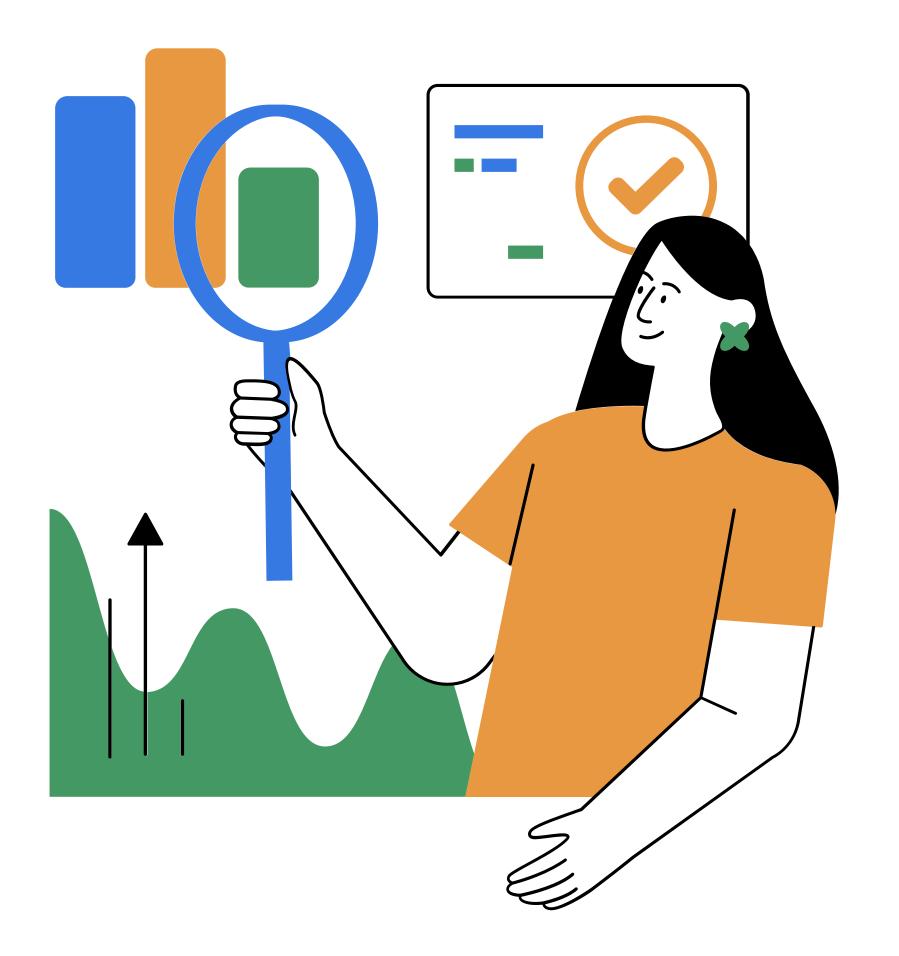


# Child Malnutrition



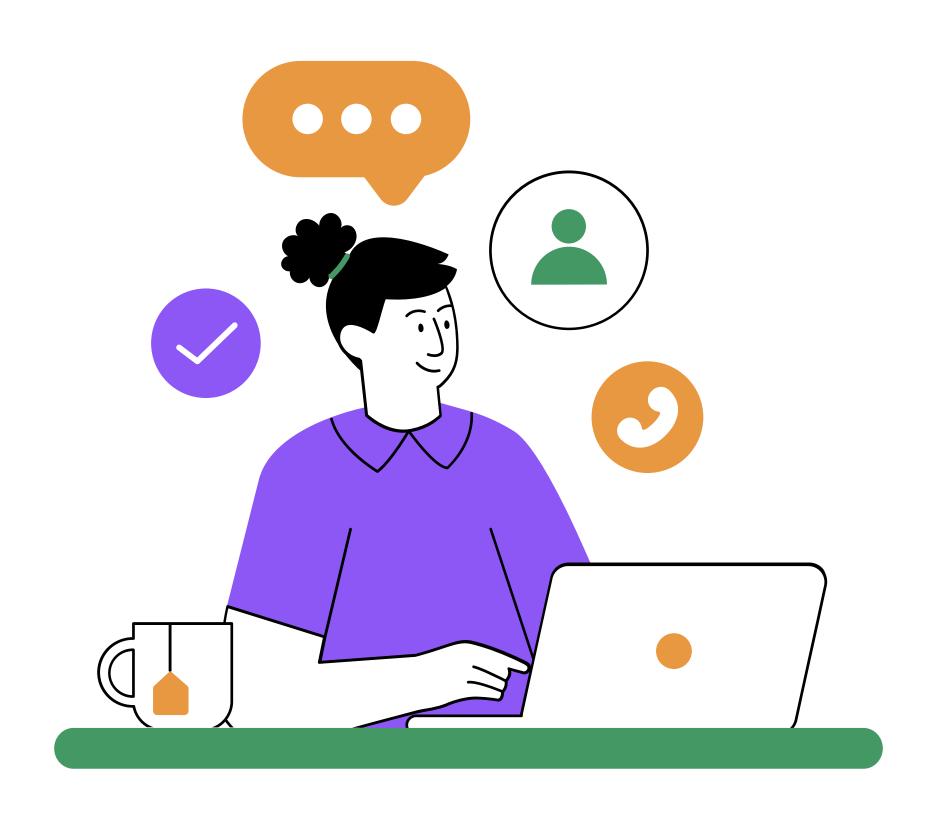


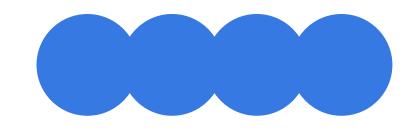
### Project Title:

Predictive Modeling of Child Malnutrition Using UNICEF Data

### Team Members:

- Mariam Goda
- Amira Yasser
- Safia Mohamed



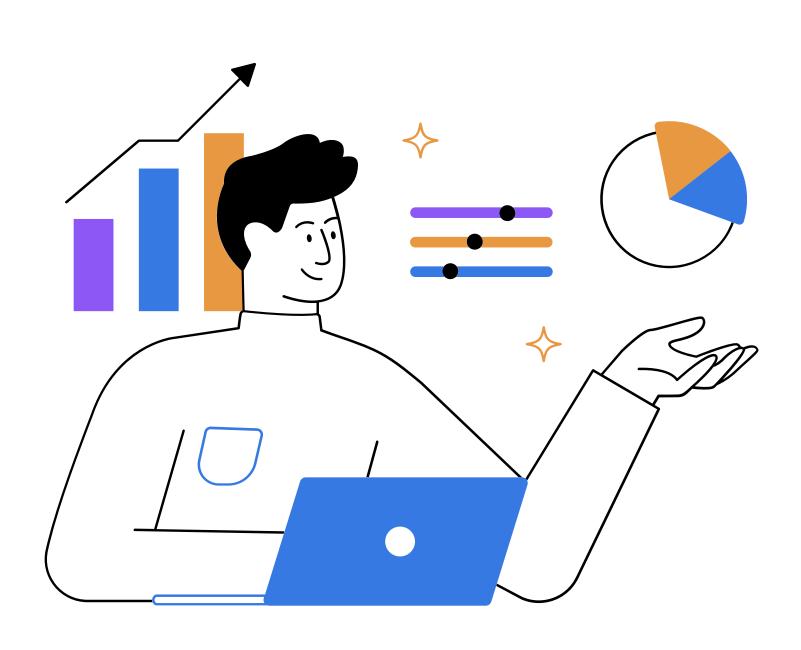


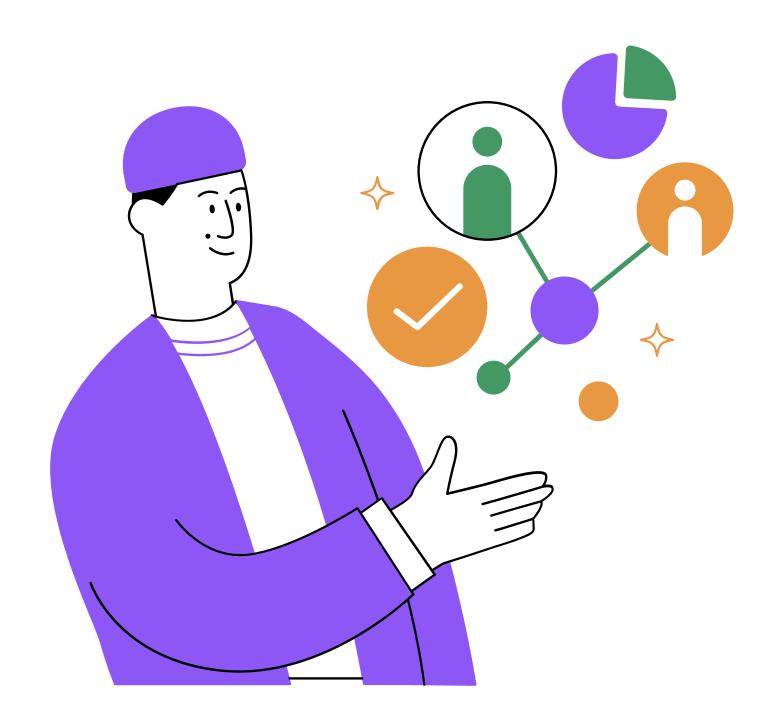
### Why we chose this dataset

**Relevance:** Provides data across multiple countries, enabling cross-regional analysis.

**Comprehensive Indicators:** Includes key malnutrition metrics—stunting, wasting, underweight, and overweight.

**Availability**: Publicly accessible and well-structured



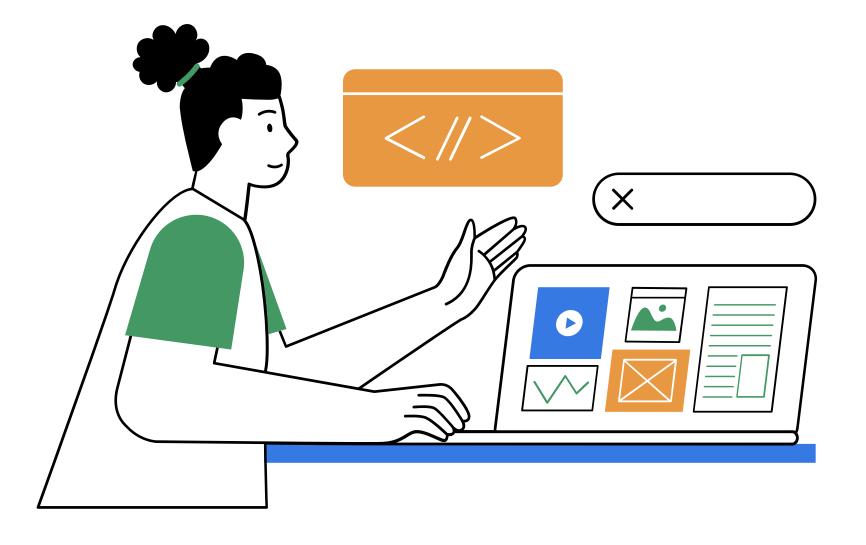


### EDA Highlights

- Data Cleaning
- Missing Values
- Outlier Treatment
- Feature Relationships

### Data Cleaning

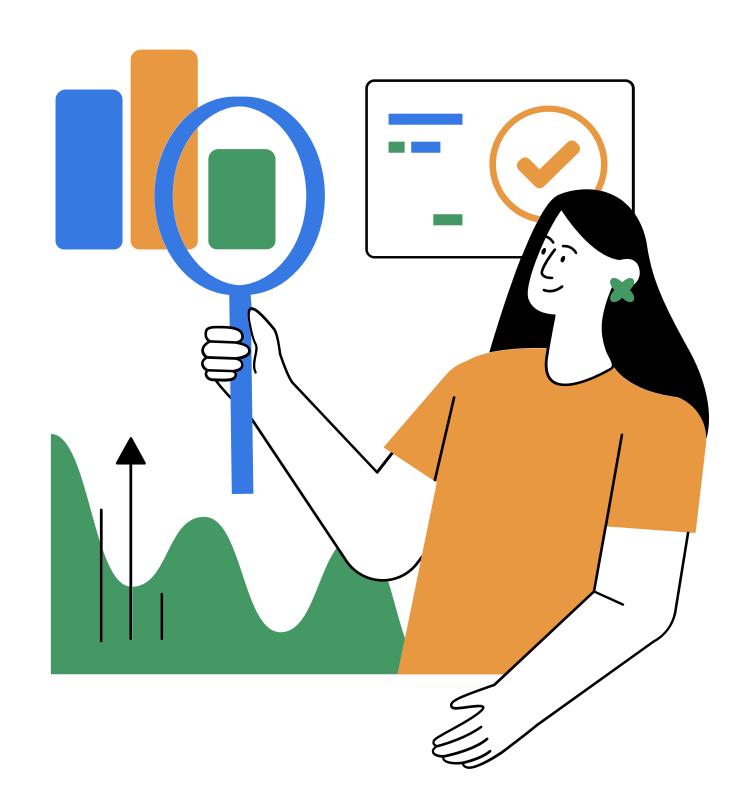
- Dropped Irrelevant Columns: Removed columns like Report Author, ISO code, UNICEF Survey ID, and notes that don't affect prediction.
- Encoded Categorical Features: Used LabelEncoder for transforming text columns into numeric values.
- Scaling: Applied StandardScaler to normalize the numerical features for better model performance.



### Missing values

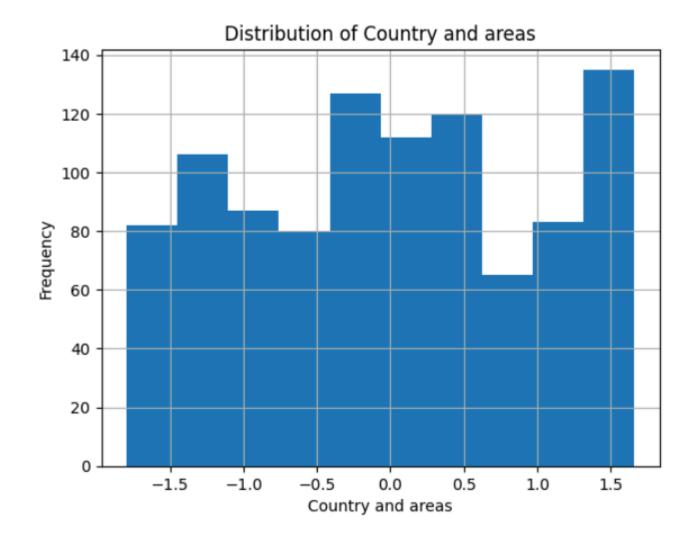
Identified columns with missing values and calculated their skewness:

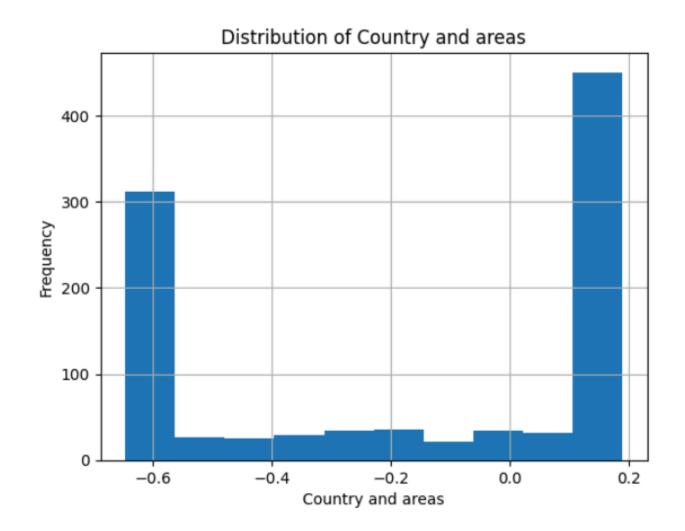
- Used median imputation for highly skewed columns.
- Used mean imputation for nearly symmetric distributions.



### Outlier Detection and Handling

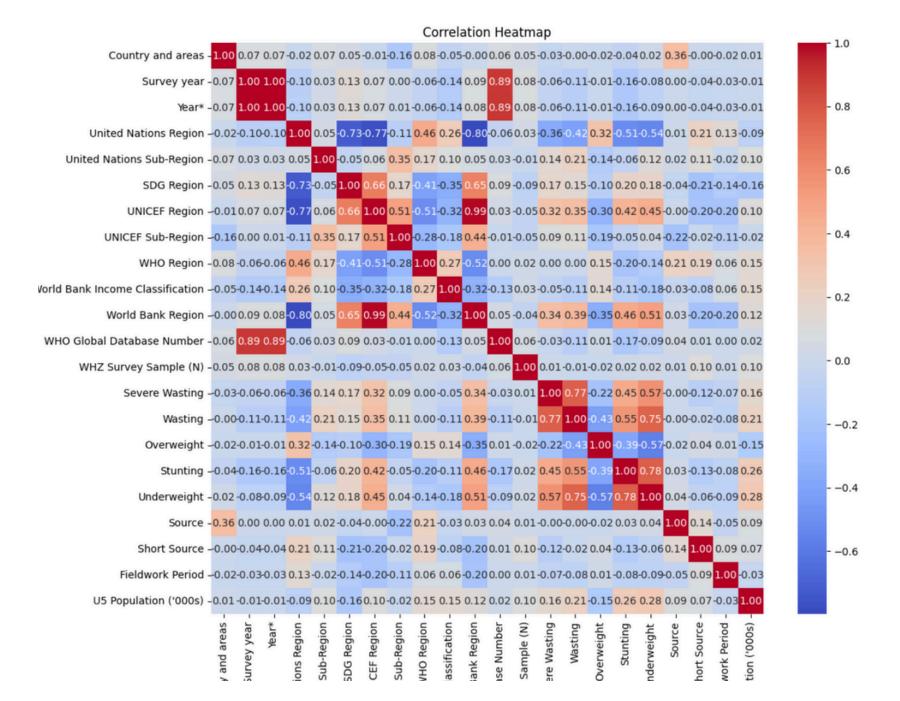
- Detected outliers using IQR.
- Applied clipping technique to reduce their impact.
- Visualized distributions before and after treatment (Box & Histogram Plots).

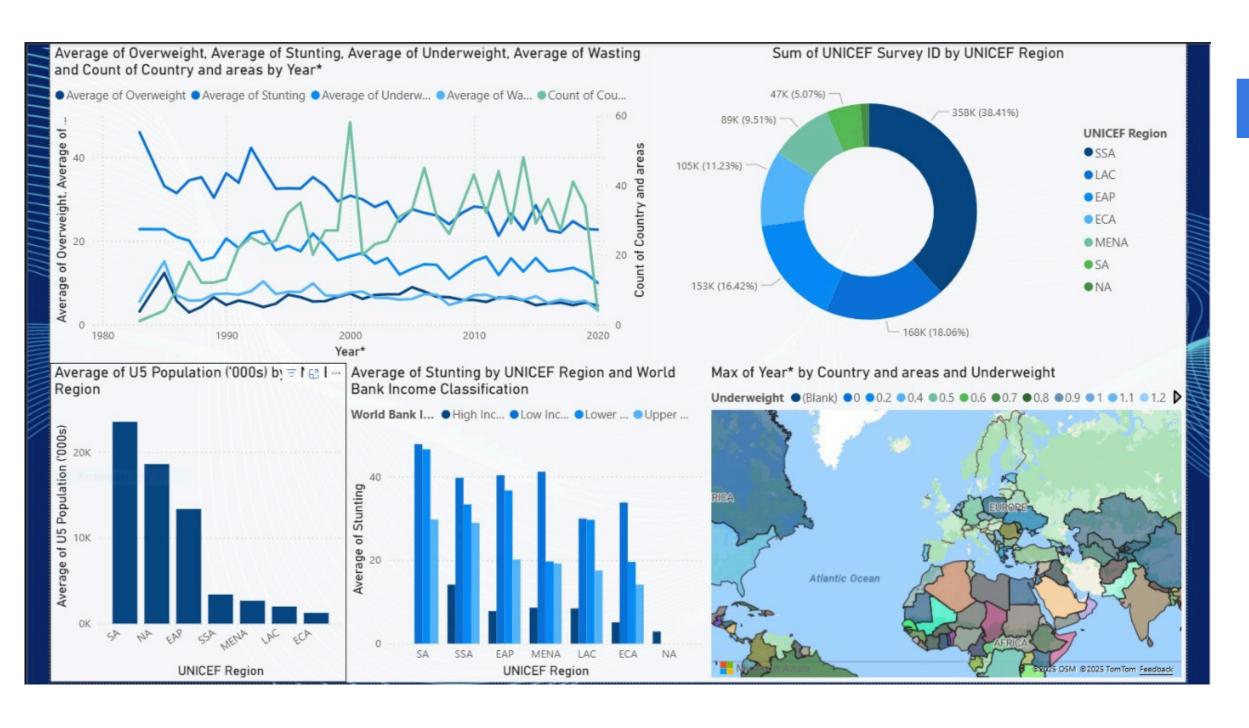




### Exploratory Visualizations

- **Histogram plots:** Showed distribution of each feature.
- Box plots: Helped identify and visualize outliers.
- Violin plots: Provided combined view of data distribution and density.
- Correlation Heatmap: Revealed relationships between features.





### Dashboard

- The UNICEF Survey ID distribution shows Sub-Saharan Africa (SSA) dominates with 47% of survey entries, followed by East Asia and Pacific (18.06%) and Latin America and Caribbean (16.42%).
- The U5 Population graph reveals significant variations across regions, with Sub-Saharan Africa having the largest under-5 population.
- Stunting rates vary dramatically by World Bank income classification and UNICEF region, with lower-income regions showing higher stunting prevalence.
- The time series data demonstrates long-term trends in child nutrition metrics, showing some improvements and fluctuations over the decades.

### Step 01

### Loads all necessary libraries for:

- Data processing: pandas, numpy
- Visualization: matplotlib, seaborn
- ML models: sklearn, xgboost
- Interpretability: SHAP, LIME

### Step 02

### **Load and Explore Cleaned Data**

• We begin by loading the cleaned survey dataset and ensuring the data is structured correctly.

### Step 03

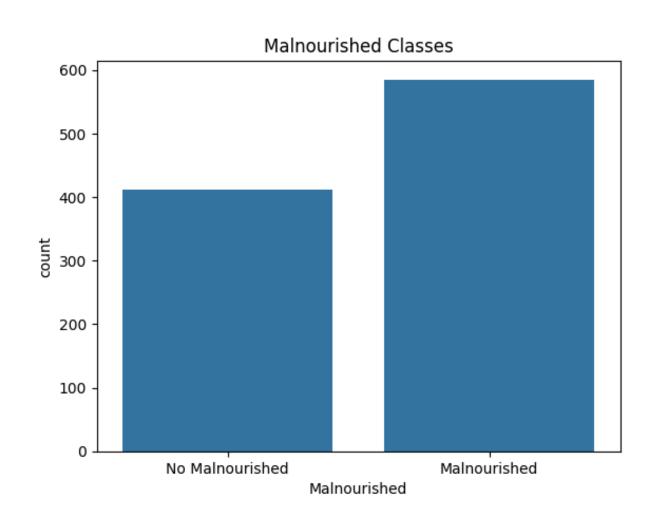
### **Feature Engineering**

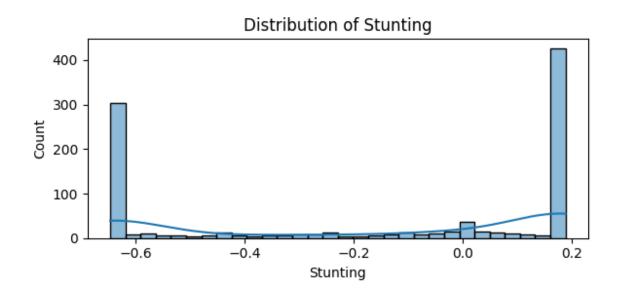


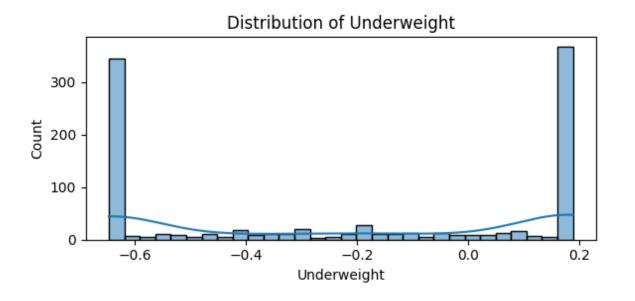
- Creates a new binary target Malnourished based on thresholds of indicators.
- Visualizes class imbalance.
- Creates an Avg\_Malnutrition column to average the malnutrition measures.
- Computes a burden estimate using population.

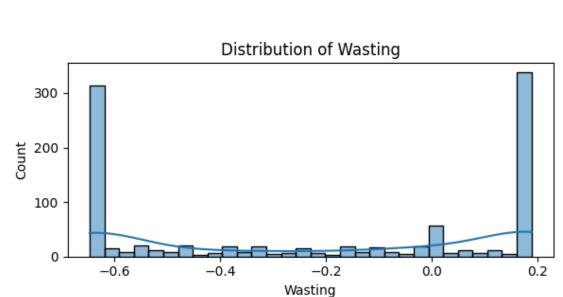
### Step 04

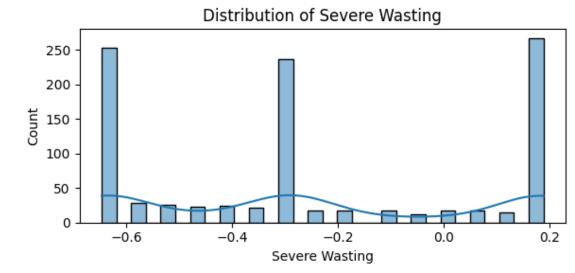
### **Data Visualization**











### Step 05

### **Supervised Classification Models**

Trains and evaluates the following models:

- Logistic Regression
- Random Forest
- XGBoost
- SVM
- K-Nearest Neighbors

```
print("Classification report is : ",classification_report(y_test,y_log_pred))

→ Classification report is:
                                            precision
                                                        recall f1-score support
              0
                      0.82
                                0.79
                                         0.80
                                                     96
                      0.81
                               0.84
                                         0.82
                                                    104
                                         0.81
                                                    200
       accuracy
                                0.81
                                         0.81
                                                    200
       macro avg
                      0.82
    weighted avg
                      0.82
                                0.81
                                         0.81
                                                    200
```

```
print("Classification report is : ",classification_report(y_test,y_rfc_pred))
→ Classification report is :
                                             precision recall f1-score support
                                          0.82
               0
                      0.81
                                0.82
                                                     96
                      0.83
                                          0.83
                                0.83
                                                     104
                                          0.82
                                                    200
        accuracy
       macro avg
                      0.82
                                0.82
                                          0.82
                                                     200
    weighted avg
                      0.83
                                0.82
                                          0.83
                                                    200
```

```
print("Classification report is : ",classification_report(y_test,y_svm_pred))
→ Classification report is :
                                            precision recall f1-score support
                                0.78
                                          0.82
                      0.86
                                                     96
                      0.81
                                0.88
                                          0.85
                                                     104
                                                    200
                                          0.83
        accuracy
                      0.84
                                          0.83
                                                     200
       macro avg
                                0.83
    weighted avg
                      0.84
                                0.83
                                          0.83
                                                    200
```

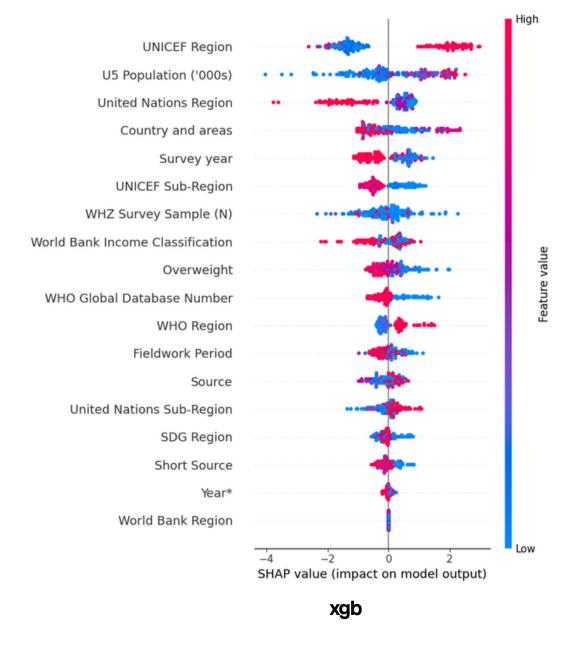
### Step 05

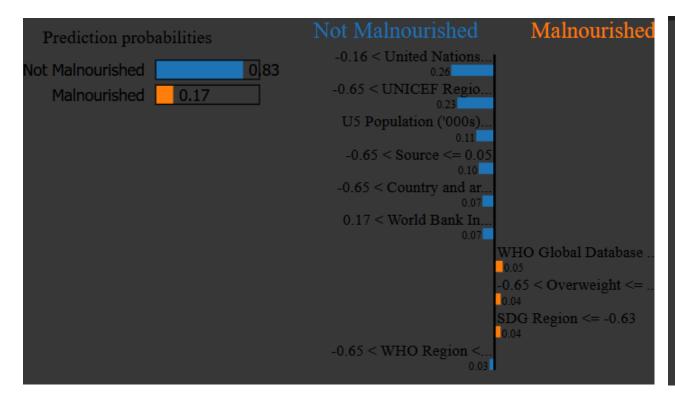
### **Supervised Classification Models**

Explainability Agnostic Models For XGBoost Classifier

local agnostic Models:

LIME SHAD





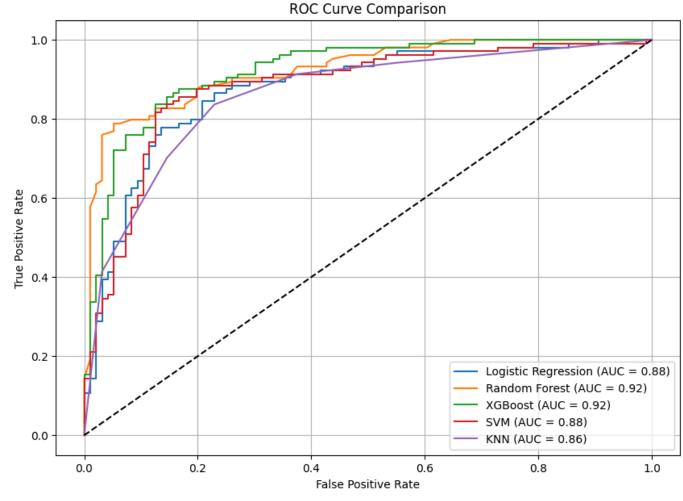
Feature	Value
United Nations Region	0.19
UNICEF Region	-0.50
U5 Population ('000s)	-0.35
Source	-0.23
Country and areas	-0.29
World Bank Income Classification	n 0.19
WHO Global Database Number	-0.65
Overweight	-0.53
SDG Region	-0.63
WHO Region	-0.42

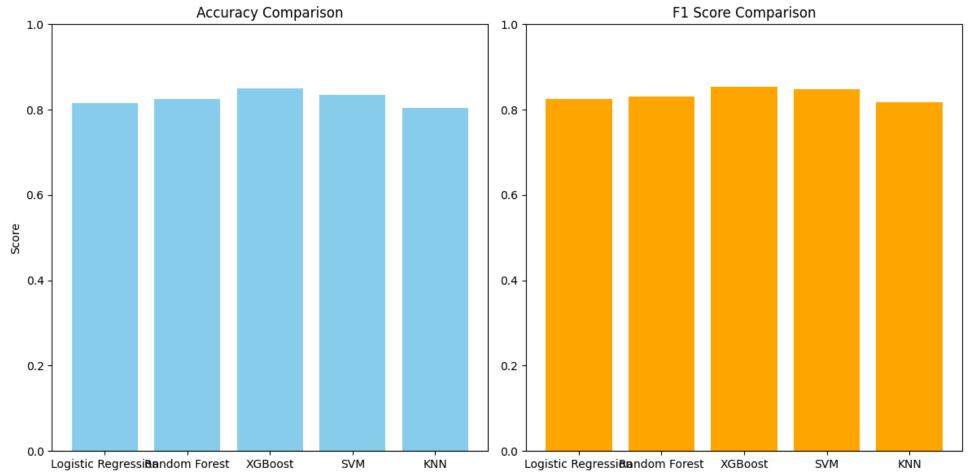
### Step 05

### **Supervised Classification Models**

**Evaluation Metrics Used:** 

- Accuracy
- Classification report
- Confusion matrix
- ROC curve
- F1, Precision, Recall



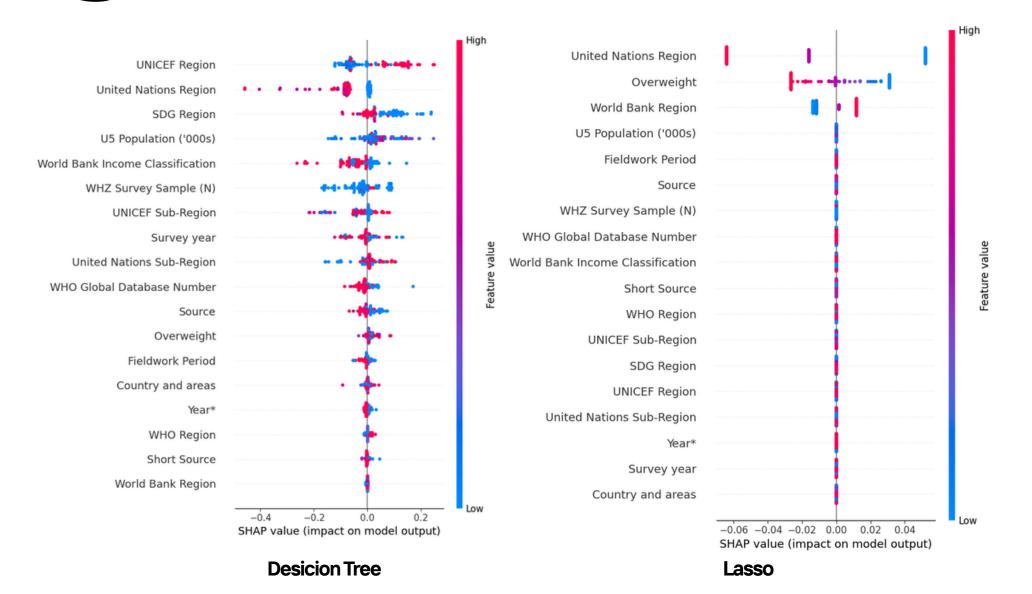


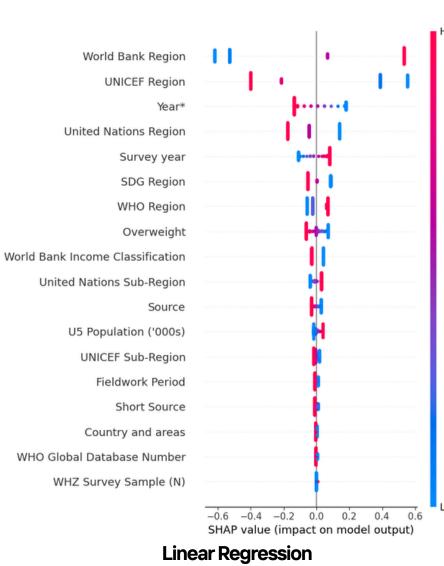
### Step 06

### **Supervised Regression Models**

Models used to predict average malnutrition score:

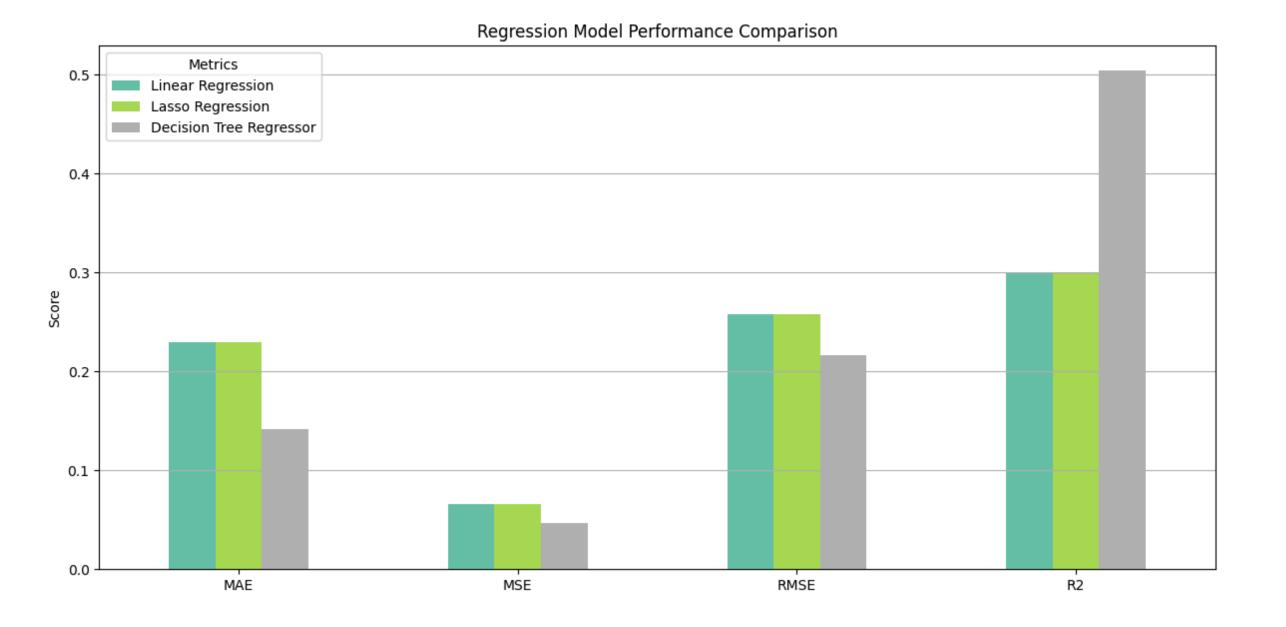
- Linear Regression
- Lasso Regression
- Decision Tree Regressor





### Step 06

Metrics Used:
 MAE, MSE, RMSE, R²





### Step 07

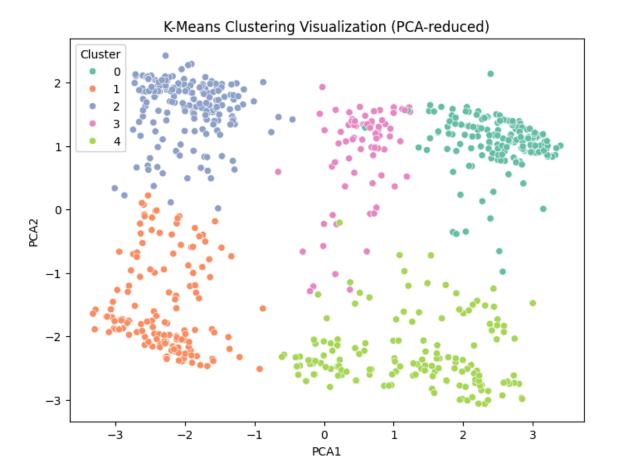
### **Unsupervised Clustering**

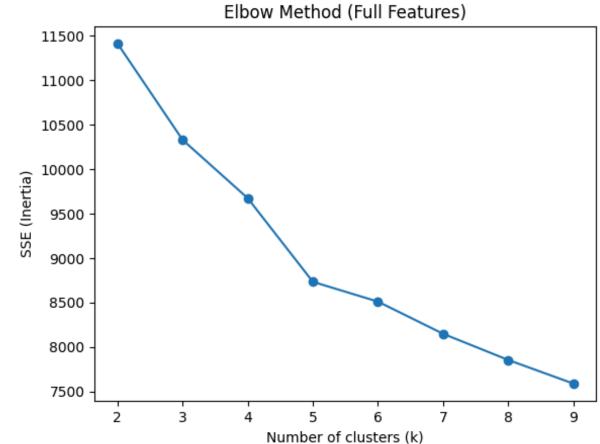
Method: K-Means

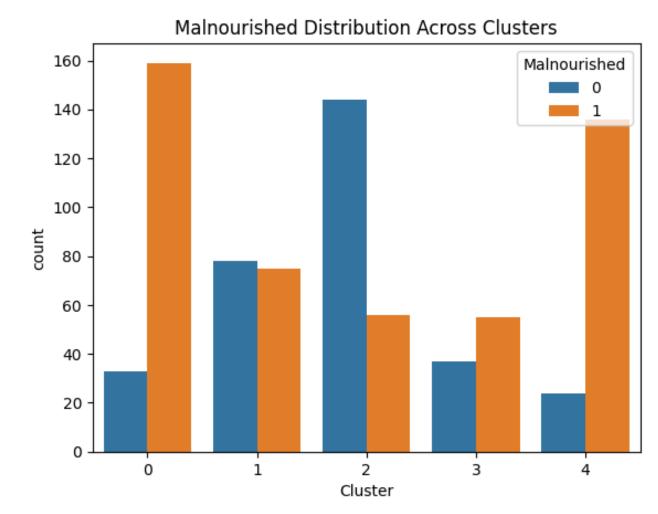
Elbow method used to determine optimal k

Clusters visualized using PCA

Silhouette Score used to assess quality

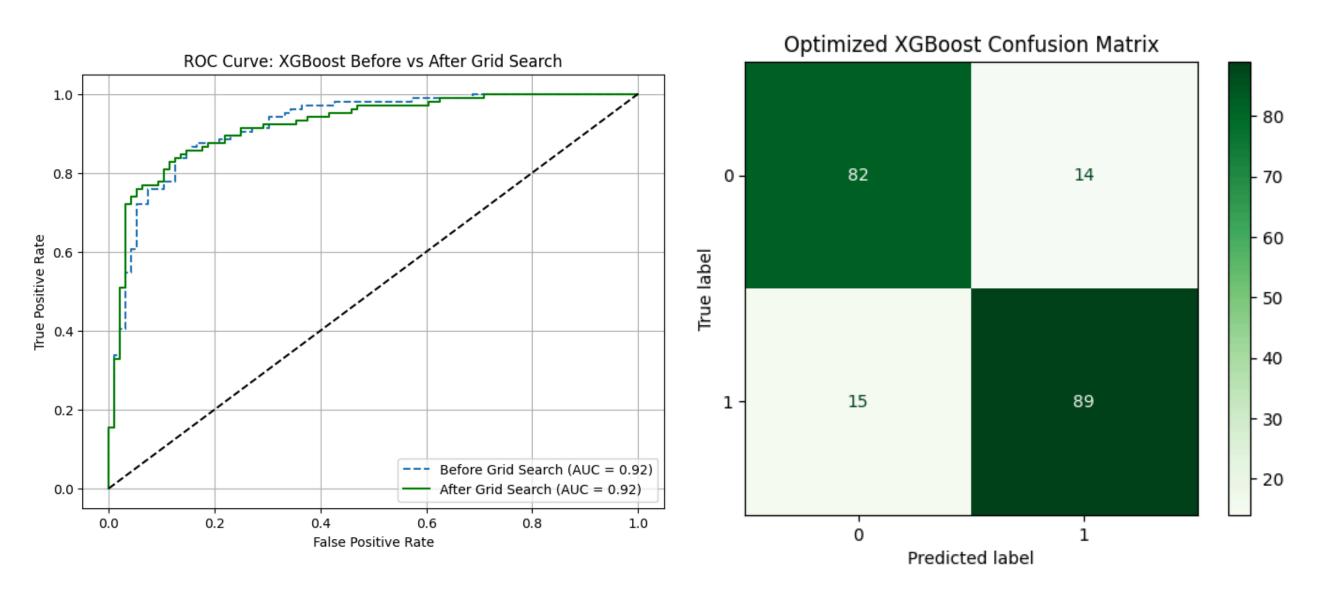


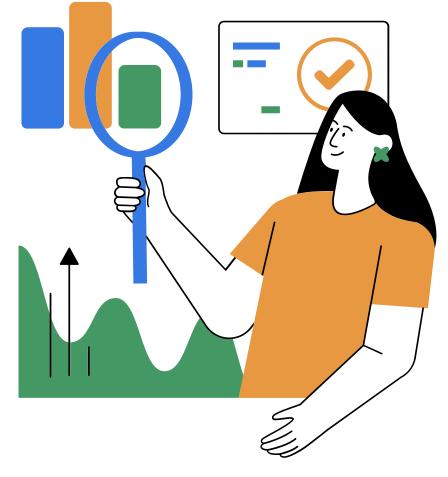




Step 08

**Model Optimization Using Grid Search** 





\*

### Thank You

