Body Level Classification

Problem and Dataset Description

We are solving a classification problem for human body level based on some given attributes related to the physical, genetic and habitual conditions. The given attributes are both categorical and continuous. The human body level can be categorized into (4 levels/classes). We are given 16 attributes and 1477 data samples, where classes are not evenly distributed. We are trying to build models that can adapt to the class imbalance to achieve the best possible results.

Exploratory Data Analysis

Dataset

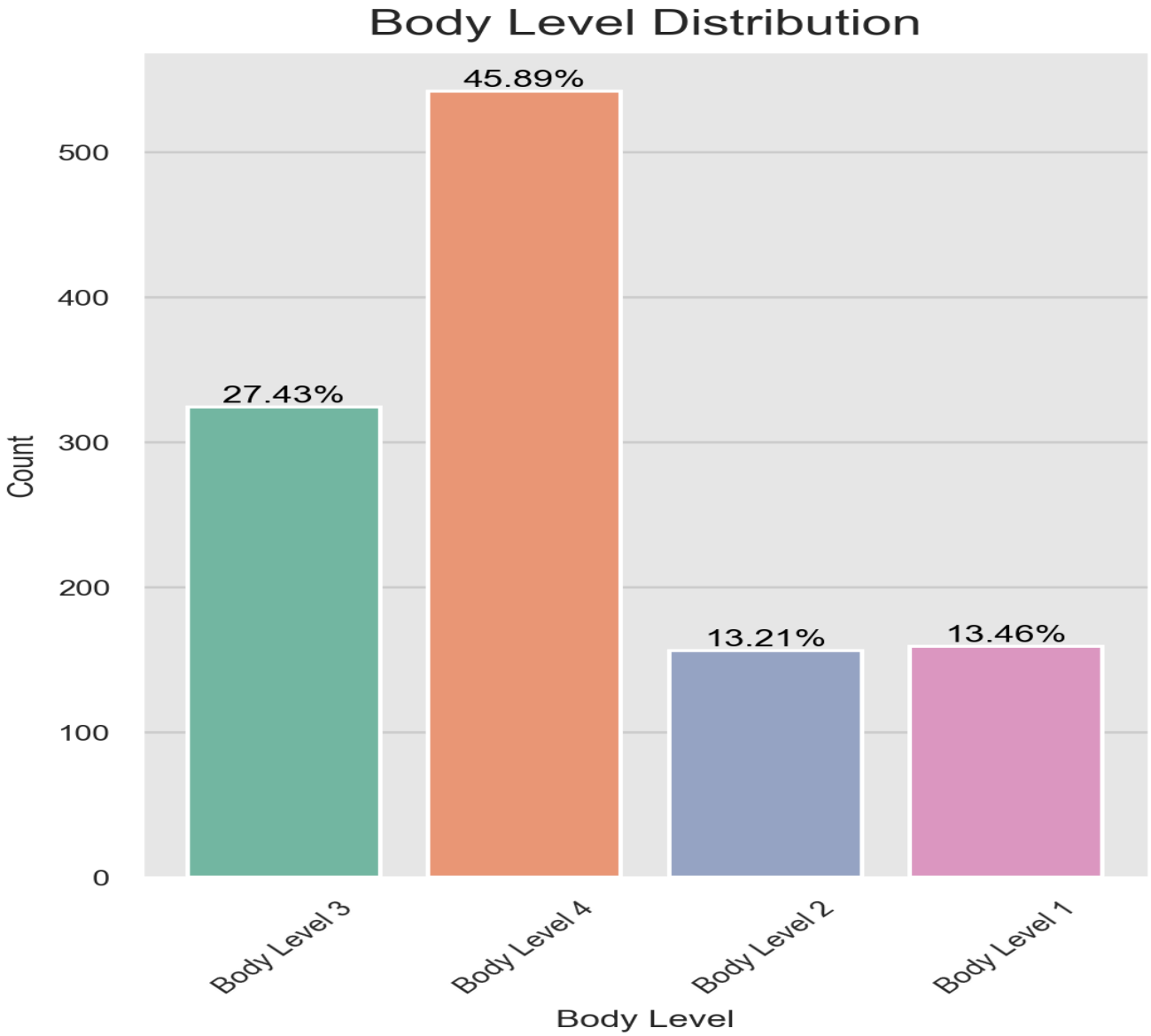
Column	Data Type	Data Format
Gender	Nominal	String
Age	Ratio	Float
Height	Ratio	Float
Weight	Ratio	Float
H_Cal_Consump	Nominal	String
Veg_Consump	Interval	Float
Water_Consump	Interval	Float
Alcohol_Consump	Nominal	String
Smoking	Nominal	String
Meal_Count	Interval	Float
Food_Between_Meals	Nominal	String
Fam_Hist	Nominal	String
H_Cal_Burn	Nominal	String
Phys_Act	Interval	Float
Time_E_Dev	Interval	Float
Transport	Nominal	String
Body_Level	Nominal	String

Univariate Analysis

The univariate analysis involves analyzing each variable individually. It looks at the range of values and the central tendency of the values. It describes the pattern of response to the variable. It represents each variable on its own.

Target Variable Analysis

We started by analyzing the distribution of the target variable and found an imbalance in our data set where one class dominated the others. This issue needs to be addressed as unequal representation of classes in our data set can lead to biased results when training machine learning algorithms. Techniques like oversampling the minority class, undersampling the majority class, or utilizing cost-sensitive sampling can be implemented to balance the data set.



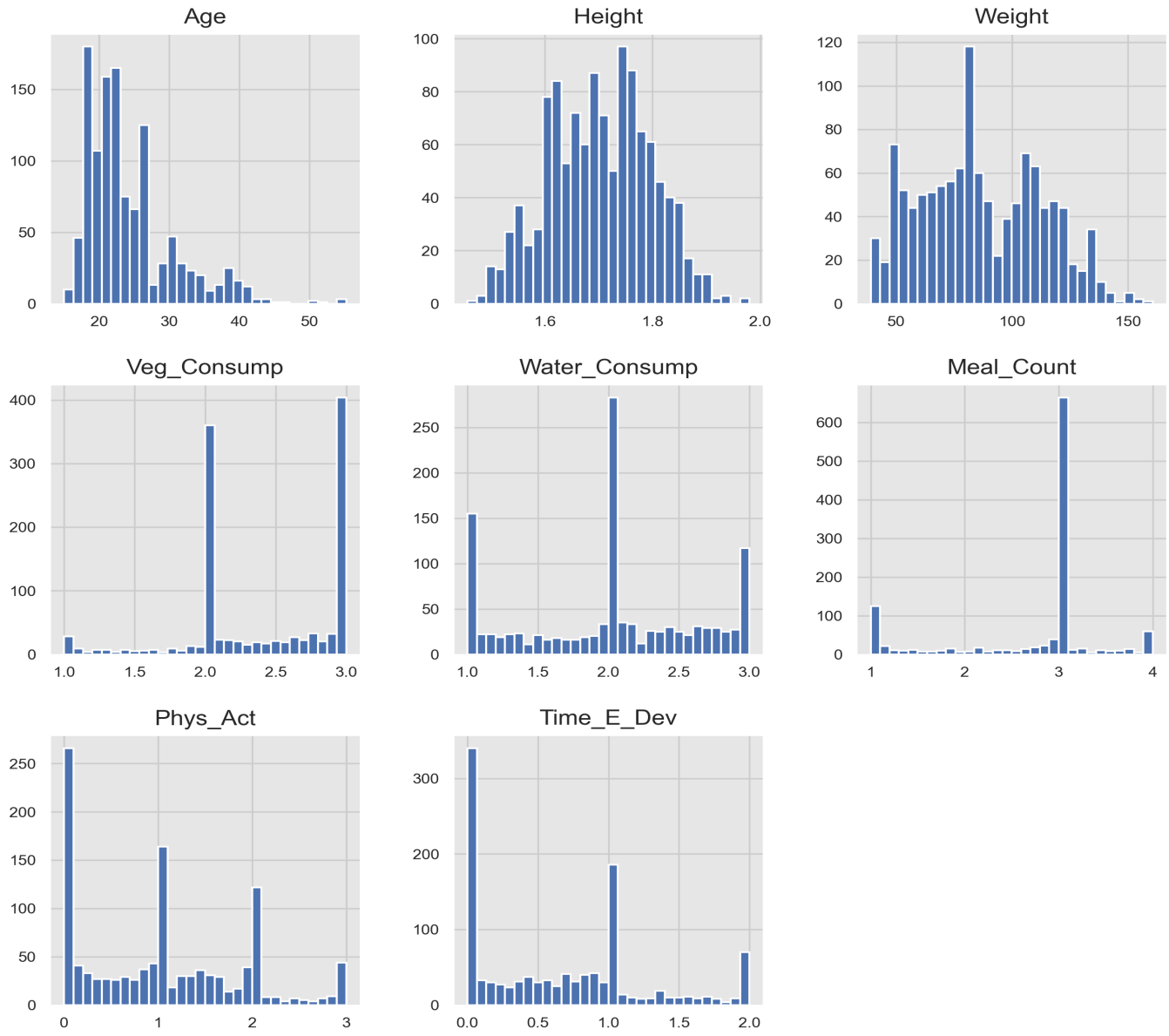
Features Analysis

Numerical Features Distribution

- We can find that the `Height` follows a normal distribution.
- We can find that the `Age` feature is left skewed, we have more values for youth than the elders.
- We can find that the `Veg_Consump`, `Water_Consump`, `Meal_Count`, `Phys_Act`, and `Tine_E_Dev` are capped to be integers.

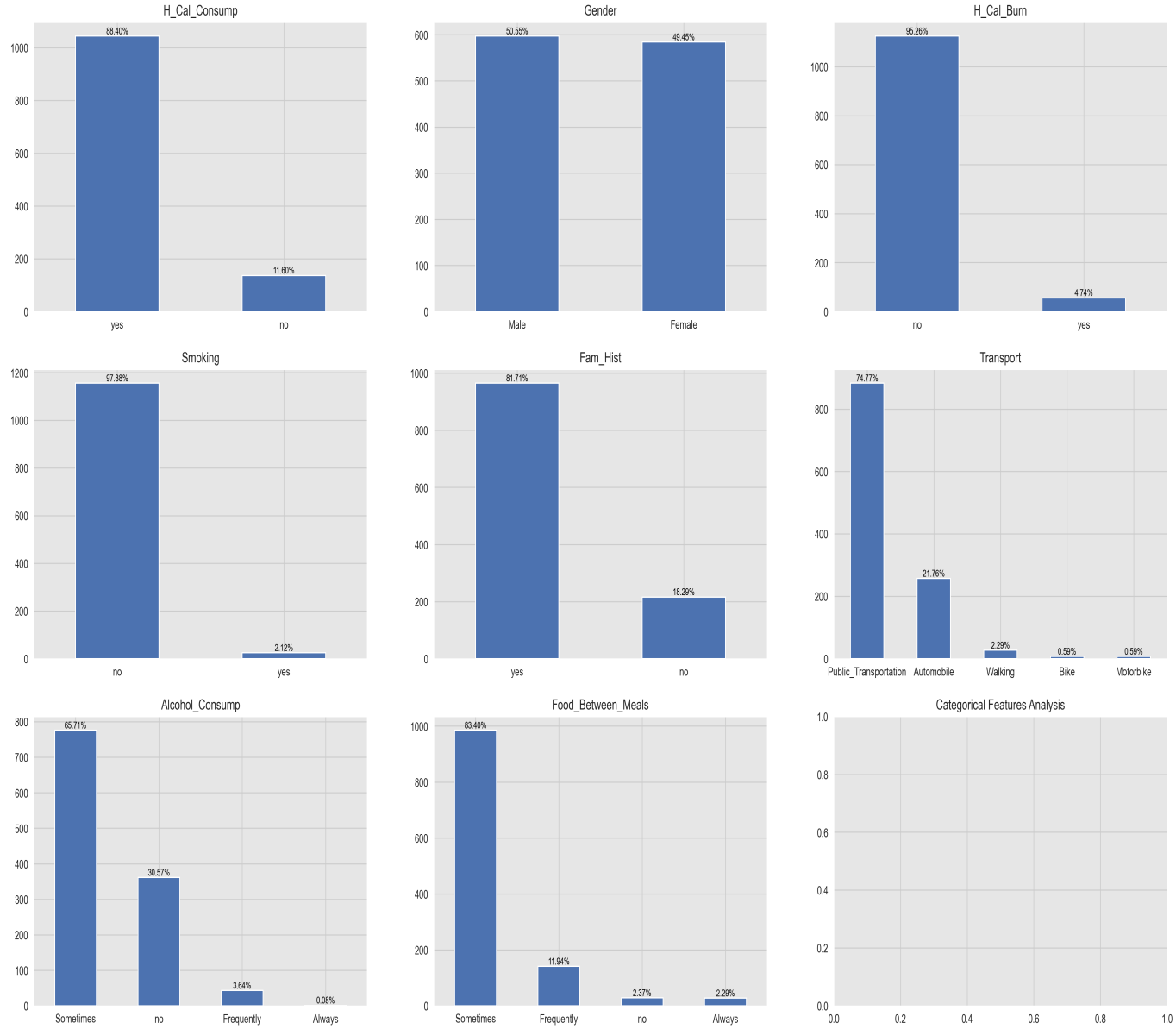
> Data capping is a technique used in data science to limit the maximum value of a variable in a dataset. This is often done to avoid the influence of outliers, or extreme values, that can skew the results of statistical analysis or machine learning models. By setting a cap, any values

> above that limit are truncated to the maximum value, allowing the analysis to focus on the most representative data points within the dataset. .



Categorical Features Distribution

- We can find that most of the features are unbalanced, this makes them somehow useless in solving our problem except for the `Gender` feature i.e. we may use this feature in our analysis.

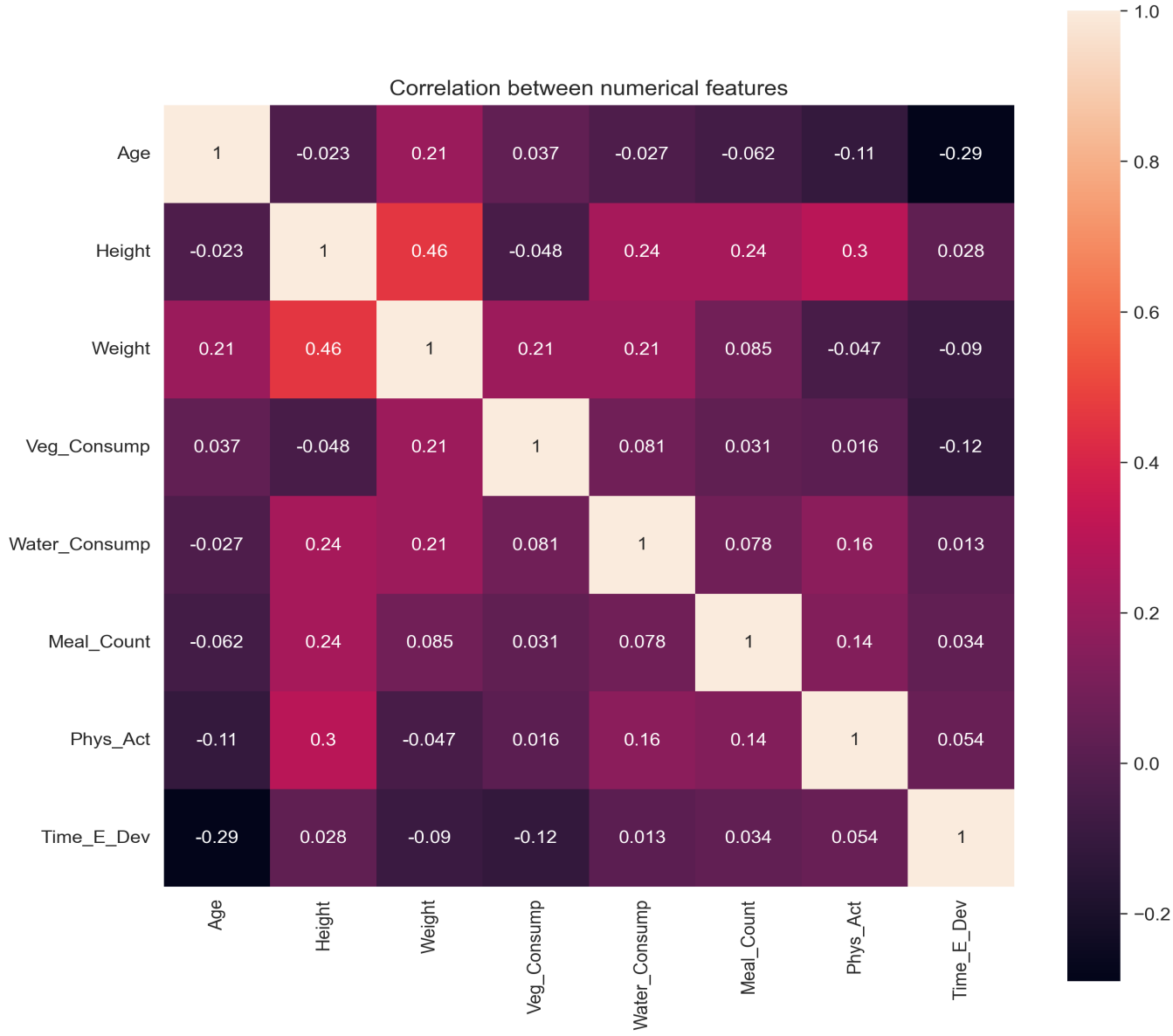


Multivariate Analysis

The multivariate analysis involves analyzing more than one variable to determine the relationship between them. It looks at the interactions between variables. It is used to identify patterns in the data set. It represents each variable in relation to all other variables.

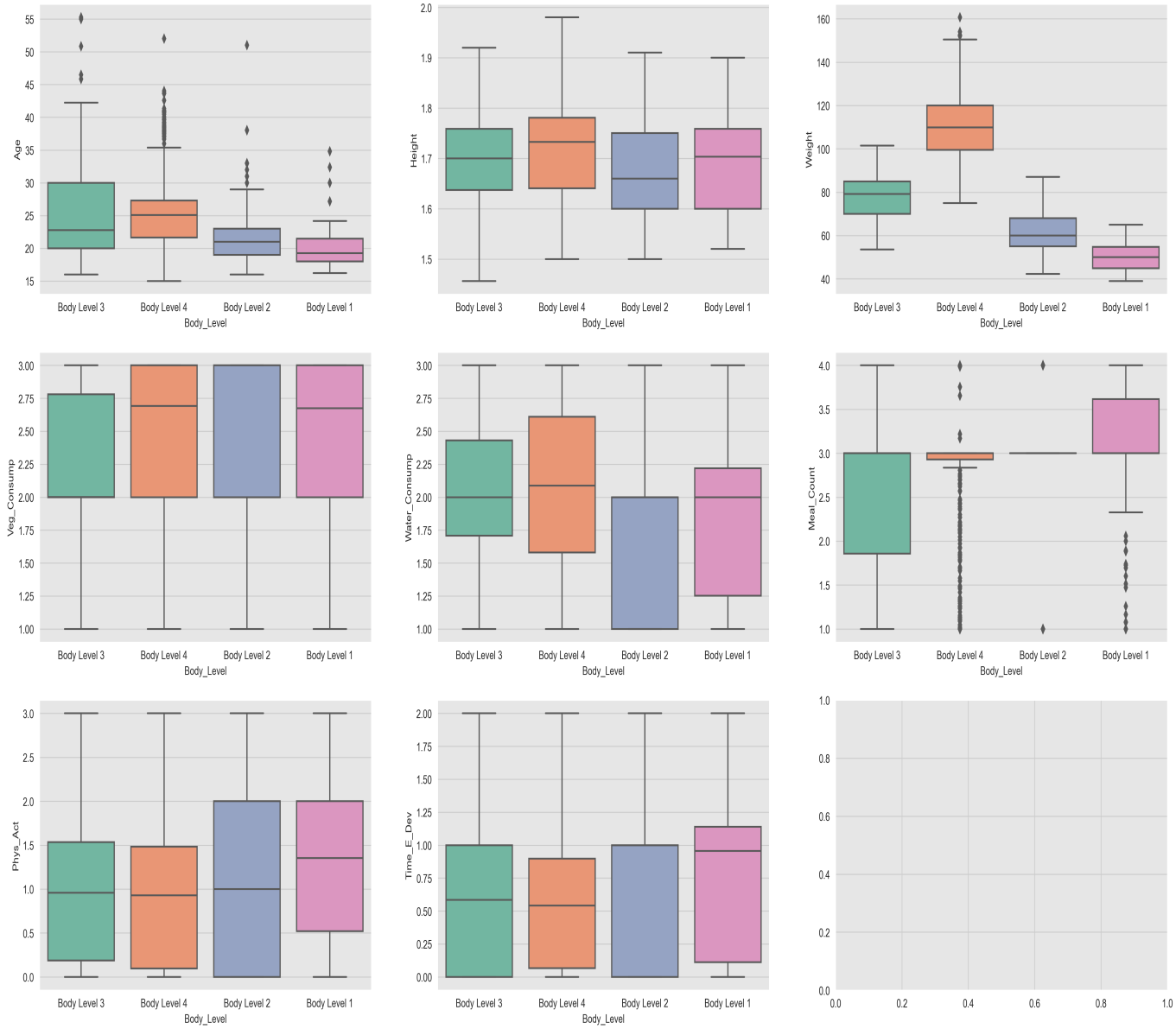
Correlation Matrix

We can find that there' a correlation between the width and the height features which is expected.



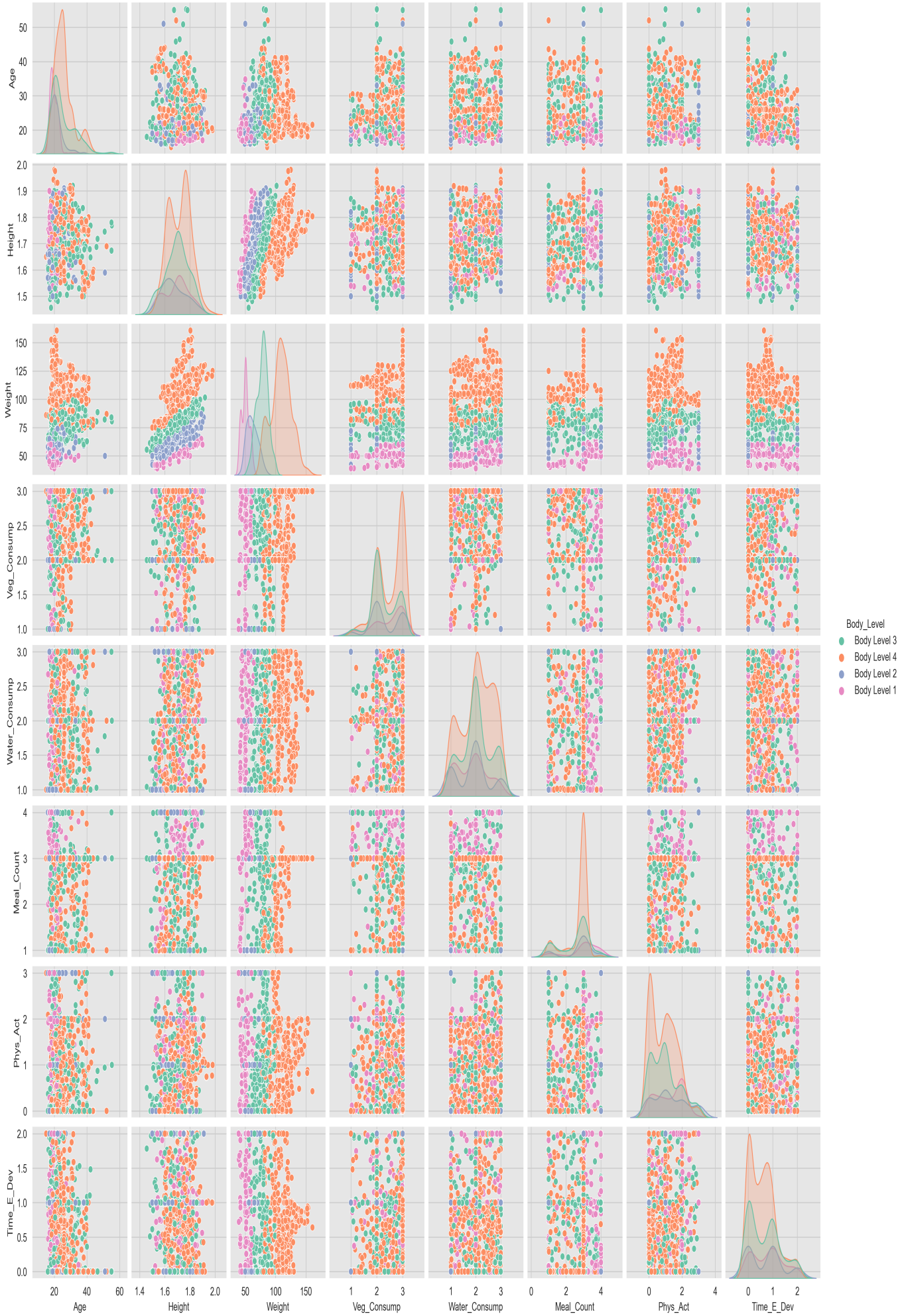
Numerical Feature Box Plot

We can notice that the `Weight` feature is an important and a significant feature. It carries a lot of predictive power and is highly correlated with the target variable. We can use it to build some models that can accurately predict the target variable.



The relation between the features and the target variable

We can notice that the `Weight` and `Height` are significant features that carry a lot of predictive power and are highly correlated with the target variable.. We can use them or a mix of them to build our models.



Models Analysis

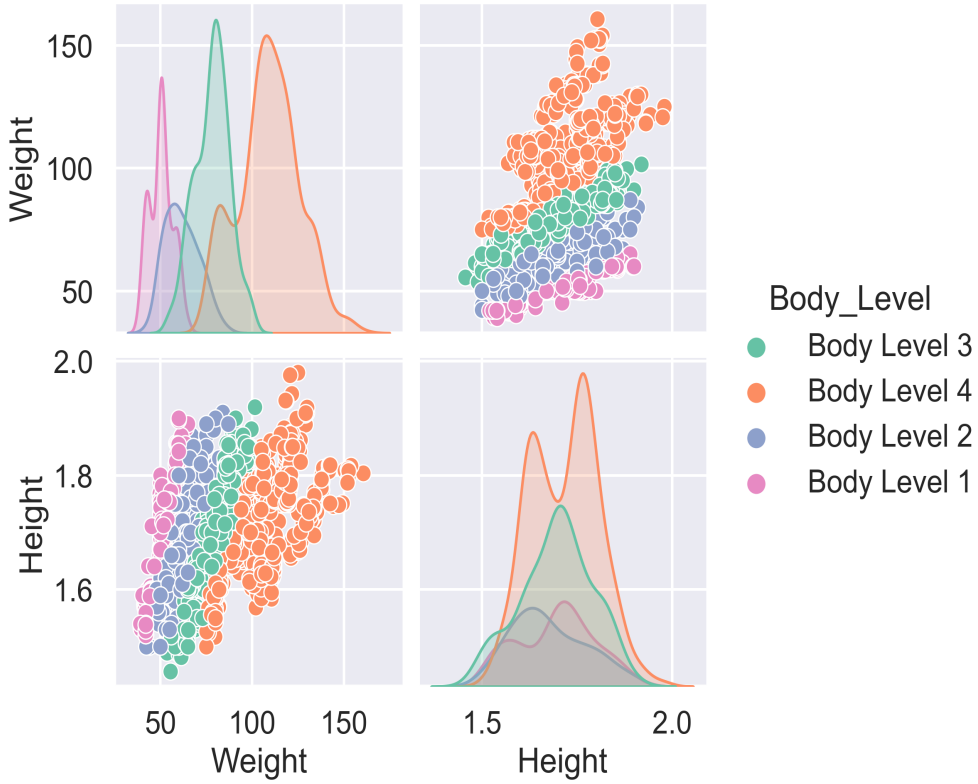
Base Model

Before working on developing sophisticated machine learning models, we used some dummy models to as a baseline model to compare the performance of more sophisticated models. By comparing the performance of a complex model to that of a simple model, we can determine if the complex model is actually providing useful predictions or if it is overfitting the data. Dummy models also help identify if the problem has any inherent bias or if the dataset is imbalanced. Overall, starting with a dummy model is a good way to get a baseline understanding of the data and the problem before moving on to more complex models.

Strategy	Description	Cross-validation with 10 folds
most_frequent	The predict method always returns the most frequent class label in the observed y argument passed to fit. The predict_proba method returns the matching one-hot encoded vector.	**accuracy**: 0.4589374732944025 **f1_macro**: 0.1572825648608684 **f1_micro**: 0.4589374732944025
stratified	The predict_proba method randomly samples one-hot vectors from a multinomial distribution parametrized by the empirical class prior probabilities. The predict method returns the class label which got probability one in the one-hot vector of predict_proba. Each sampled row of both methods is therefore independent and identically distributed.	**accuracy**: 0.32177040307648486 **f1_macro**: 0.24690614458225352 **f1_micro**: 0.32177040307648486
uniform	Generates predictions uniformly at random from the list of unique classes observed in y, i.e. each class has equal probability	**accuracy**: 0.23281583819968663 **f1_macro**: 0.21401372344564545 **f1_micro**: 0.23281583819968663

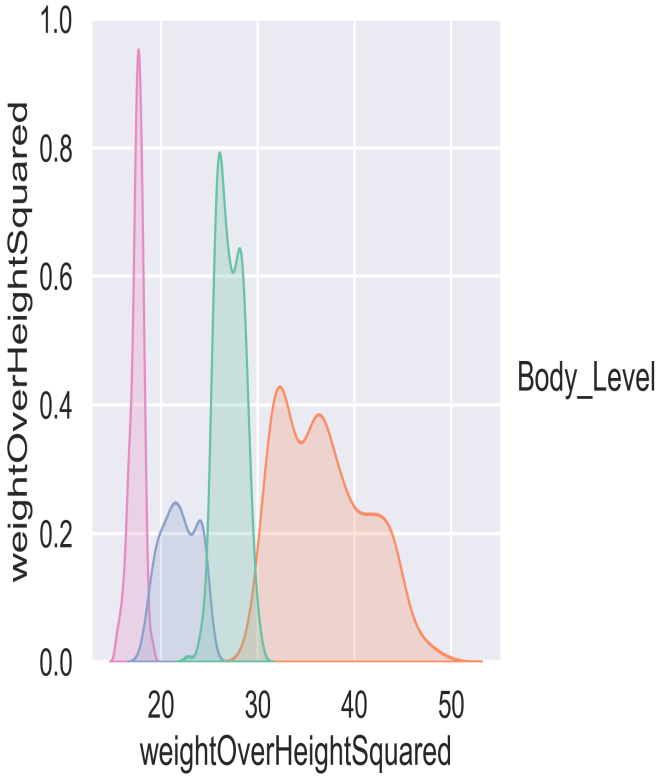
Conclusion

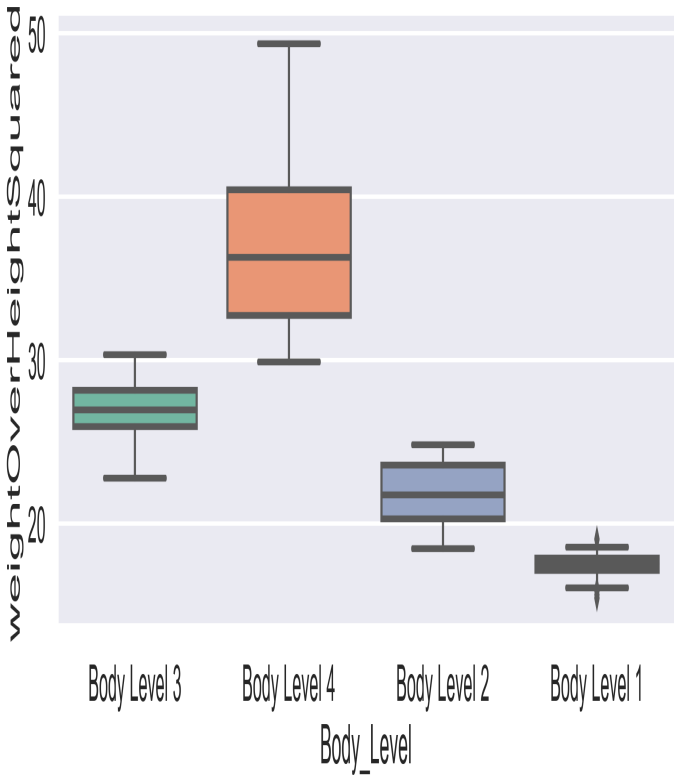
After some data exploration, we noticed that there is an obvious relation between the target variable and the weight, and height as shown here:



We tried to find the best formula that can represent this relation and decided to use the following formula and got some fascinating results:

$$weightOverHeightSquared = \frac{weight}{height^2}$$





ThresholdClassifier:

We constructed a custom classifier called `ThresholdClassifier`, that uses the aforementioned formula to predict the body level based on some thresholds.

Threshold Selection:

We tried using different thresholds to predict the body level like the following:

- Using the **min value** of the weightOverHeightSquared as a threshold.
- Using the **25th percentile** of the weightOverHeightSquared as a threshold.
- Using the **mean value** of the weightOverHeightSquared as a threshold.

We found that using the min value of the weightOverHeightSquared as a threshold gives the best results.

We undergone more research and found that that this metric is called BMI(Body Mass Index). Where: $$BMI = \frac{weight}{height^2}$$

Body Level	Threshold	Health Implication
Underweight	<18.5	Increased risk of health problems such as osteoporosis, heart disease, and diabetes
Normal	18.5-24.9	Healthy body weight
Overweight	25-29.9	Increased risk of health problems such as heart disease, stroke, type 2 diabetes, and certain types of cancer
Obesity	30<	Significantly increased risk of health problems such as heart disease, stroke, type 2 diabetes, and certain types of cancer

Henceforth, we decided to use the BMI thresholds to predict the body level and got the following results after running a cross-validation with 10 folds:

Metric	Value
accuracy	0.9864549209514315
f1_macro	0.982450234501931
f1_micro	0.9864549209514315