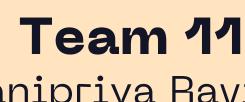
## Obesity Data Analysis



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#### Introduction

- Obesity is a growing public health issue affecting millions worldwide.
- Predicting obesity levels can help healthcare providers take preventive measures.
- Our project aims to classify obesity levels, predict BMI, and group individuals into clusters based on their health and lifestyle factors.

# Data Preprocessing & Feature Selection

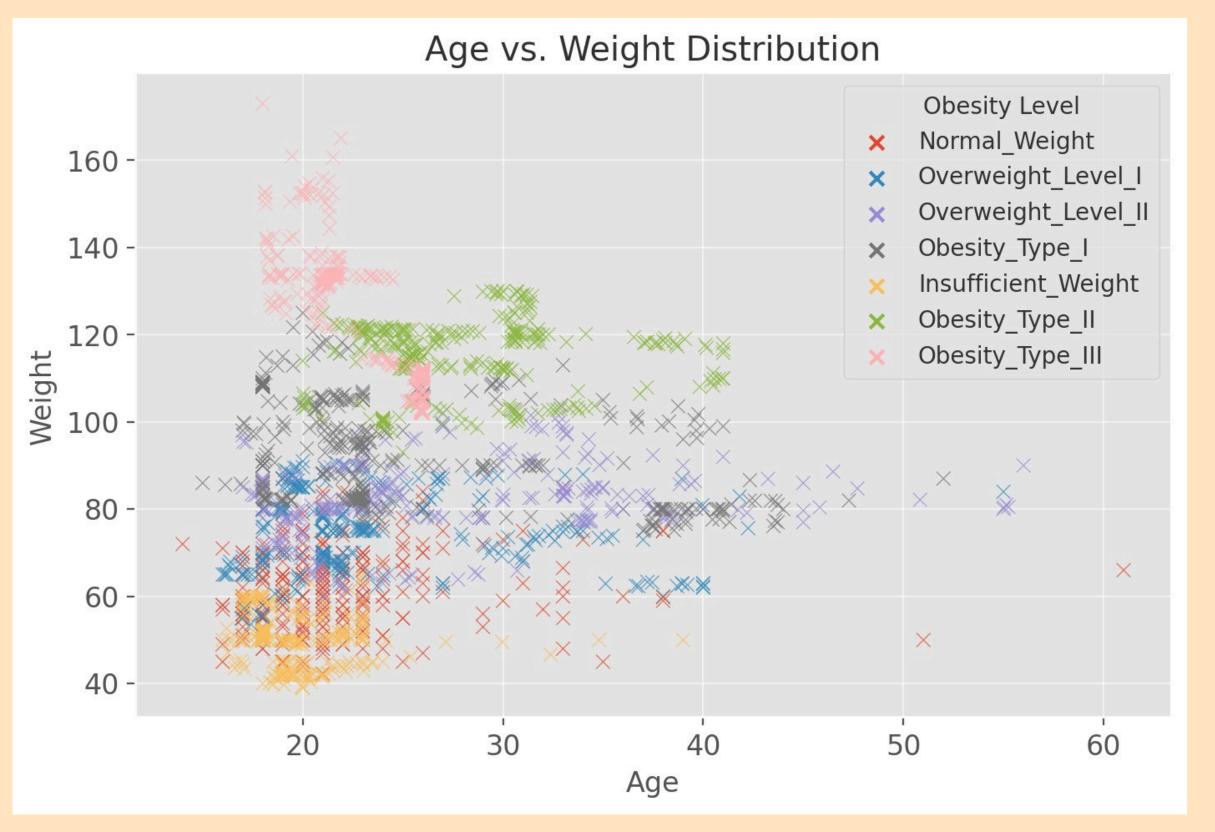
- Dataset Name: Estimation of Obesity levels
- Source: Public health dataset
- Features: Age, Height,
   Weight, Food Consumption,
   Physical Activity, Water
   Intake, Transportation Mode.

## Data Preprocessing & Feature Selection

#### Data Cleaning:

- Handled missing values.
- Normalized numerical features.
- Regression Features: Weight, Age, Height, Physical Activity Frequency (FAF), Number of Meals (NCP).
- Clustering Features: Age, Height, Weight, FCVC, NCP, CH2O, FAF, TUE.
- Classification Target: BMI as the target variable.







#### Exploratory Data Analysis (EDA)



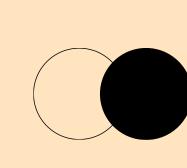
#### Correlation Analysis:

- Weight had the strongest correlation with BMI (0.935).
- Weak correlation for Age and Height.

#### Visualization:

 Histograms, scatter plots, and bar charts to identify obesity trends.

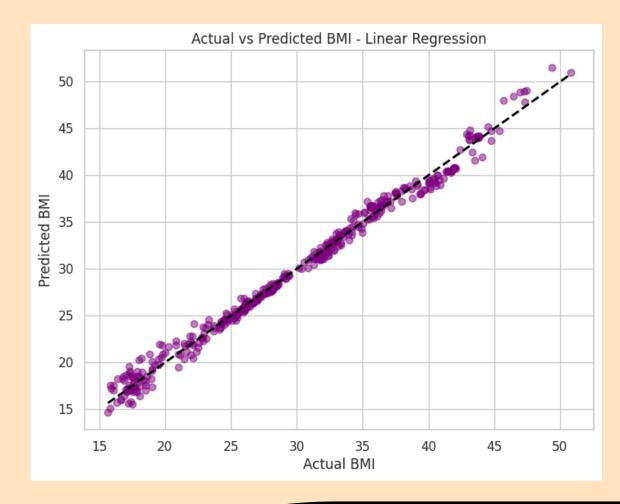
Correlation Heatmap of Numerical Features												
Age	1.00	-0.03	0.20	0.02	-0.04	0.09	-0.12	-0.12	0.02	0.24		
Height	-0.03	1.00	0.46	-0.04	0.24	0.06	-0.13	0.27	0.13	0.13	- 0.8	
Weight	0.20	0.46	1.00	0.22	0.11	0.03	-0.20	0.08	0.25	0.93		
FCVC	0.02	-0.04	0.22	1.00	0.04	0.01	0.07	0.05	0.08	0.26	- 0.6	
NCP	-0.04	0.24	0.11	0.04	1.00	0.01	-0.02	0.07	0.09	0.04	- 0.4	
SMOKE	0.09	0.06	0.03	0.01	0.01	1.00	0.05	-0.02	0.05	-0.00	0.4	
SCC	-0.12	-0.13	-0.20	0.07	-0.02	0.05	1.00	0.05	-0.02	-0.18	- 0.2	
FAF	-0.12	0.27	0.08	0.05	0.07	-0.02	0.05	1.00	-0.03	-0.03		
CALC	0.02	0.13	0.25	0.08	0.09	0.05	-0.02	-0.03	1.00	0.22	- 0.0	
BMI	0.24	0.13	0.93	0.26	0.04	-0.00	-0.18	-0.03	0.22	1.00	-0.2	
	Age	Height	Weight	FCVC	NCP	SMOKE	SCC	FAF	CALC	BMI	-0.2	





#### Regression

- Objective: Predict BMI based on patient features.
- Models Used:
  - Linear Regression: R<sup>2</sup> Score = 0.76
  - Random Forest Regressor: R<sup>2</sup> Score =
     0.89 (Best Model)
- Conclusion: Weight, Height, and Number of Meals were key predictors of BMI.





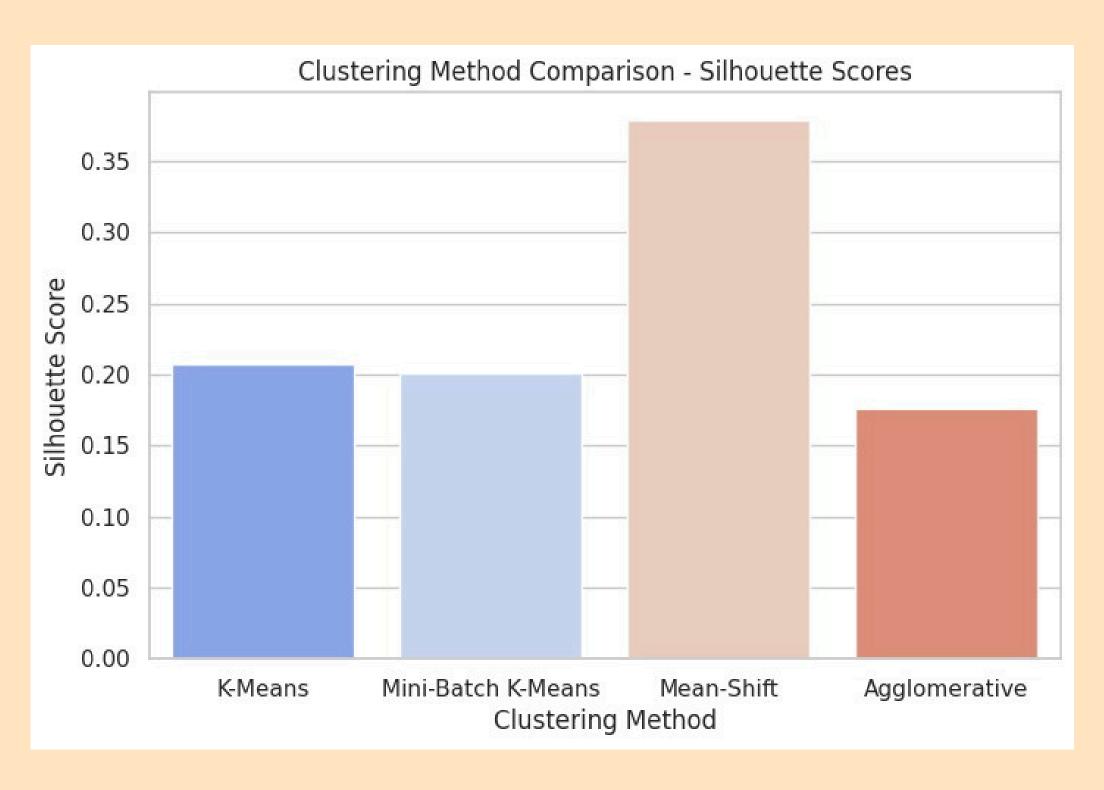
#### Clustering Analysis

Objective: Identify patterns among obesity groups.

#### Methods Used:

- K-Means = 0.2068
- Mini-Batch K-Means = 0.2012
- Agglomerative Clustering = 0.1762
- Mean-Shift (Best) = 0.3794

#### Clustering Analysis



## Classification Models and Configurations

Model	Configuration					
Logistic Regression	max_iter=1000, random_state=42					
K-Nearest Neighbors (KNN)	n_neighbors=5, metric='minkowski', p=2					
Decision Tree	max_depth=None, criterion='gini', random_state=42					
Random Forest	n_estimators=100, criterion='gini', random_state=42					
Support Vector Machine (SVM)	C=1.0, kernel='rbf', gamma='scale', random_state=42					
Naive Bayes	GaussianNB()					
Neural Networks (MLPClassifier)	hidden_layer_sizes=(100,), max_iter=1000, random_state=42					

#### Classification Analysis

Objective: Classify individuals into obesity categories (Normal Weight, Overweight, Obese, Underweight). Methods Used:

- Logistic Regression = 82%
- K-Nearest Neighbors (KNN) = 94%
- Decision Trees = 96%
- Support Vector Machine (SVM) = 95%
- Naive Bayes = 90%
- Neural Networks = 94%

Best Model: Decision Trees.

Alternative: Support Naive Bayes.

#### Key Takeaways

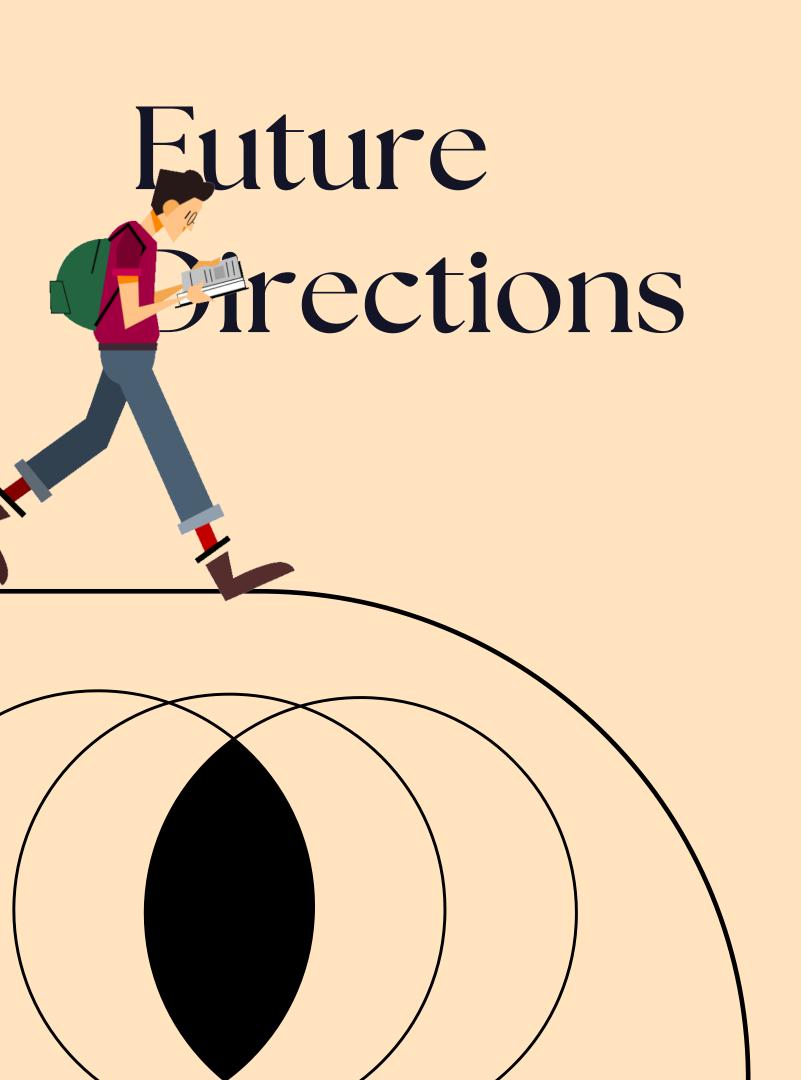


- Regression showed that BMI is influenced by weight, height, and eating habits.
- Mean-Shift Clustering provided the best grouping of obesity risk factors.
- Proper feature selection and preprocessing significantly improved model performance.



## Challenges Faced S

- Feature Selection: Identifying the most relevant predictors.
- Imbalanced Data: Some obesity categories had fewer samples.
- Model Optimization:
   Hyperparameter tuning improved results.
- Overfitting: Decision Tree achieved 96% accuracy but required careful validation.



- Improve Feature Engineering: Include additional lifestyle factors.
- Balance Class Distribution: Apply oversampling/undersampling.
- Optimize Model Performance: Implement deep learning techniques.
- Deploy as a Decision Support System for Healthcare Providers.

# Thank you!