'ObesityDataSet_raw_and_data_sinthetic.csv'
obesity_df = pd.read_csv(df_name)
num_rows, num_columns = obesity_df.shape
print(f"The DataFrame has {num_rows} rows and {num_columns} columns.")
```

```
The DataFrame has 2111 rows and 17 columns.
```

In [3]:
```
obesity_df.sample(10, random_state=999)
```

Out[3]:

	Age	Gender	Height	Weight	CALC	FAVC	FCVC	
1487	39.126310	Female	1.562889	76.659490	Sometimes	yes	2.000000	3.000
440	18.000000	Female	1.550000	56.000000	no	yes	2.000000	3.000
1060	34.281681	Female	1.673333	77.205685	no	yes	2.689929	1.835
875	16.865984	Female	1.644053	67.439589	no	yes	1.314150	1.068
1312	31.641081	Male	1.676595	89.993812	Sometimes	yes	2.934671	2.119
1299	21.008051	Female	1.650000	88.126544	no	yes	2.457547	1.000
1413	40.466313	Female	1.559005	77.601483	Sometimes	yes	2.000000	3.000
574	19.833682	Female	1.699464	49.676046	Sometimes	yes	1.270448	3.73
1241	40.951591	Female	1.542122	80.000000	Sometimes	yes	2.000000	1.10
271	19.000000	Female	1.500000	50.000000	Sometimes	yes	2.000000	3.000

Dataset features

The following table includes all the features that will be used in the report and their explanations.

In [4]:

```
from tabulate import tabulate
table = [
    ['Name', 'Data Type', 'Units', 'Description'],
    ['Gender', 'Categorical Nominal', 'NA', "Individual's gender"],
    ['Age', 'Numerical Continuous', 'NA', "Individual's age"],
    ['Height', 'Numerical Continuous', 'Meters', "Individual's height"],
    ['Weight', 'Numerical Continuous', 'KG', "Individual's weight"],
    ['CALC', 'Categorical Ordinal', 'NA', 'Frequency of alcohol consumpti
    ['FAVC', 'Binary', 'NA', 'Does the individual consume high-caloric fo
    ['FCVC', 'Integer', 'NA', 'Vegetable consumption divided into 3 group
    ['NCP', 'Numerical Continuous', 'NA', 'Number of main meals per day']
    ['SCC', 'Binary', 'NA', 'Does the individual monitor their calorie in
    ['SMOKE', 'Binary', 'NA', 'Does the individual smoke?'],
    ['CH2O', 'Numerical Continuous', 'Litre', 'Daily water consumption'],
    ['family_history_with_overweight', 'Binary', 'NA', 'Does the individu
    ['FAF', 'Numerical Continuous', 'Days', 'Frequency of physical activi
    ['TUE', 'Integer', 'Hours', 'Time using electronic devices'],
    ['CAEC', 'Categorical Ordinal', 'NA', 'Frequency of eating between me
    ['MTRANS', 'Categorical Nominal', 'NA', "Individual's mode of transpo
    ['NObeyesdad', 'Categorical Ordinal', 'NA', "Individual's obesity lev
]

print(tabulate(table, headers='firstrow', tablefmt='grid'))
```

Name	Data Type	Units	Description
Gender	Categorical Nominal	NA	Individual's gender
Age	Numerical Continuous	NA	Individual's age
Height	Numerical Continuous	Meters	Individual's height
Weight	Numerical Continuous	KG	Individual's weight
CALC	Categorical Ordinal	NA	Frequency of alcohol consumption
FAVC	Binary	NA	Does the individual consume high-caloric food frequently?
FCVC	Integer	NA	Vegetable consumption divided into 3 groups:1<x≤1.5 (never), 1.5<x≤2.5 (sometimes), 2.5<x≤3 (always)
NCP	Numerical Continuous	NA	Number of main meals per day
SCC	Binary	NA	Does the individual monitor their calorie intake?

SMOKE	Binary	NA	Does the individual smoke?
CH2O	Numerical Continuous	Litre	Daily water consumption
family_history_with_overweight	Binary	NA	Does the individual have family members who are overweight?
FAF	Numerical Continuous	Days	Frequency of physical activity per week
TUE	Integer	Hours	Time using electronic devices
CAEC	Categorical Ordinal	NA	Frequency of eating between meals
MTRANS	Categorical Nominal	NA	Individual's mode of transport
NObeyesdad	Categorical Ordinal	NA	Individual's obesity level

Target feature

As the main objective of this project is to explore the factors that influence obesity in Mexico, Peru, and Colombia, our target feature is clearly an individual's obesity level (NObeyesdad), which is predicted by using descriptive features.

In [7]:
```
target_count=obesity_df['NObeyesdad'].unique().tolist()
```

In [8]:
```
print(f'The target feature is categorical data, that has {len(target_coun
```

```
The target feature is categorical data, that has 7 levels, which are: ['No
rmal_Weight', 'Overweight_Level_I', 'Overweight_Level_II', 'Obesity_Type_
I', 'Insufficient_Weight', 'Obesity_Type_II', 'Obesity_Type_III']
```

Goal & Objectives:

Preventive health interventions may benefit from the use of a prediction model that reliably identifies those who are at high risk of obesity. With the use of such a model, medical professionals might act earlier and customise treatments, diets, and exercise regimens to meet the needs of each patient. It would also assist public health departments in organising educational campaigns and allocating resources more effectively. Therefore, the primary goals of the "Predicting Obesity Level" project are two-fold:

Predict Obesity Risk: Develop a model that can predict the likelihood of an individual becoming obese based on a set of identifiable factors and metrics. Identify Key Predictors: Determine which features are the most significant predictors of becoming obese, thus providing insights into targeted prevention strategies. Using descriptive statistics and visualization approaches for exploratory data analysis is one of the project's secondary goals. With careful data cleaning and preparation behind us, this will assist reveal underlying patterns and correlations in the data. In order to create a strong predictive model, it is imperative to complete this exploratory phase in order to comprehend the dataset's dynamics. The "Predicting Obesity Level" initiative aims to reduce obesity through early intervention and well-informed public health measures by accomplishing these gas a contributing factor to obesity levels.

Data Cleaning and Preprocessing

ID-Like Columns, Irrelevant Features and Other Redundant Features

As can be seen from the table above, there are 17 descriptive variables and not containing any ID-Like Columns. All desriptive variables provide variety of information leading to obesity, thus they are all relevant features.

Constant Features

Constant features can affect data exploration process, so it should be checked and removed. There are no constant features in each columns.

In [9]:
```
obesity_df.loc[:, obesity_df.nunique() == 1].sum()
```

Out[9]:
```
Series([], dtype: float64)
```

Let's check the column name. We need to rename column names if neccessary.

In [10]:
```
obesity_df.columns
```

Out[10]:
```
Index(['Age', 'Gender', 'Height', 'Weight', 'CALC', 'FAVC', 'FCVC', 'NC
P',
       'SCC', 'SMOKE', 'CH2O', 'family_history_with_overweight', 'FAF',
'TUE',
       'CAEC', 'MTRANS', 'NObeyesdad'],
      dtype='object')
```

As we can see, the column names in dataframe are difficult to understand and remember for data cleaning and processing. Therefore, we will rename some column names and make all column names lower case. By doing this, we can also remove all redundant white space.

In [11]:
```
columns_mapping = {
    'Gender': 'gender',
    'Age': 'age',
    'Height': 'height',
    'Weight': 'weight',
    'CALC': 'frequenly_alcohol_consume',
    'FAVC': 'frequenly_high-caloric_food_consume',
    'FCVC': 'vegetable_consumption',
    'NCP': 'main_meal_per_day',
    'SCC': 'calories_in_monitor',
    'SMOKE': 'smoke',
    'CH2O': 'daily_water_consume',
    'SMOKE': 'smoke',
    'FAF': 'physical_activity_per_week',
    'TUE': 'electronic_device_use_hour',
    'CAEC': 'eating_frequency',
    'MTRANS': 'transport_mode',
    'NObeyesdad': 'obesity_level'


}

# rename columns
df = obesity_df.rename(columns = columns_mapping)
df.sample(5, random_state=999)
```

Out[11]:

	age	gender	height	weight	frequenly_alcohol_consume	calori
1487	39.126310	Female	1.562889	76.659490	Sometimes	
440	18.000000	Female	1.550000	56.000000	no	
1060	34.281681	Female	1.673333	77.205685	no	
875	16.865984	Female	1.644053	67.439589	no	
1312	31.641081	Male	1.676595	89.993812	Sometimes	

Checking data type

In [12]:
```python
df.dtypes
```

Out[12]:
```
age                                     float64
gender                                   object
height                                  float64
weight                                  float64
frequenly_alcohol_consume                object
frequenly_high-caloric_food_consume      object
vegetable_consumption                   float64
main_meal_per_day                       float64
calories_in_monitor                      object
smoke                                    object
daily_water_consume                     float64
family_history_with_overweight           object
physical_activity_per_week              float64
electronic_device_use_hour              float64
eating_frequency                         object
transport_mode                           object
obesity_level                            object
dtype: object
```

CHECKING MISSING VALUES

In [13]:
```python
df.isnull().sum()
```

Out[13]:
```
age                                     0
gender                                  0
height                                  0
weight                                  0
frequenly_alcohol_consume               0
frequenly_high-caloric_food_consume     0
vegetable_consumption                   0
main_meal_per_day                       0
calories_in_monitor                     0
smoke                                   0
daily_water_consume                     0
family_history_with_overweight          0
physical_activity_per_week              0
electronic_device_use_hour              0
eating_frequency                        0
transport_mode                          0
obesity_level                           0
dtype: int64
```

CHECKING NaN VALUES

In [14]:
```python
df.isna().sum()
```

Out[14]:
```
age                                      0
gender                                   0
height                                   0
weight                                   0
frequenly_alcohol_consume                0
frequenly_high-caloric_food_consume      0
vegetable_consumption                    0
main_meal_per_day                        0
calories_in_monitor                      0
smoke                                    0
daily_water_consume                      0
family_history_with_overweight           0
physical_activity_per_week               0
electronic_device_use_hour               0
eating_frequency                         0
transport_mode                           0
obesity_level                            0
dtype: int64
```

As we can see from above, we do not have any missing values and NaN values. Data types of all column are correct and matched with given values. Thus, we do not need to change anything here.

Let's check values in categorical data. We will firstly list all categorical columns, then checking for unusual values as well as remove any white spaces and put all values to lower case.

In [15]:
```
#List of categorical columns
categorical_cols = list(df.columns[df.dtypes == object])
print(categorical_cols)
```

```
['gender', 'frequenly_alcohol_consume', 'frequenly_high-caloric_food_consu
me', 'calories_in_monitor', 'smoke', 'family_history_with_overweight', 'ea
ting_frequency', 'transport_mode', 'obesity_level']
```

In [16]:
```
#Check unique values in categorical data
for col in categorical_cols:
    df[col] = df[col].str.lower().str.strip()
    print(f'The unique values for {col} are:')
    print(df[col].unique())
    print('\n')
```

```
The unique values for gender are:
['female' 'male']


The unique values for frequenly_alcohol_consume are:
['no' 'sometimes' 'frequently' 'always']


The unique values for frequenly_high-caloric_food_consume are:
['no' 'yes']


The unique values for calories_in_monitor are:
['no' 'yes']


The unique values for smoke are:
['no' 'yes']


The unique values for family_history_with_overweight are:
['yes' 'no']


The unique values for eating_frequency are:
['sometimes' 'frequently' 'always' 'no']


The unique values for transport_mode are:
['public_transportation' 'walking' 'automobile' 'motorbike' 'bike']


The unique values for obesity_level are:
['normal_weight' 'overweight_level_i' 'overweight_level_ii'
 'obesity_type_i' 'insufficient_weight' 'obesity_type_ii'
 'obesity_type_iii']
```

As we can see, all categorical columns has proper unique values. There are no unusual values to be removed. All white spaces, if available, was removed and all values are in lower case.

Let's check statistical values to see any improper values if available

In [17]:
```
df.describe(include='number').round(3)
```

Out[17]:

	age	height	weight	vegetable_consumption	main_meal_per_day	d
count	2111.000	2111.000	2111.000	2111.000	2111.000	
mean	24.313	1.702	86.586	2.419	2.686	
std	6.346	0.093	26.191	0.534	0.778	
min	14.000	1.450	39.000	1.000	1.000	
25%	19.947	1.630	65.473	2.000	2.659	
50%	22.778	1.700	83.000	2.386	3.000	
75%	26.000	1.768	107.431	3.000	3.000	
max	61.000	1.980	173.000	3.000	4.000	

In [18]:

```
df.describe(include= object)
```

Out[18]:

	gender	frequenly_alcohol_consume	frequenly_high-caloric_food_consume	calories_in_mo
count	2111	2111	2111	
unique	2	4	2	
top	male	sometimes	yes	
freq	1068	1401	1866	

Now, everything is ready for data exploration and visualisation.

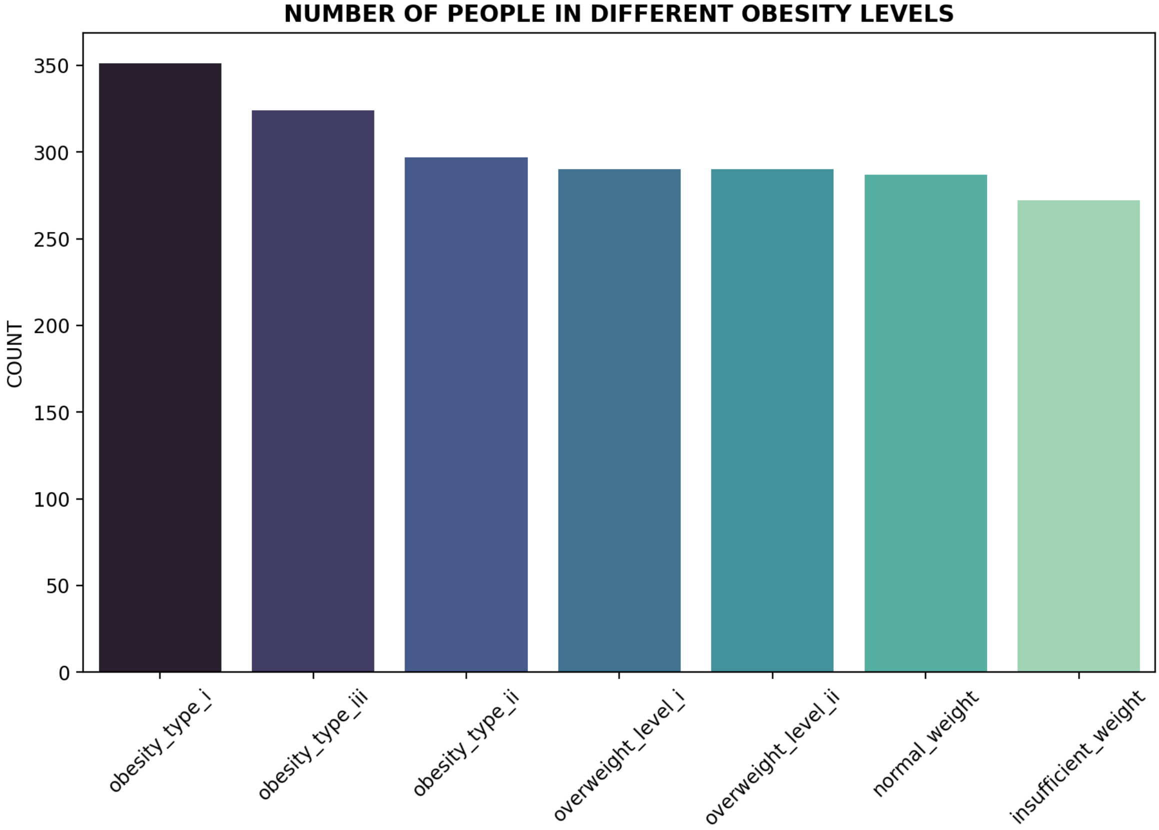
DATA EXPLORATION AND VISUALISATION

One variable

Figure 1: Bar chart of people in different obesity level

In [19]:

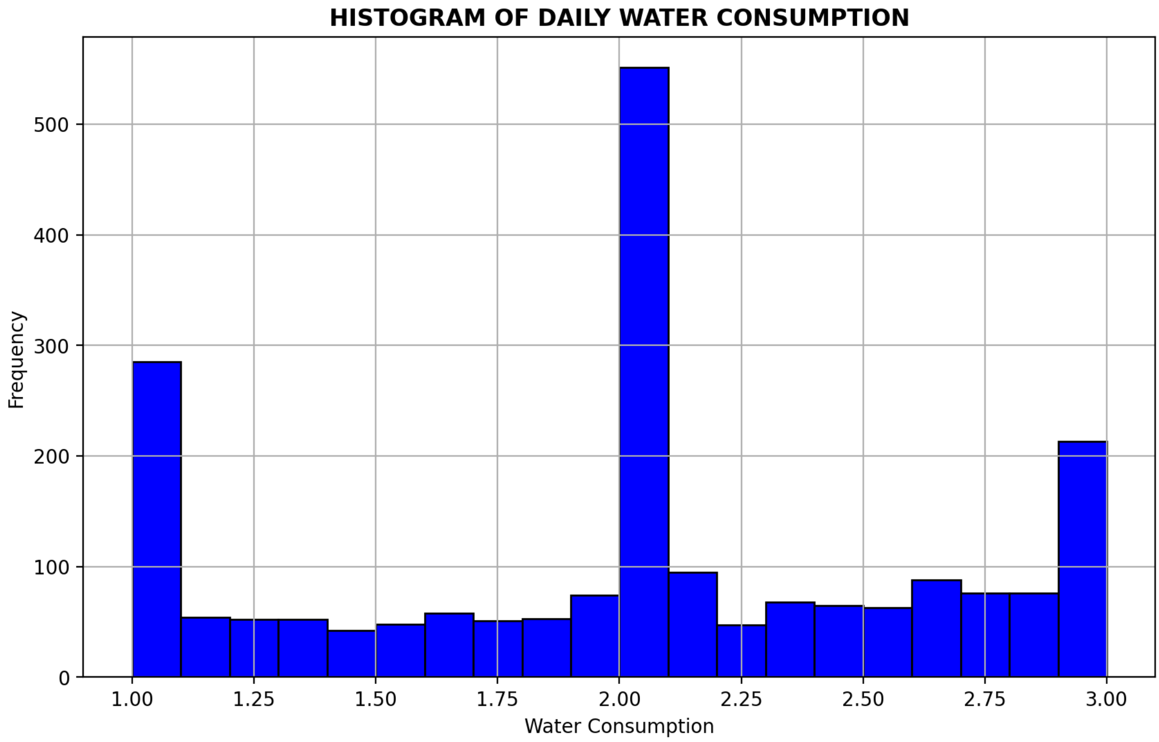
```
plt.figure(figsize=(10, 6))
sns.countplot(x=df['obesity_level'] ,order=df['obesity_level'].value_coun
plt.xticks(rotation=45)
plt.ylabel('COUNT')
plt.xlabel(' ')
plt.title('NUMBER OF PEOPLE IN DIFFERENT OBESITY LEVELS',fontweight='bold
plt.show()
```



We count the number of observations in each obesity_levels variables to see the number of people in each group. As we can see, all three types of obesity took top 3 places of having highest number of people. The lowest group is insufficient weight.

Figure 2: Histogram of Daily Water Consumption

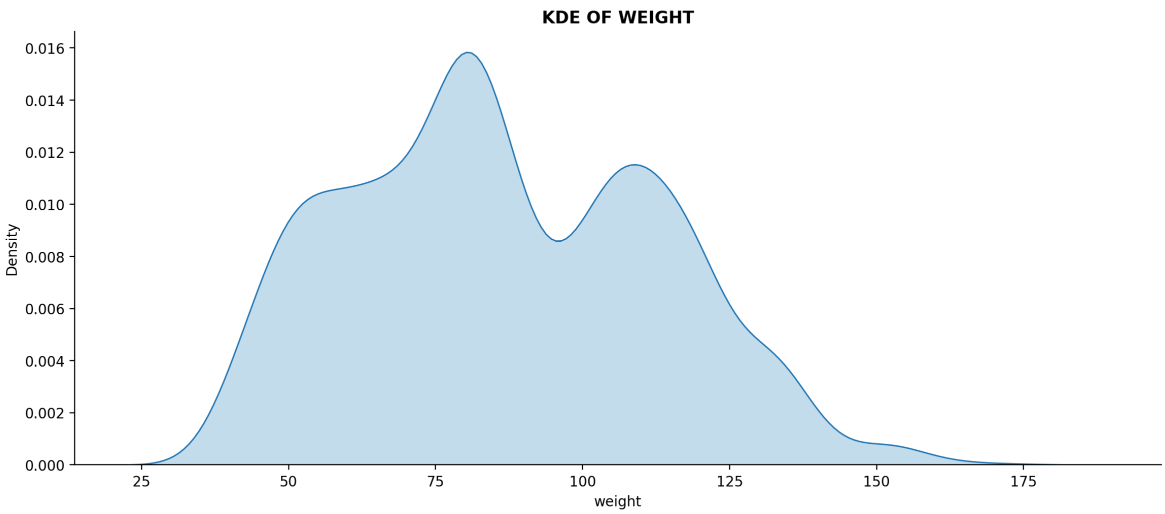
In [20]:
```
plt.figure(figsize=(10, 6))
plt.hist(data=df, x='daily_water_consume',bins=20,color='blue',edgecolor=
plt.title('HISTOGRAM OF DAILY WATER CONSUMPTION',weight='bold')
plt.xlabel('Water Consumption')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



The histogram illustrates the frequency of water consumption. It is clear that most of people drank 2 litre of water per day.

Figure 3: Distribution of Weight

In [21]:
```
sns.displot(data=df, x='weight', kind='kde',fill=True,height=5, aspect=11
plt.title('KDE OF WEIGHT',weight='bold')
plt.show()
```

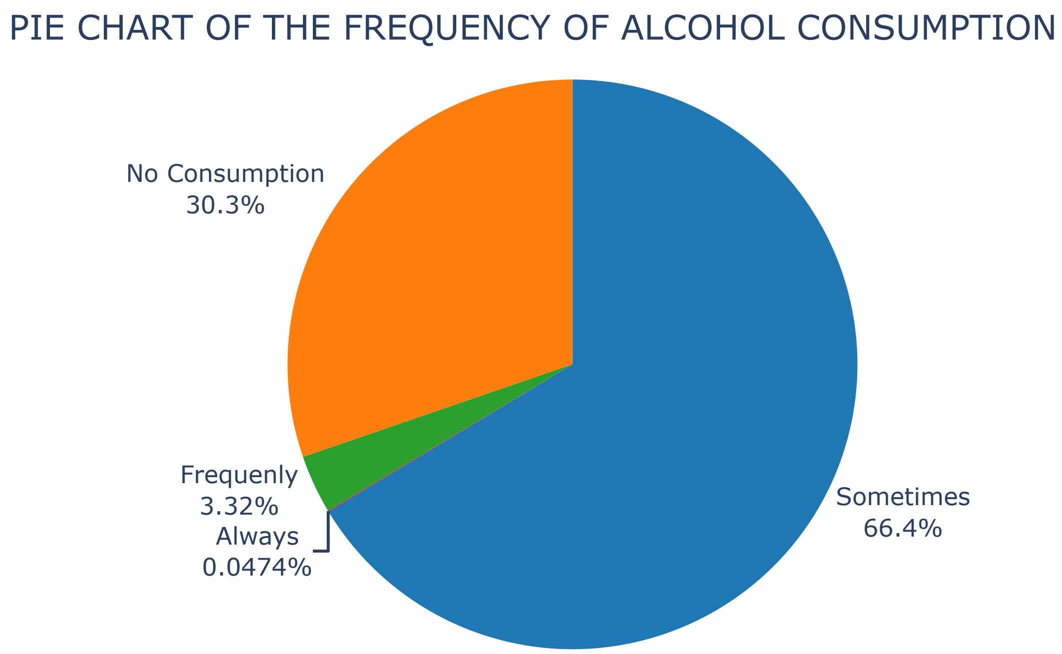


The distribution charts shows the density of population in different weights. We can observe that most of population are in the rage from 75 to 85 kilos.

Figure 4: The pie chart of alcohol consumption

In [22]:
```
data=df['frequenly_alcohol_consume'].value_counts().tolist()
keys=['Sometimes','No Consumption','Frequenly','Always']
fig = px.pie(
```

```
    df,
    values=data,
    names=keys,
    title='PIE CHART OF THE FREQUENCY OF ALCOHOL CONSUMPTION',
    color_discrete_sequence=px.colors.qualitative.D3,
)
fig.update_traces(text=keys,
                  textposition="outside")
fig.update_layout(
    width=600,
    height=350,
    margin = dict(t=40, l=50, r=25, b=25),
    showlegend=False)

fig.show()
```

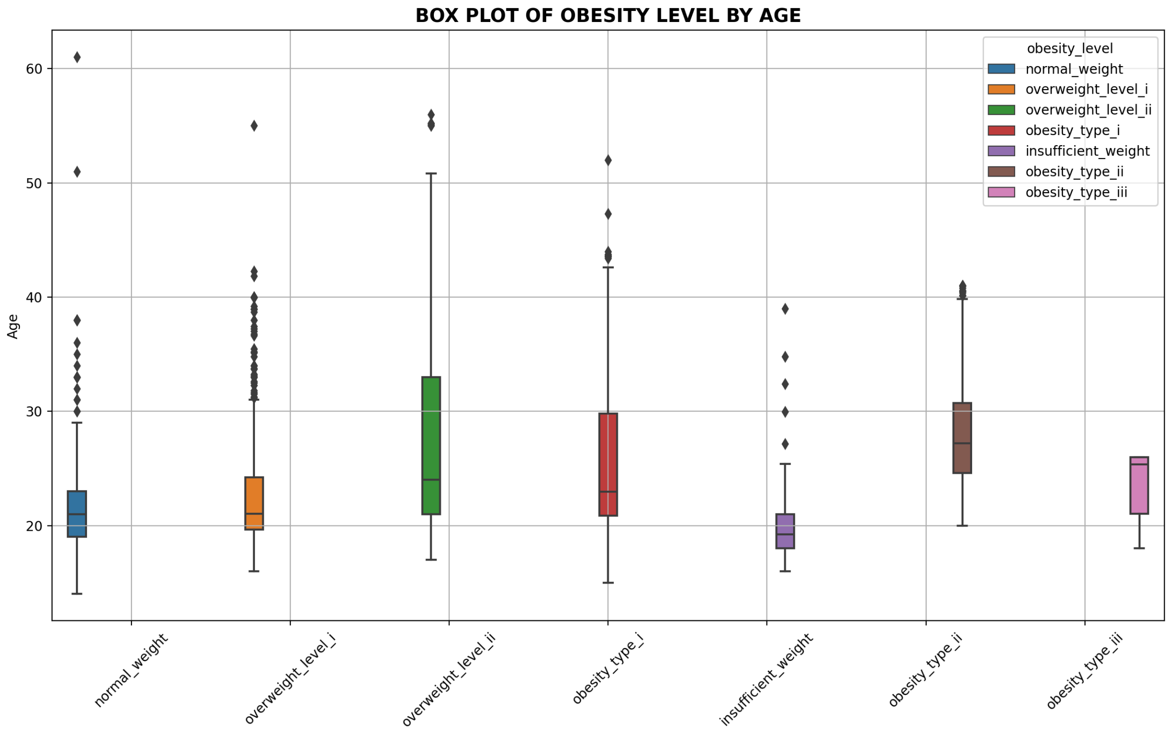


The pie chart show us the percentage of alcohol consumption in the population. 66.4% of people sometimes drank alcohol, which is double the number of people did not consume alcohol. The following are frequent consumption and always consumptions with 3.32% and 0.0474% respectively.

Two variable plot

Figure 5: Box Plot of Obesity Level by Age

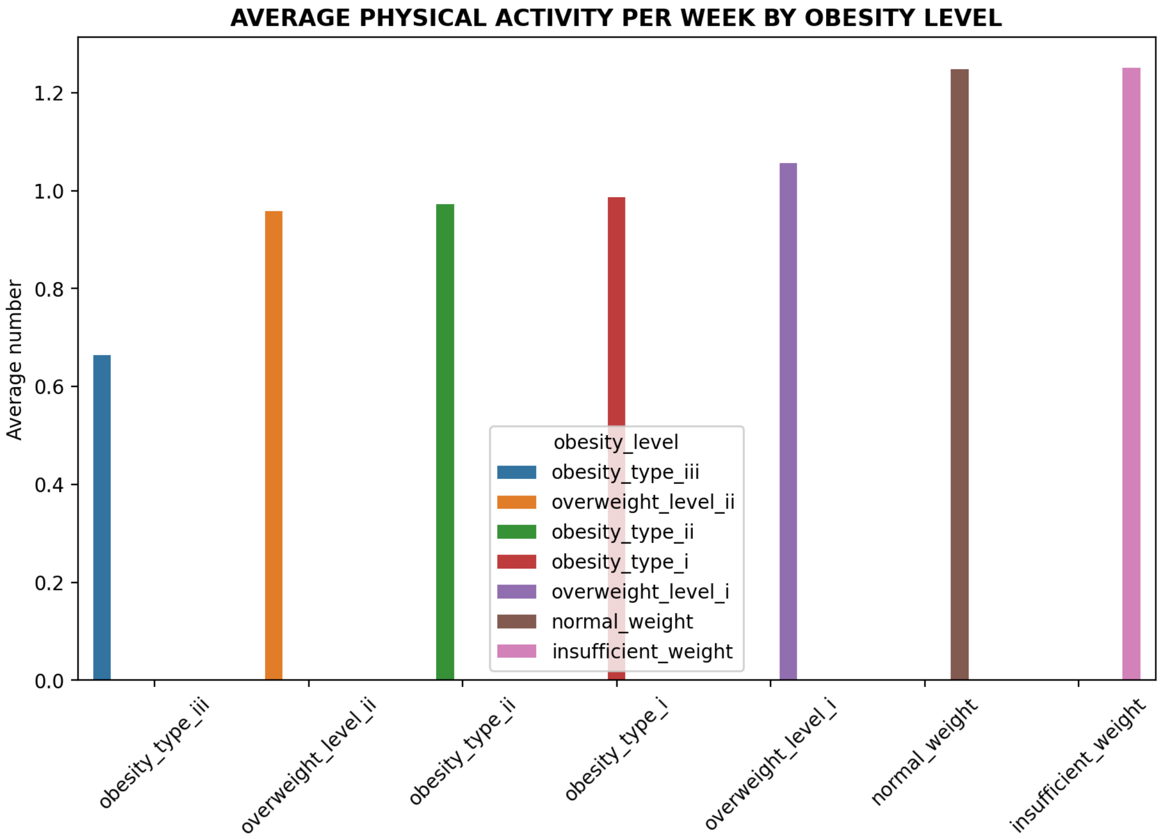
In [23]:
```
plt.figure(figsize=(15, 8))
sns.boxplot(data=df, x='obesity_level', y='age',hue='obesity_level')
plt.ylabel('Age')
plt.xlabel('')
plt.xticks(rotation=45)
plt.grid(True)
plt.title('BOX PLOT OF OBESITY LEVEL BY AGE',fontsize=14,weight='bold');
```



The boxplot compares obesity levels by ages. Most of observation are under 30 years old. The range of age having overweight levels are biggest, followed by obesity type 1. Most of obesity_levels are right-skewd.

Figure 6: Bar chart of Average Physical Activity per Week of Each Obesity Class

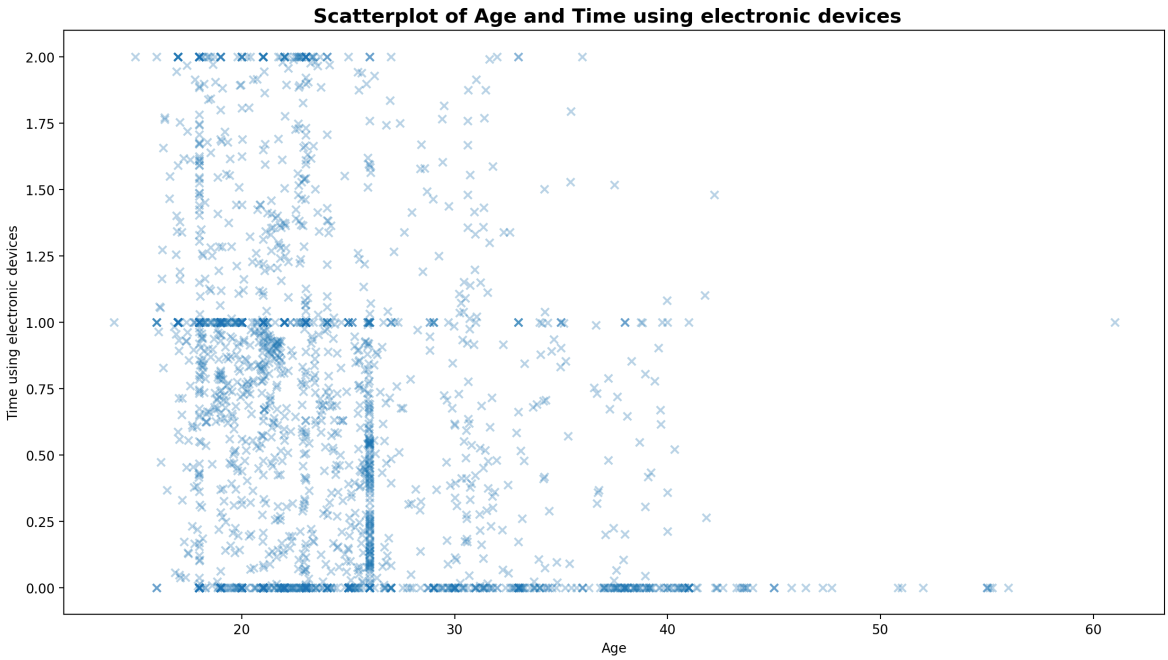
In [24]:
```
a = df.groupby('obesity_level')[['physical_activity_per_week']].mean().so
a = a.reset_index()
plt.figure(figsize=(10,6))
sns.barplot(data=a, x='obesity_level', y='physical_activity_per_week', hu
plt.title('AVERAGE PHYSICAL ACTIVITY PER WEEK BY OBESITY LEVEL', weight='
plt.xticks(rotation=45)
plt.xlabel('')
plt.ylabel('Average number')
plt.show()
```



As we can see from the chart, the more exercise and weekly activity the population do, the higher probability of avoiding overweight and obesity they have. Normal_weight and insufficient weight people did more physical activity than the other groups, while obesity type 3 had the lowest physical activity per week.

Figure 7: Scatter plot of age and time using electronic devices

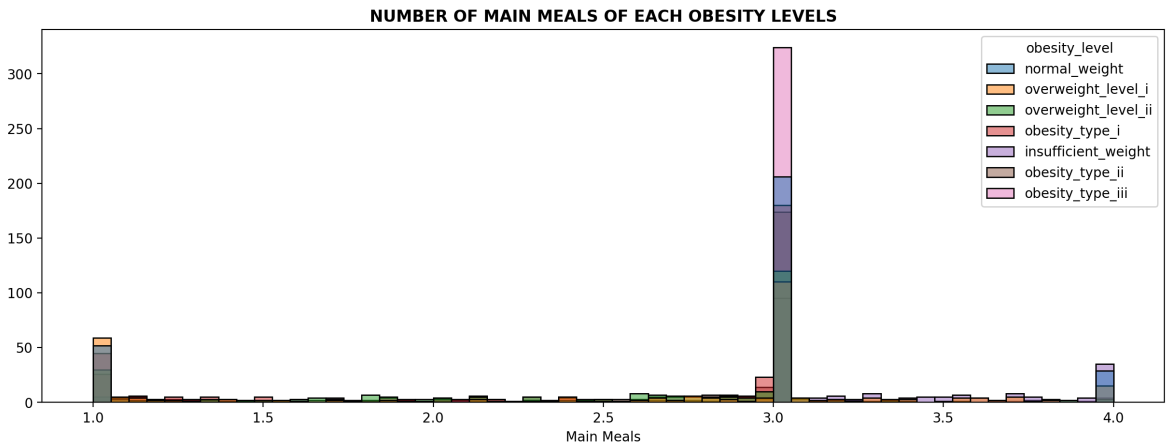
In [25]:
```
plt.figure(figsize = (15,8))
plt.scatter(df['age'], df['electronic_device_use_hour'], alpha = 0.3,mark
plt.title('Scatterplot of Age and Time using electronic devices  ', fonts
plt.xlabel('Age')
plt.ylabel('Time using electronic devices')
plt.show();
```



The scatter plot points out that people aged from 20 to 27 spent more time on electronic devices than other ages. This might be one of reasons causing overweight and obesity in young generation.

Figure 8: Stacked Bar Chart of Main Meals in Obese People

In [26]:
```
plt.figure(figsize=(15,5))
sns.histplot(data=df,x=df['main_meal_per_day'],hue=df['obesity_level'])
plt.title("NUMBER OF MAIN MEALS OF EACH OBESITY LEVELS", weight='bold')
plt.xlabel('Main Meals')
plt.ylabel('')
plt.show()
```

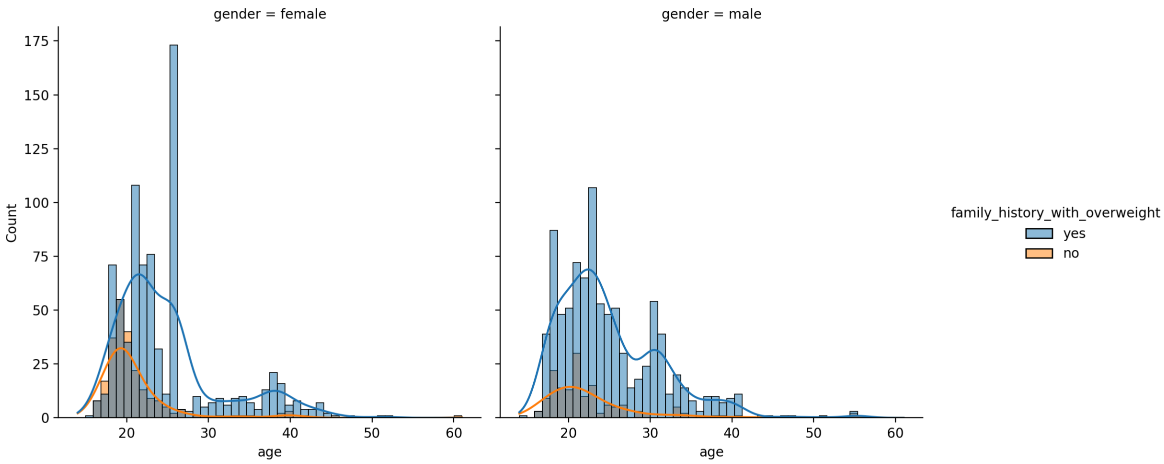


The figure demonstrates that most of interviewd people have 3 main meals a day, regardless of their obesity levels. Number of main meals might not affect people's weight generally.

Three Variables

Figure 9: Distribution plot of age, family history and gender

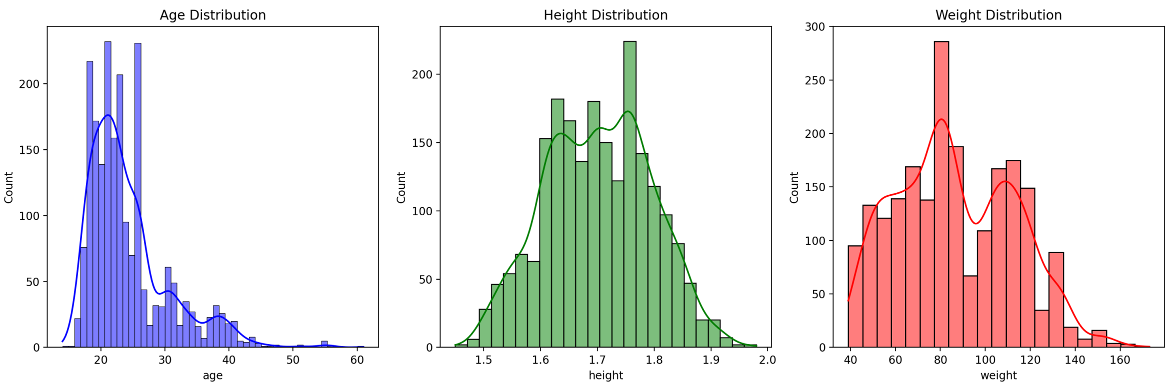
In [27]:
```
sns.displot(data=df, x='age', col='gender', hue='family_history_with_over
plt.show()
```



As we can see, family history and age has a significant effect on human weight regardless of gender.

Figure 10: Distribution of Age, Height and Weight

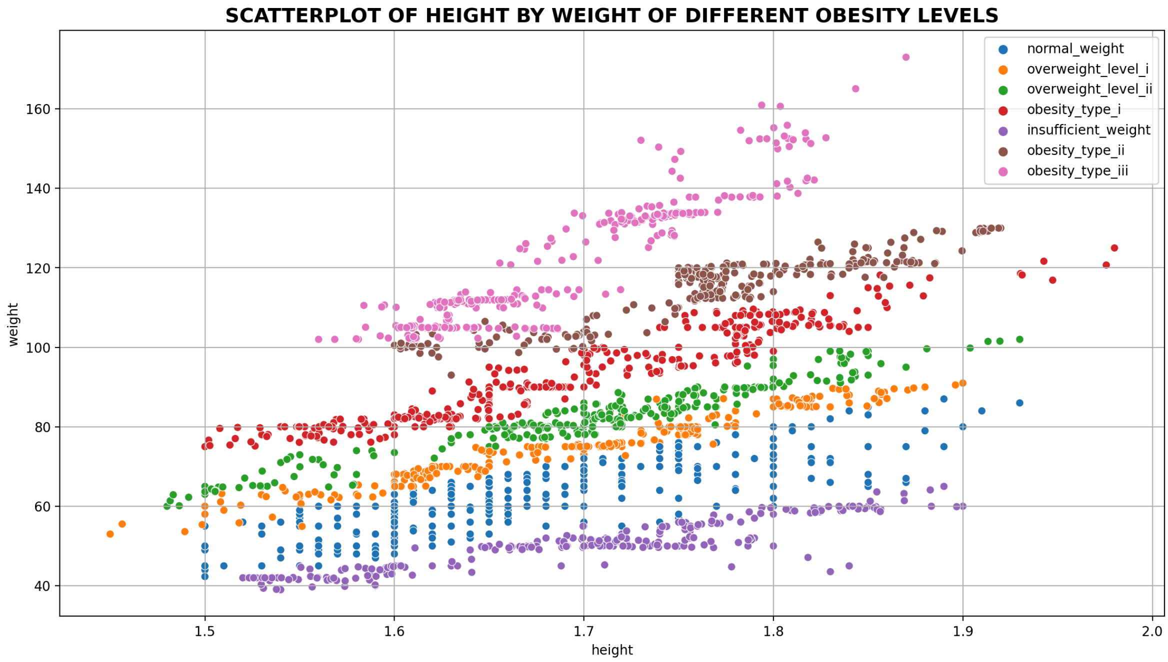
In [28]:
```
# Create a figure for plotting
plt.figure(figsize=(15, 5))

# Plotting histograms for Age, Height, and Weight
plt.subplot(1, 3, 1)
sns.histplot(df['age'], kde=True, color='blue')
plt.title('Age Distribution')

plt.subplot(1, 3, 2)
sns.histplot(df['height'], kde=True, color='green')
plt.title('Height Distribution')

plt.subplot(1, 3, 3)
sns.histplot(df['weight'], kde=True, color='red')
plt.title('Weight Distribution')

# Show the plots
plt.tight_layout()
plt.show()
```



The Age Distribution is right skewd, which mean the age population of dataset is younger and may not give the good picture of a whole population.While height distribution is normality, weight distribution is not and having high variance.

Figure 11: Scatter plot of the relationship of Height and weight on Obesity

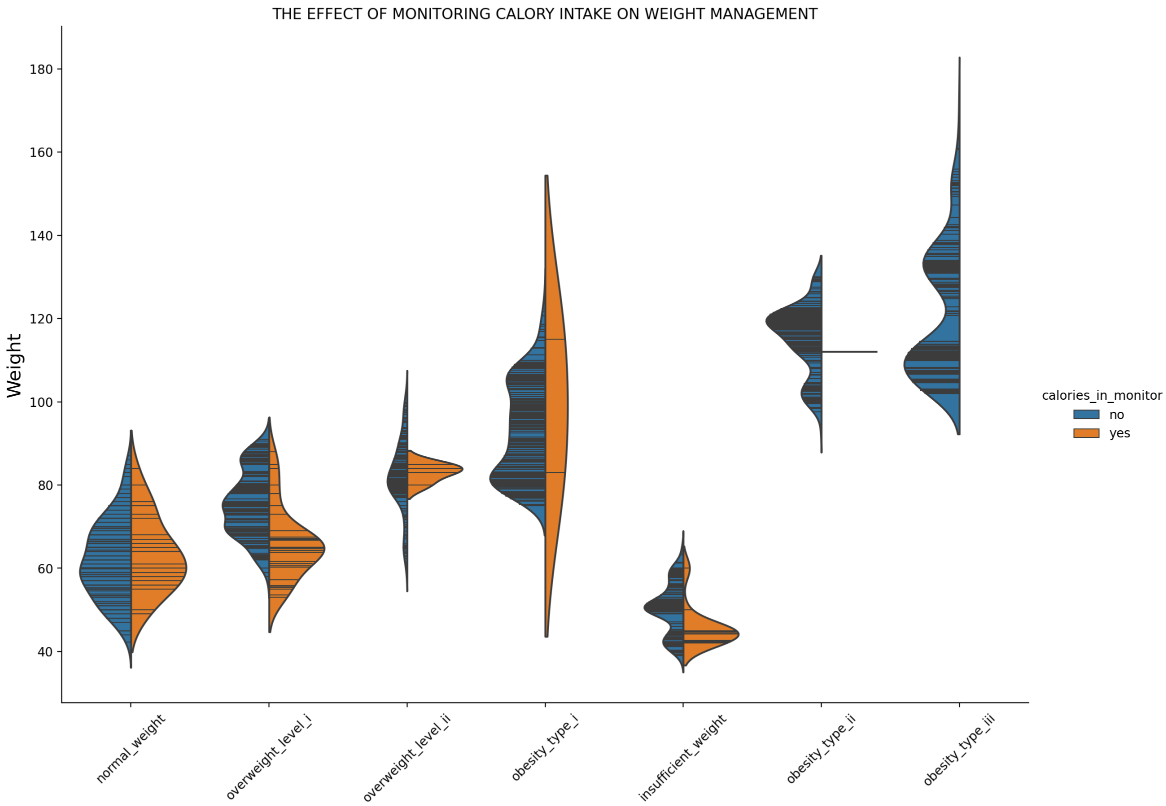
In [29]:
```
plt.figure(figsize = (15,8))
sns.scatterplot(x=df['height'], y=df['weight'], hue = df['obesity_level']
plt.title('SCATTERPLOT OF HEIGHT BY WEIGHT OF DIFFERENT OBESITY LEVELS',
plt.legend(loc = 'upper right')
plt.grid(True)
plt.show();
```



It is clear to see from the plot that there might not have effect of height and weight on obesity levels

Figure 12: Violin Plot of relationship between calories intake and weight management

In [30]:
```
sns.catplot(
    data=df, x="obesity_level", y="weight", hue="calories_in_monitor",
    kind="violin", inner="stick", split=True,height=8.27, aspect=11.7/8.2
)
plt.xticks(rotation=45)
plt.xlabel(' ')
plt.ylabel('Weight',fontsize=15)
plt.title('THE EFFECT OF MONITORING CALORY INTAKE ON WEIGHT MANAGEMENT')
plt.show()
```



The violin plot demonstrates the importance of monitoring calories intake to weight, which is a factor to evaluate obesity level. Controlling calories intake can help people controlling weight as people monitoring their calories tends to avoid all types of obesity.

Literature review

Obesity is a critical problem that poses health emergency for any country and community. There are many negative effects that obesity impacts on people's life. According to Han & Lean, obesity can lead to metabolic syndrome, a cluster of conditions such as high blood pressure and high blood sugar, which ultimately increases the risk of heart-related diseases. (Han & Lean, 2016). The article by Djalalinia and colleagues analyse extensive health consequences of obesity, highlighting its serious physical, mental, social, and spiritual impacts. It includes depression, low esteem, mood disorder, facing discrimination in educational, professional and healthcare environment. Spiritually, the study notes a connection between poor spiritual health and emotional eating, especially in women (Djalalinia et al,. 2015). The 2021 Nutrition Society Winter Conference by Hall (2022) focused on the consequences of obesity on brain health, discussing how it negatively affects cognitive functions and memory. It also explored various related topics, such as the impacts of artificial sweeteners, new approaches to treating binge eating disorders, and how obesity can lead to cognitive decline.

The reason behind obesity, according to Lin and Li (2021) is complex causes of the global obesity epidemic, emphasising the important roles that genetics, environment, and lifestyle choices. In order to evaluate which factor has the most impact on obesity, many model based on machine learning has been built which brought slightly different results.In the study of Thamrin and his colleagues (2021), significant factors affecting obesity included demographic and lifestyle such as location, marital status, diet (including consumption of sweet drinks, fatty/oily foods, and alcoholic drinks), and lifestyle behaviors (such as physical activity and smoking). The Logistic Regression method was identified as the most effective among models that applying these factors to predict obesity status in adults (Thamrin et al., 2021). Another study from Yagin and colleague used machine learning to predict obesity levels based on food habits and physical activity. It discovered that eating habits, alcohol intake, and physical activity all had a substantial impact on obesity. The research achieved great accuracy in diagnosing obesity levels by highlighting the crucial significance of certain eating behaviours and physical activity in obesity prediction, using a trained neural network optimised using Bayesian approaches (Yagin etal.,2023). In the study of Gozukara Bag and colleagues (2023) examined dietary patterns and physical activity levels to identify obesity levels using a tree-based machine learning algorithm. Based on health-related behaviours, it was discovered that XGBoost, random forest, and logistic regression models are all good at predicting obesity. The greatest results were produced by the logistic regression model, particularly when feature selection was used to increase prediction efficiency and accuracy. This emphasises how important it is to manage obesity with individualised interventions based on each person's activity level and food preferences (Gozukara Bag et al,. 2023). One of the most common methods to resolve obesity is weight management through diet and exercise in mitigating these risks, with additional discussion on the potential roles of pharmacological treatments and bariatric surgery for more severe cases (Han & Lean, 2016). In the Nordic Obesity Meeting ,experts states that both external and internal motivation impact physical activity, with highly motivated people being less impacted by their surroundings than lowly motivated people (Aasheim et al,. 2009). Changes in the environment should concentrate on making activities more pleasurable, accessible, and affordable in order to encourage physical activity across all age groups. Local communities have a significant role in putting these changes into action with funding from the state (Aasheim et al,. 2009). The conclusion of the 9th International Conference on Obesity by Wang highlighted the urgent need for innovative treatments for obesity, given its increasing prevalence and severe health consequences. In order to identify novel pharmaceutical targets, conference discussions emphasised the significance of expanding research in cutting-edge disciplines like functional genomics and proteomics. Such developments are essential for creating safe and effective treatments tailored to the needs of obese patients (Wang 2009) The conference emphasised the links between obesity and oral health by Tinanoff & Holt, especially when looking at sugar consumption as a risk factor for both conditions. The main goals were to increase awareness of the connection between obesity and dental health, advocate obesity prevention techniques, and encourage teamwork to reduce paediatric obesity. The publications and discussions that followed highlighted tactics that oral health practitioners can use to combat and prevent childhood obesity. These tactics include recommending that kids consume less sugar, screening for obesity, and referring children who are at-risk for nutritional counselling (Tinanoff & Holt 2017) Opportunity and Chalenge of Applied Machine Learning in Healthcare field: This review offers a thorough overview of the several artificial intelligence approaches used in the field of obesity research, with a focus on machine learning and deep learning. In order to promote further adoption and innovation in AI within obesity research, the article outlines potential future trends, including multimodal AI models, synthetic data generation, and human-in-the-loop approaches. It also details how AI has been effectively used to measure, predict, and treat obesity-related outcomes by analysing various data types (An et al., 2022).

By enabling comprehensive disease management, predictive analytics, and enhanced patient care through the analysis of massive volumes of data from sources including imaging, genetic research, and electronic health records, big data in healthcare is revolutionising the sector. Modern medicine and patient care strategies are advanced by this broad data integration, which improves operational efficiency of healthcare services and allows for the customisation of personalised treatment programmes (Dash et al., 2019)

However, many issues arise when using big data in healthcare, such as managing massive amounts of different and quickly created data, guaranteeing data veracity, and protecting privacy and security. To fully utilise Big Data's promise to enhance patient outcomes through better informed decision-making and individualised treatment plans, these obstacles must be removed. Furthermore, for successful deployment, it is imperative to address the notable skills gap in data science within the healthcare workforce and integrate Big Data analytics into the current healthcare systems

Summary and Conclusion:

Accuracy predict healthcare will help obeses people have more chance to prevent worst scenario while helping healthcare system give proper treatment to overcome the situation. Our goal is ennhancing the predictive accuracy of the model to determine obesity levels, facilitating improved preventative measures and treatment approaches in healthcare. In the first phase of our project, we concentrated on data preprocessing and cleaning. We opted to retain all variables within our dataset, each deemed crucial for the accuracy of our obesity prediction model. This comprehensive approach helps ensure that no potential predictive factors are omitted. The integrity of the data was reinforced through meticulous checks for missing values and outliers, aiming to enhance the reliability and robustness of the subsequent analysis. Our preliminary analysis revealed several notable trends: a predominant prevalence of overweight and obesity conditions within the population studied, regular water consumption paired with occasional alcohol intake, and a significant lack of physical activity. Notably, the usage of electronic devices emerged as a potential risk factor for obesity among individuals aged 20-30. Additionally, family history was identified as a contributing factor to obesity levels.

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