kaggle competition 2024

Multi-Class Prediction

Obesity Risk

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Role

- Data analysis & Model training:
  Lim Yewon, Yoon Jihoon, Weon Joosung
- Documentation: Lim Yewon
- Presentation: Lim Yewon, Yoon Jihoon

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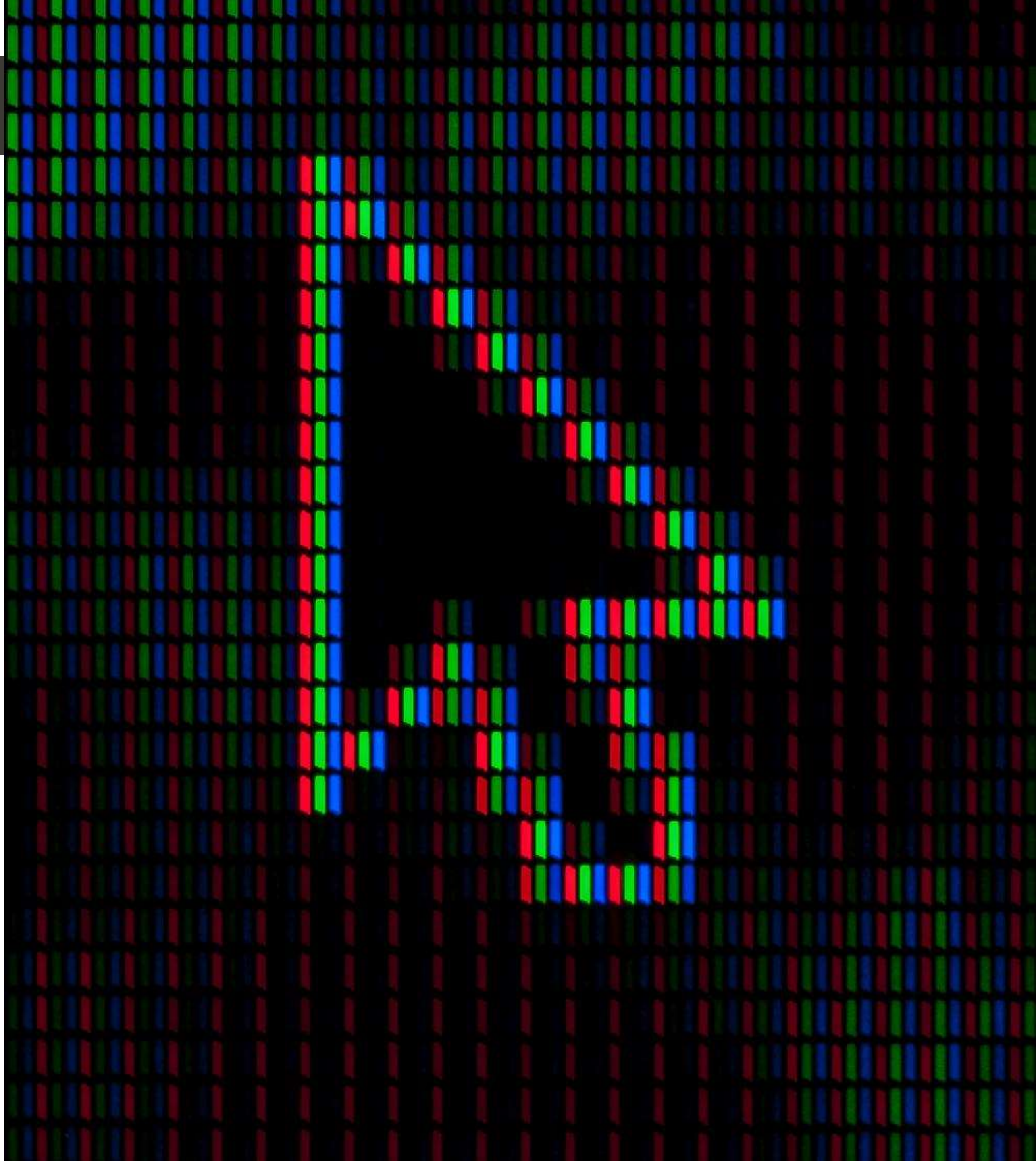

Part 1 INTRODUCTION

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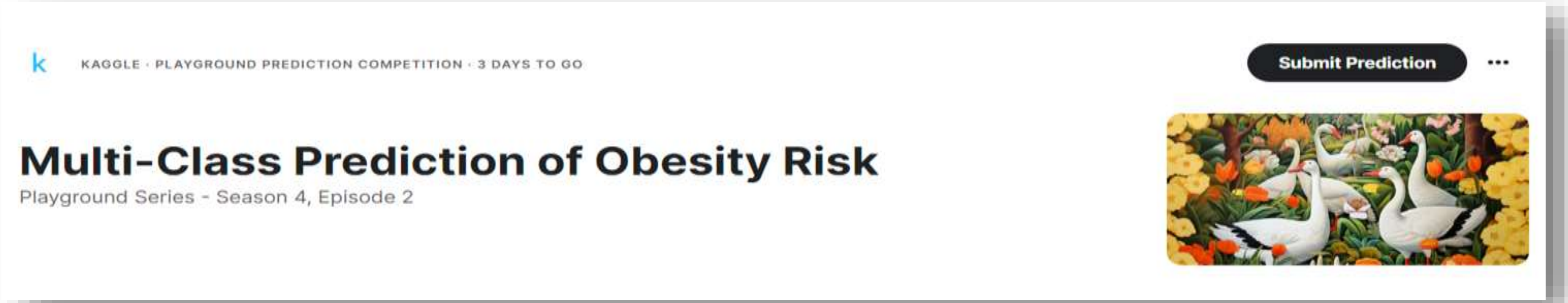
Overview of Competition



Competition Timeline	Feb 1, 2024 ~ Mar 1, 2024
Final Submission Deadline	Feb 29, 2024
Duration of participation	5 days (Feb 26 2024 ~ Mar 1 2024)
Evaluation	Submissions are evaluated using the accuracy score.
Kaggle Notebook	https://www.kaggle.com/competitions/playground-series-s4e2/overview

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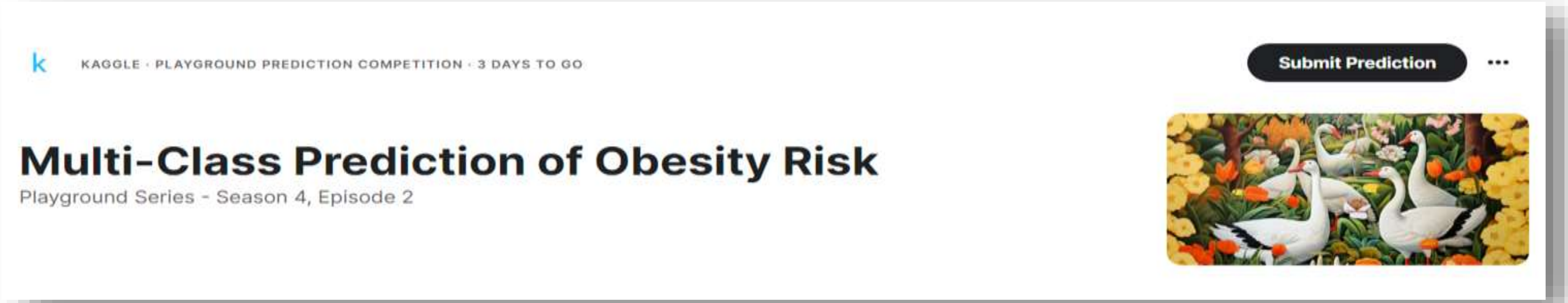
01 Overview of Competition



Goal:

The goal of this competition is to use various factors to predict obesity risk in individuals, which is related to cardiovascular disease.

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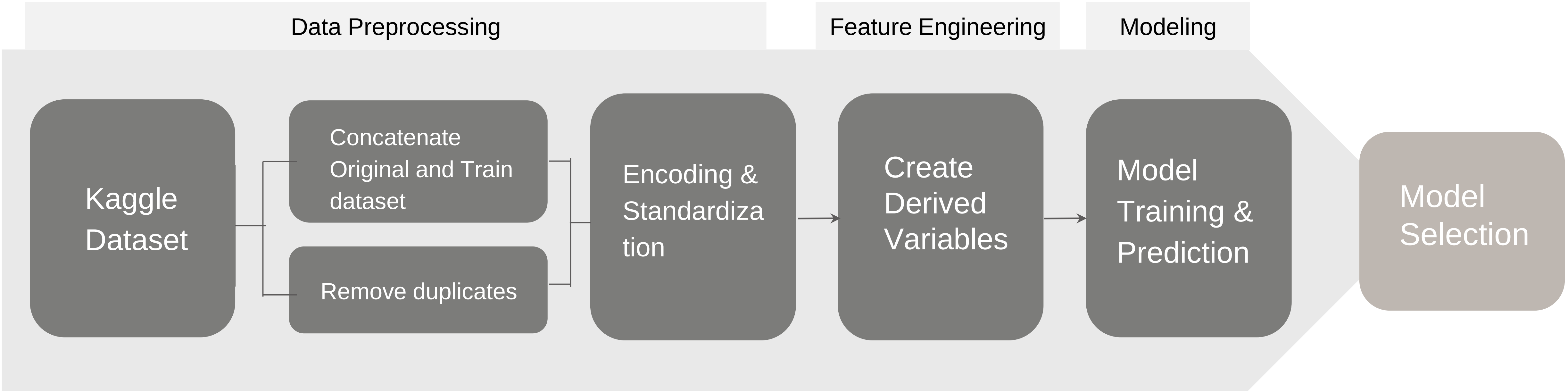
02 Process Flow



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Introduction of Dataset

Train

(20758, 18)

Test

(13840, 17)

Original

(2111, 17)

Submission

(13840, 2)

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03

Introduction of Dataset

◆ **Column Description**

- **'id'** : id
- **'Gender'** : Gender
- **'Age'** : Age
- **'Height'** : Height is in meter
- **'Weight'** : Weight is between 39 to 165
- **'family_history_with_overweight'** : family history with overweight yes or no
- **'FAVC'** : Frequent consumption of high calorie food yes or no
- **'FCVC'** : Frequency of consumption of vegetables yes or no
- **'NCP'** : Number of main meals
- **'CAEC'** : Consumption of food between meals
- **'SMOKE'** : yes or no
- **'CH2O'** : Consumption of water daily
- **'SCC'** : Calories consumption monitoring yes or no
- **'FAF'** : Physical activity frequency
- **'TUE'** : Time using technology devices "How long using technology devices to track your health"
- **'CALC'** : Consumption of alcohol
- **'MTRANS'** : Transportation used
- **'NObeyesdad'** : Target Obesity

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03

Introduction of Dataset

Continuous Variables

- Age
- Height
- Weight
- FCVC
- NCP
- CH2O
- FAF
- TUE

= total 8

16 features in total

Categorical Variables

- Gender
- family_history_with_overweight
- FAVC
- CAEC
- SMOKE
- SCC
- CALC
- MTRANS

= total 8

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Part 2　Data Processing & EDA

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Data Preprocessing

Independent variables

Continuous variables
StandardScaler()

Categorical variables
OneHotEncoder()

Column Transformer →

Standardization

Dummy variables

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Data Preprocessing

Dependent Variable

Categorical Variable

'NObeyesdad'

Obesity_Type_III
Obesity_Type_II
Obesity_Type_I
Overweight_Level_II
Overweight_Level_I
Normal_Weight
Insufficient_Weight

Label Encoder →

Numeric Variable

'NObeyesdad'

0
1
2
3
4
5
6

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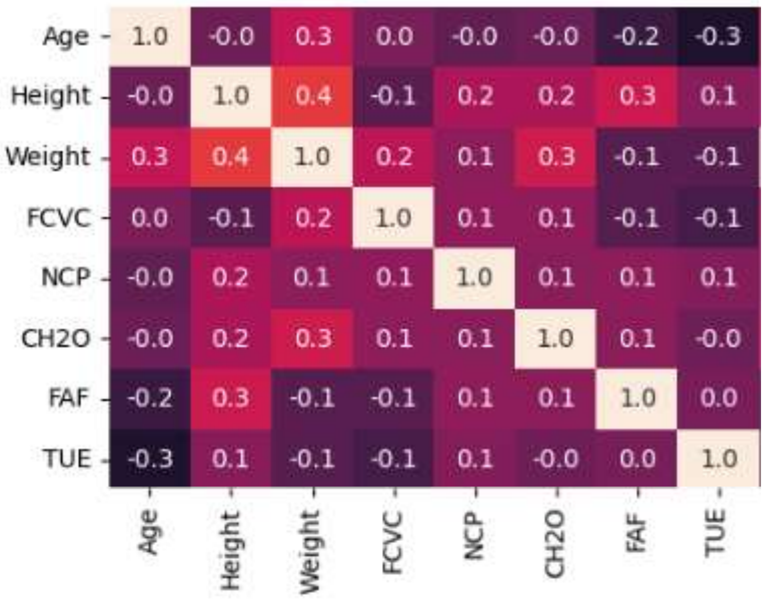
02 Feature Engineering

□ There is no feature with strong correlation
- we can avoid multicollinearity and proceed with feature engineering
- to better understand and classify the risk of obesity



Feature engineering →

BMI : Weight / Height
Tech Usage Score : TUE / Age
Meal Habits : FCVC / NCP

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02 Feature Engineering

□ These features capture nuanced aspects of physical health, lifestyle choices, and nutritional habits.

Derived feature	Description
Body Mass Index (BMI)	- The first step was to calculate BMI using 'Height' and 'Weight', a key metric for indicating obesity by accurately showing the weight-height relationship.
Meal Habits	- The 'Meal_Habits' feature combines 'FCVC' (Frequency of consumption of vegetables) and 'NCP' (Number of main meals), capturing overall dietary patterns by considering both variables.
Tech Usage Score	- 'Tech_Usage_Score' weights the frequency of technology usage ('TUE') by the individual's age, offering a nuanced perspective on technology habits by quantifying average time spent using technology relative to age.

Features above were created by Luca Massaron

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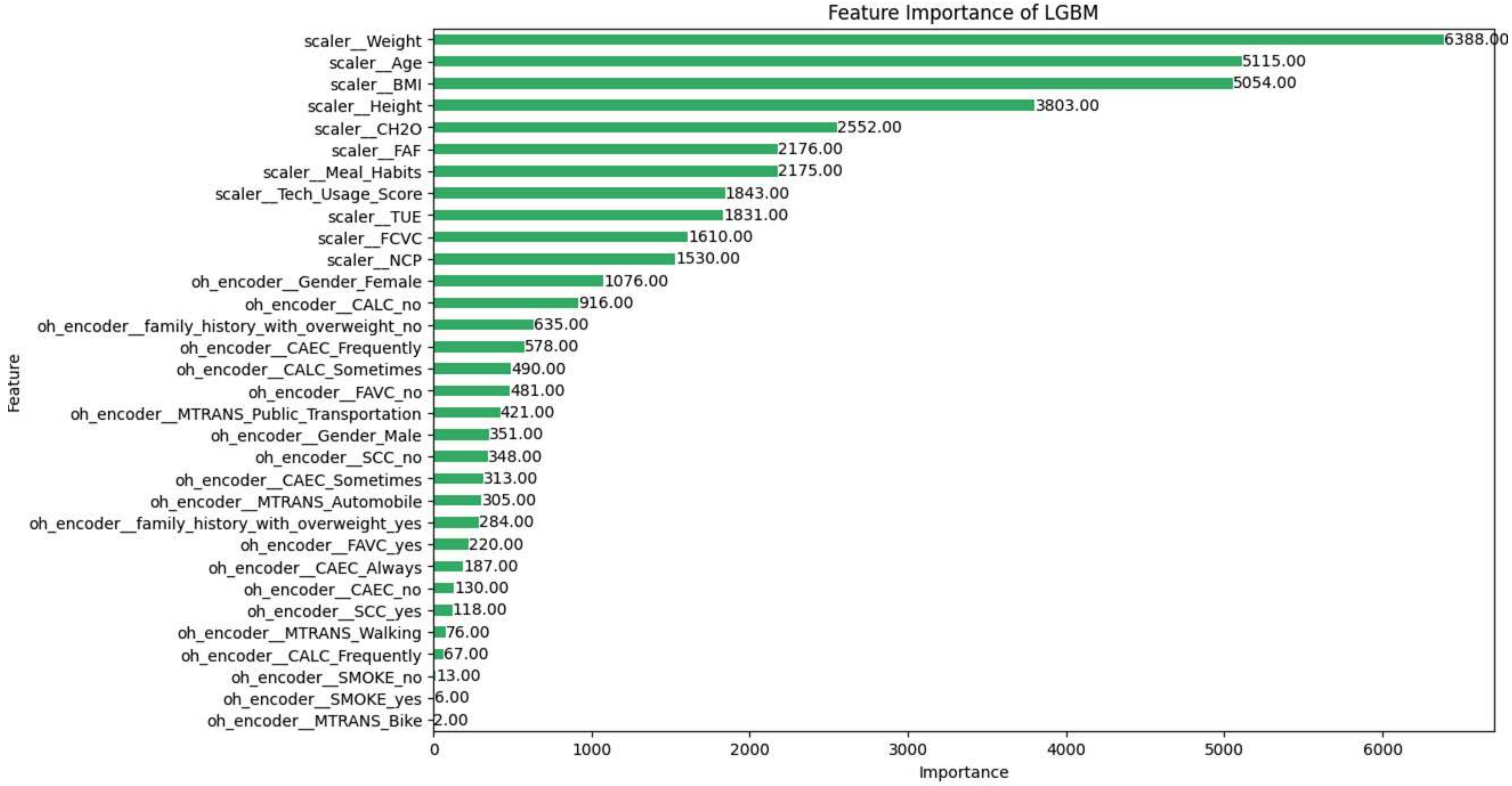
Feature Importance

- Different models are based on different learning algorithms
  - Each algorithm operates differently based on the characteristics of the data.



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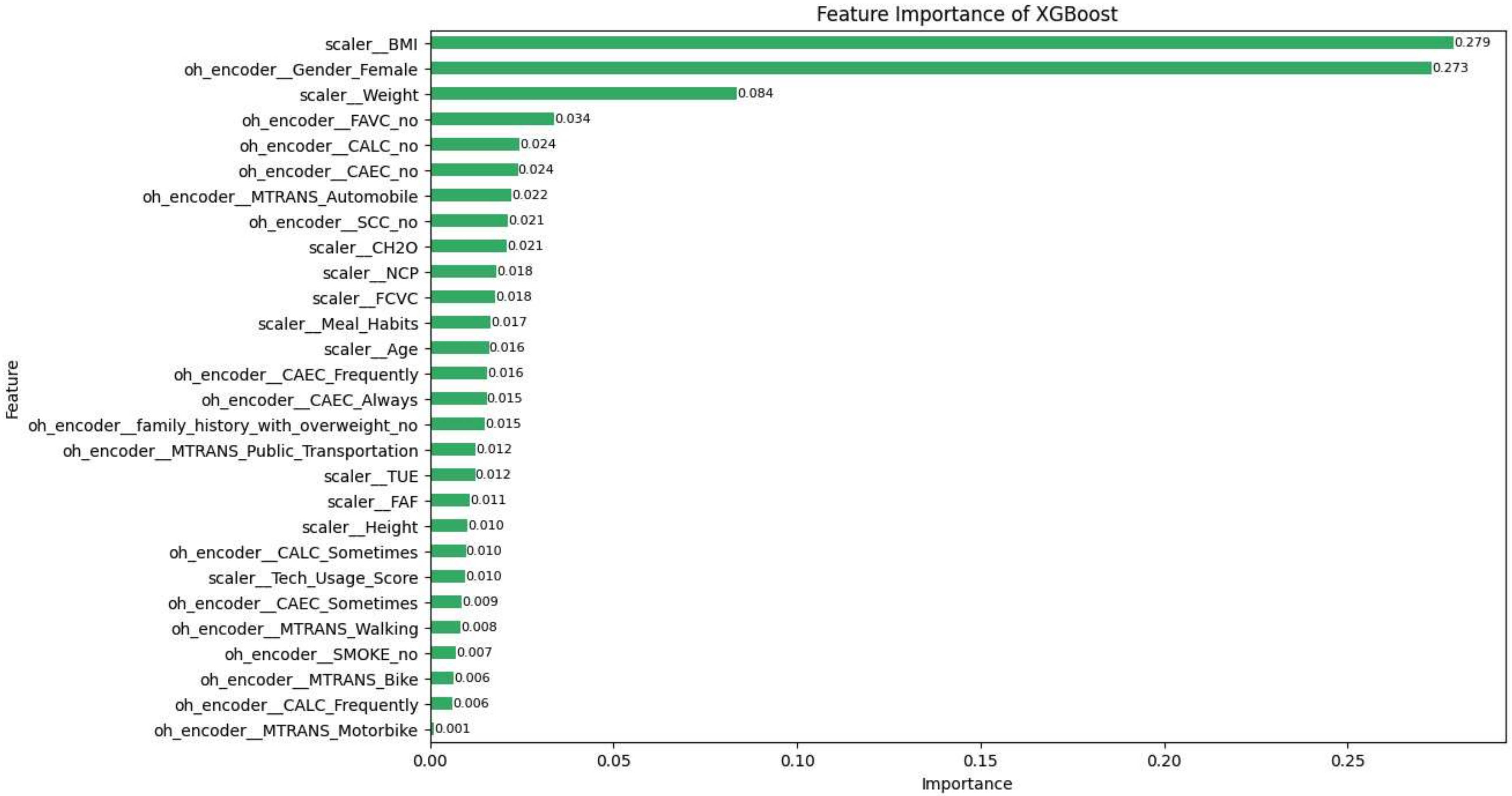
03 Feature Importance



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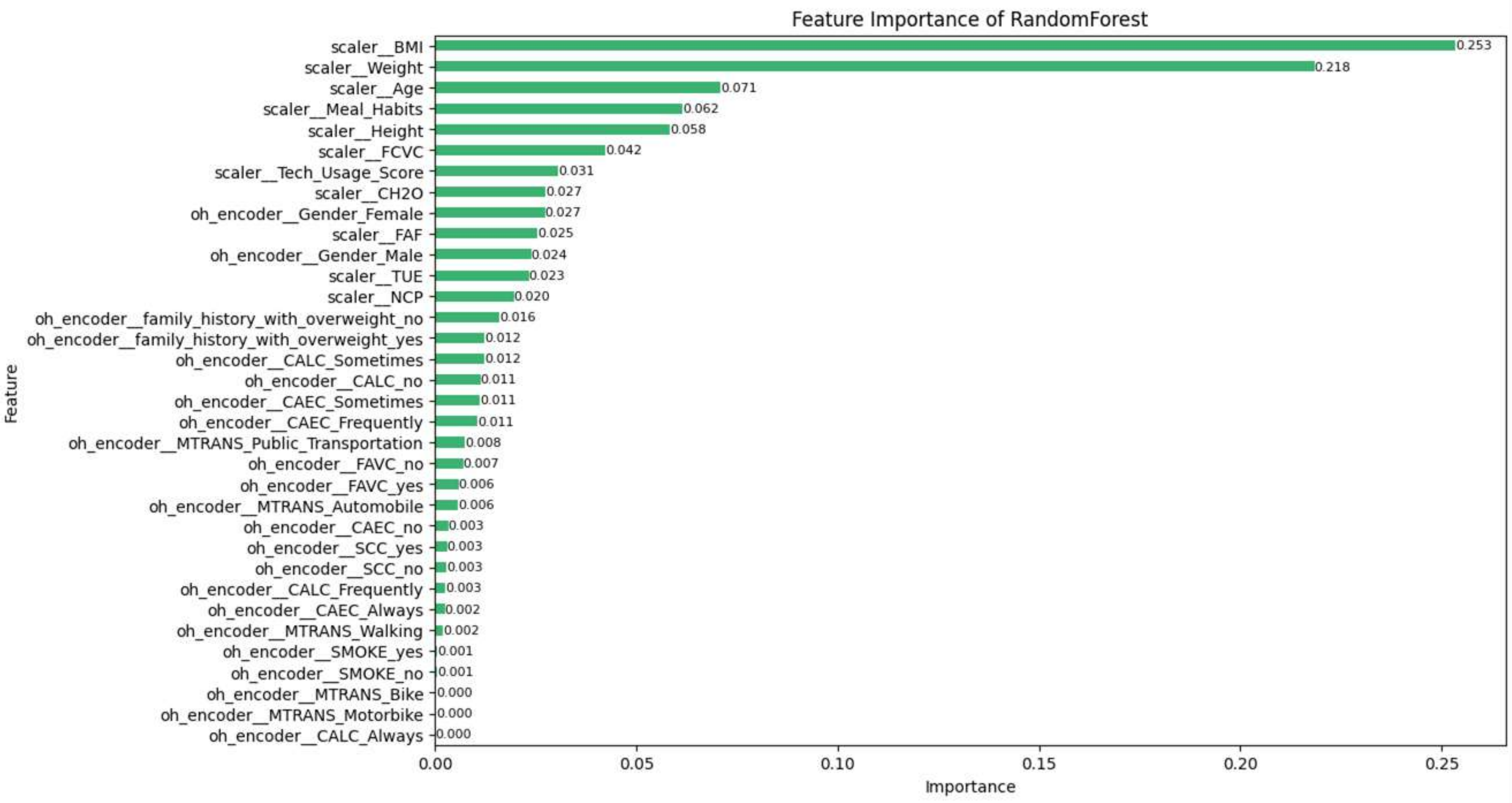
Feature Importance



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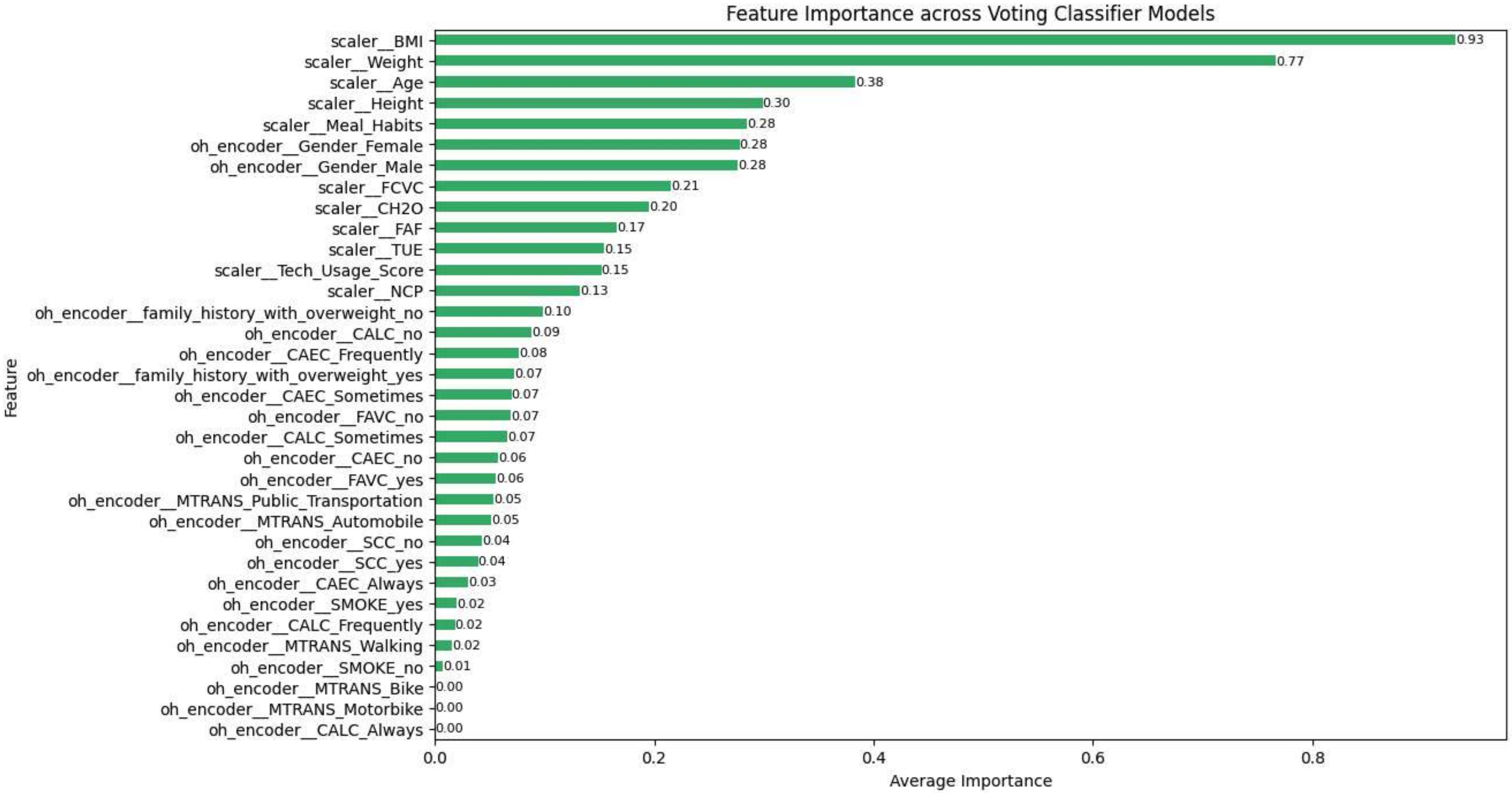
Feature Importance



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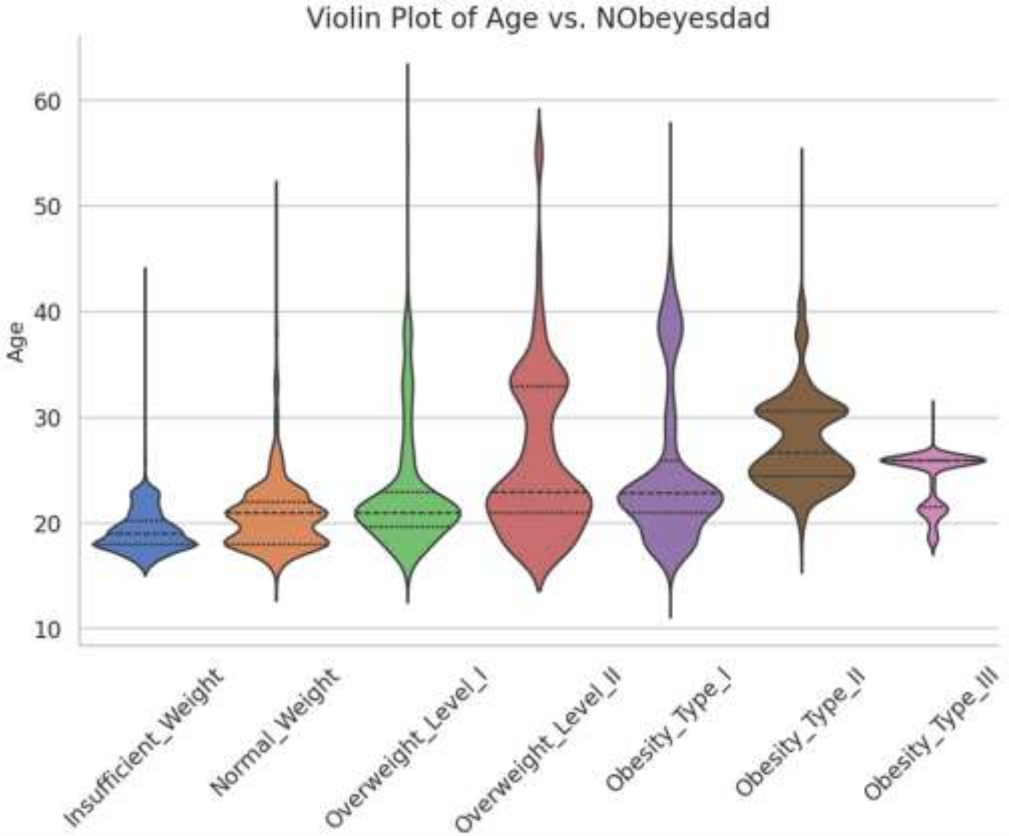
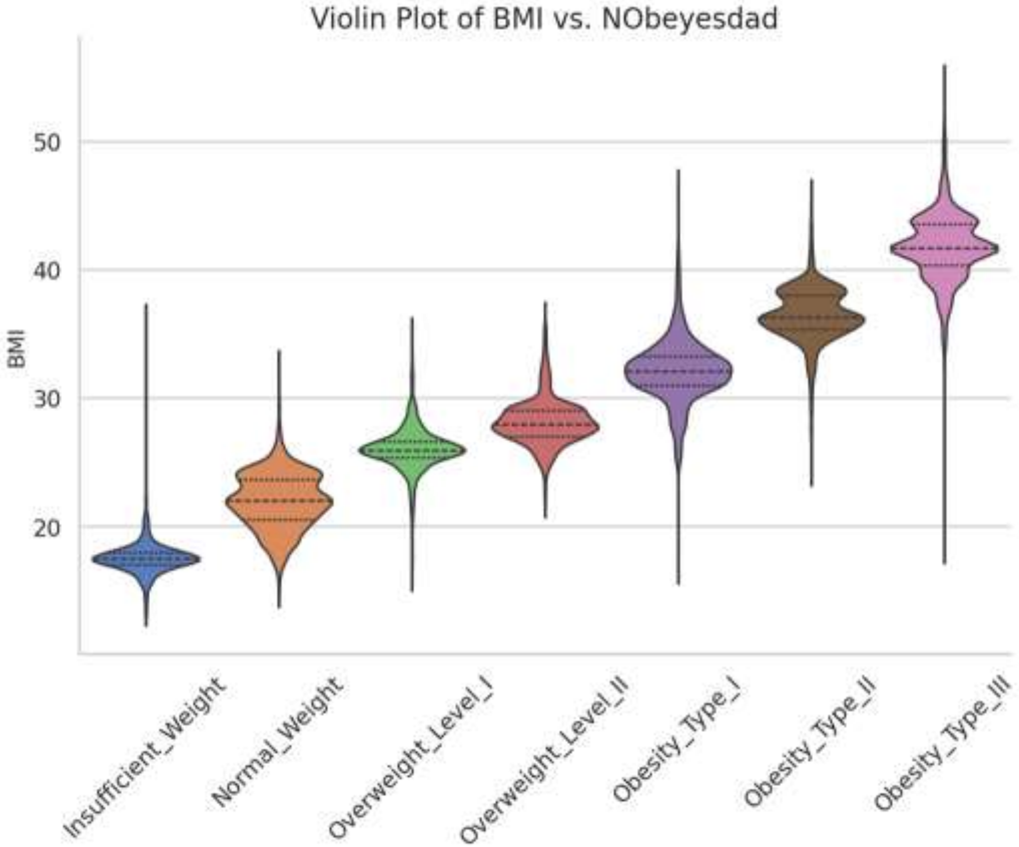
04 EDA with Important Features

 Top 5 important features from voting classifier were taken for visualization.

- BMI, age, meal_habits, CH2O, FAF





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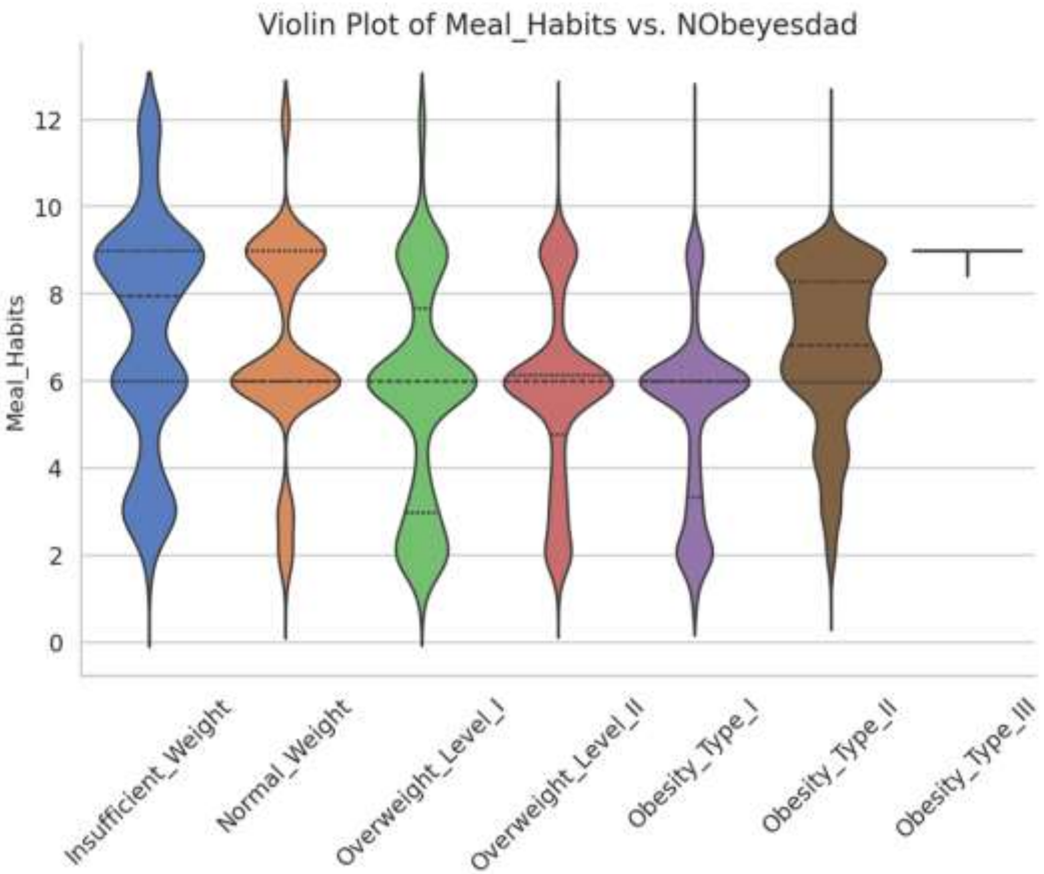
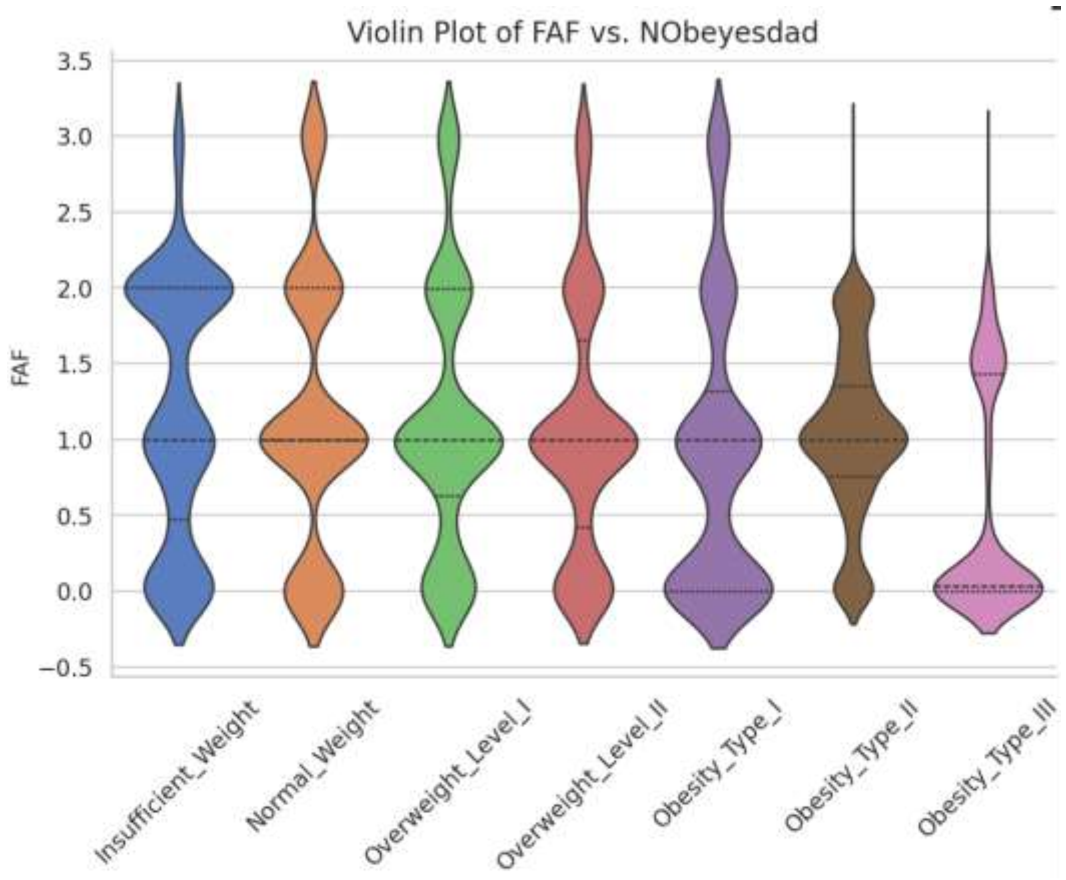
EDA with Important Features





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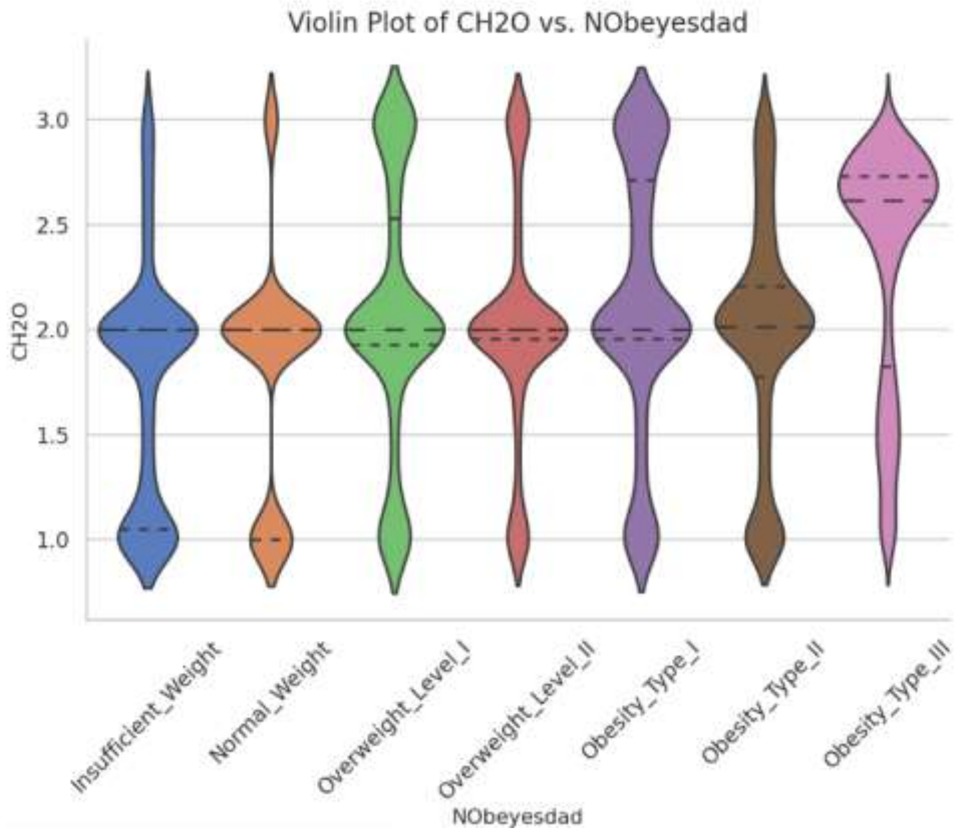
04

EDA with Important Features

- In CH2O, there's not much significant visible difference between groups.



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Part 3 MODEL SELECTION

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01 Pipeline

Gradient Boosting

LGBM

XGBoost

RandomForest

- We compared 4 baseline models to see which one shows the best performance.

- We followed the recommended pipeline method to prevent data leakage.

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01 Pipeline

Gradient Boosting

LGBM

XGBoost

RandomForest

- Utilizes a leaf-centered tree growth method, prioritizing leaf creation to minimize data loss
- Enables fast learning speed and efficient memory usage, suitable for high-dimensional and large-scale datasets
- Particularly effective for processing large amounts of data quickly due to its lightweight design

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01

Pipeline

Gradient Boosting

LGBM

XGBoost

RandomForest

- Provides high speed and efficiency while maximizing prediction accuracy
- Includes a regularization function to prevent overfitting, ensuring robust performance on complex datasets
- Widely used in machine learning due to its optimization for processing large datasets and excellent prediction performance

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Key Factors

Feature Engineering

Parameter Tuning

Target Encoding

Cross-validation

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03 LightGBM

Algorithm	Target encoding	Derived variables	Stratified K-fold	Hyperparameter tuning	Accuracy	Public score	Private score
LightGBM	X	X	X	X	0.91378	0.91401	0.90435
LightGBM	X	X	X	O	0.91308	0.91293	0.90354
LightGBM	O	O	X	O	0.907	0.9104	0.90408
LightGBM	O	O	O	O	0.935	0.9057	0.90534

- Based on the gap between public and private score, we can see that conducting cross-validation 5 times significantly reduced overfitting.

- Conducting target encoding and feature engineering helps improve the performance of the model.

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04 XGBoost

Algorithm	Target encoding	Derived variables	Stratified K-fold	Hyperparameter tuning	Accuracy	Public score	Private Score
XGBoost	O	O	X	X	0.909	0.91401	0.90245
XGBoost	O	O	X	O	0.907	-	-
XGBoost	O	O	O	O	0.937	0.90859	0.90652

- XGBoost showed better performance than LGBM under the same condition.

- Using the model with highest private score, we conducted further experiment to observe the impact of including derived variables in the model and optimizing the number of boosting iterations.

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04 XGBoost

Algorithm	Target encoding	Derived variables	Stratified K-fold	Hyperparameter tuning	Accuracy	Public score	Private Score
XGBoost	O	O	O	O(iter 1224)	0.937	0.90859	0.90652
XGBoost	O	O	O	O(iter 612)	0.914	0.90751	0.90706
XGBoost	O	X	O	O(iter 612)	0.909	0.91437	0.90697
XGBoost	O	X	O	O(iter 1224)	0.916	0.91437	0.90679

- Reducing the number of boosting iteration(n_estimators) may decrease the accuracy. However, this helped prevent overfitting and resulted in improved performance in both public score and private score.

- Also, including derived variables showed slightly better performance than the model without them.

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05 Final Model Selection

Algorithm	Target encoding	Derived variables	Stratified K-fold	Hyperparameter tuning	Accuracy	Public score	Private score
Soft Voting (lgbm, xgboost, randomforest)	O	X	O	O (iter 612)	0.9662	0.91221	0.90742
Soft Voting (lgbm, xgboost, randomforest)	O	O	O	O (iter 612)	0.9669	0.90823	0.90606

- We compared voting classifiers with reduced n-estimators for xgb model - one including derived variables and one that didn't.

- Although in the latter the gap between public and private score was lower which means less overfitting, private score was the highest in the former.

- However, overfitting was detected in voting model.

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06 Kaggle Ranking

➤ Final submission: 1580/3746 (Top 42%)

- we mistakenly chose this model due to its high public score.

Algorithm	Target encoding	Derived variables	Stratified K-fold	Hyperparameter tuning	Accuracy	Public score	Private score
LightGBM	X	X	X	X	0.91378	**0.91401**	**0.90435**

➤ Late submission: est. Top **18~19%**

- we went back to our previous model and made late submission.

Algorithm	Target encoding	Derived variables	Stratified K-fold	Hyperparameter tuning	Accuracy	Public score	Private score
Soft Voting (lgbm, xgboost, randomforest)	O	X	O	O (iter 612)	0.9662	**0.91221**	**0.90742**

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Part 4 Conclusion

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01 Conclusion

Data Analysis	- In regards to feature importance, BMI, age, Meal_Habits, CH2O, FAF and such demonstrate high importance across three models. The features influencing performance vary depending on the structure and algorithm of the model.
Model Training	- Cross-validation and hyperparameter optimization is essential. - Choosing ideal number of cross-validation folds and boosting iterations is needed to prevent overfitting and improve model's generalization performance.
Feature Engineering	- Incorporating derived variables showed the best performance when using a single XGBoost model. However, when employing soft voting, the result was the opposite. - Reason for this remains unanswered, necessitating further study.

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02 Limitations

1	- Limitation in sorting out the best combination of hyperparameters
2	- Limitation in figuring out why incorporating derived variables showed different performance in different models.
3	- Limitation in identifying ways to reduce overfitting.

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Thank you.