EWD Project

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Goal of the experiment

The goal of the project is to build the predicting model to predict the obesity level of persons.

Data

Link to the data: https://www.kaggle.com/datasets/fatemehmehrparvar/obesity-levels/data

Features:

Gender: Feature, Categorical, "Gender"
Age : Feature, Continuous, "Age"
Height: Feature, Continuous
Weight: Feature Continuous
family_history_with_overweight: Feature, Binary, " Has a family member suffered or suffers from overweight? "
FAVC : Feature, Binary, " Do you eat high caloric food frequently? "
FCVC : Feature, Integer, " Do you usually eat vegetables in your meals? "
NCP : Feature, Continuous, " How many main meals do you have daily? "
CAEC : Feature, Categorical, " Do you eat any food between meals? "
SMOKE : Feature, Binary, " Do you smoke? "
CH2O: Feature, Continuous, " How much water do you drink daily? "
SCC: Feature, Binary, " Do you monitor the calories you eat daily? "
FAF: Feature, Continuous, " How often do you have physical activity? "
TUE : Feature, Integer, " How much time do you use technological devices such as cell phone, videogames, television, computer and
CALC : Feature, Categorical, " How often do you drink alcohol? "
MTRANS : Feature, Categorical, " Which transportation do you usually use? "
NObeyesdad : Target, Categorical, "Obesity level"

Exploratory Data Analysis – head of the dataset

```
obesity_df.head()
```

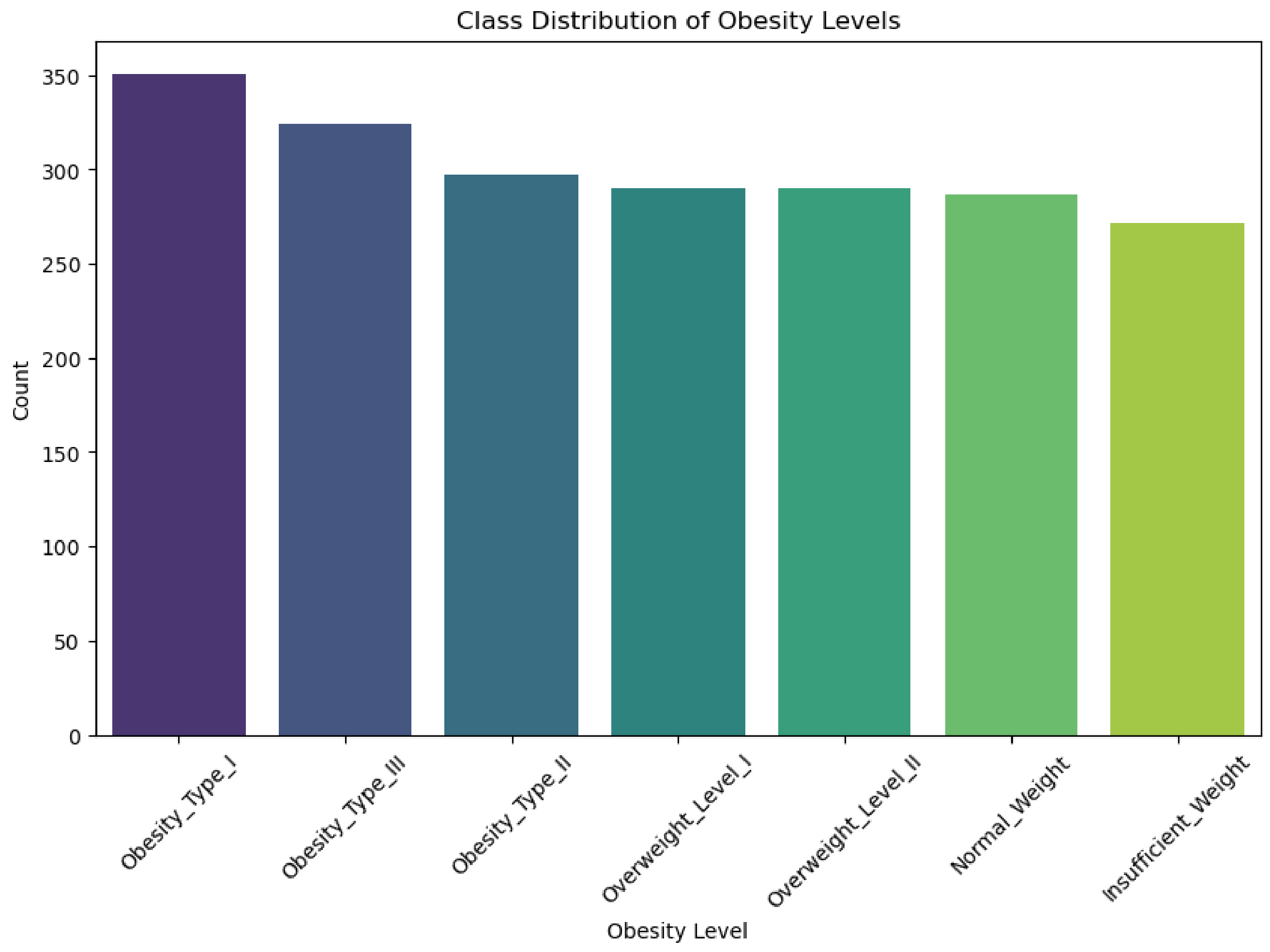
	Age	Gender	Height	Weight	CALC	FAVC	FCVC	NCP	SCC	SMOKE	CH2O	family_history_with_overweight	FAF	TUE	CAEC	MTRANS	NObeyesdad
0	21.0	Female	1.62	64.0	no	no	2.0	3.0	no	no	2.0	yes	0.0	1.0	Sometimes	Public_Transportation	Normal_Weight
1	21.0	Female	1.52	56.0	Sometimes	no	3.0	3.0	yes	yes	3.0	yes	3.0	0.0	Sometimes	Public_Transportation	Normal_Weight
2	23.0	Male	1.80	77.0	Frequently	no	2.0	3.0	no	no	2.0	yes	2.0	1.0	Sometimes	Public_Transportation	Normal_Weight
3	27.0	Male	1.80	87.0	Frequently	no	3.0	3.0	no	no	2.0	no	2.0	0.0	Sometimes	Walking	Overweight_Level_I
4	22.0	Male	1.78	89.8	Sometimes	no	2.0	1.0	no	no	2.0	no	0.0	0.0	Sometimes	Public_Transportation	Overweight_Level_II

Exploratory Data Analysis – information about dataset

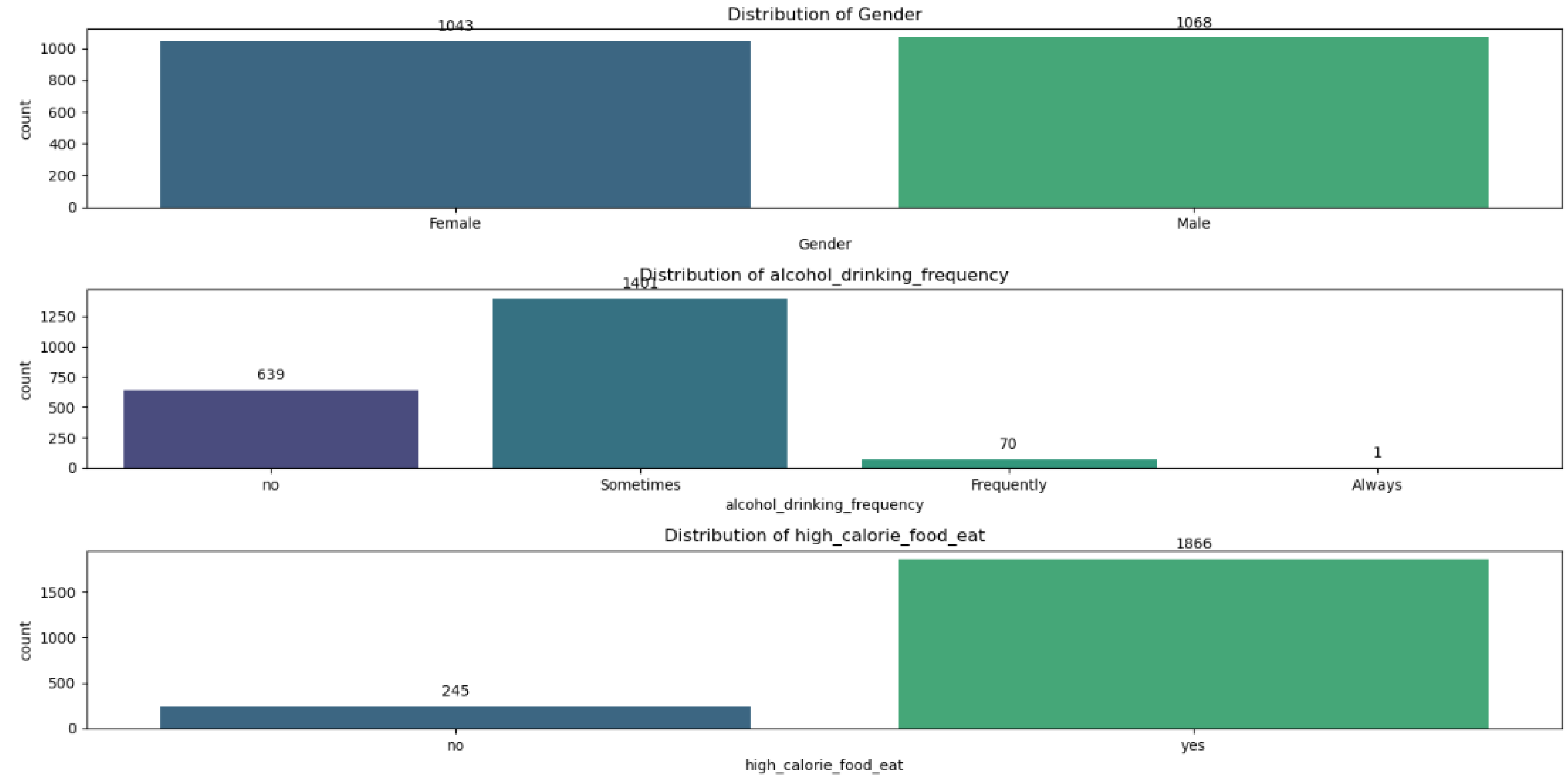
```
obesity_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2111 entries, 0 to 2110
Data columns (total 17 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   Age                             2111 non-null   float64
 1   Gender                          2111 non-null   object 
 2   Height                          2111 non-null   float64
 3   Weight                          2111 non-null   float64
 4   CALC                            2111 non-null   object 
 5   FAVC                            2111 non-null   object 
 6   FCVC                            2111 non-null   float64
 7   NCP                             2111 non-null   float64
 8   SCC                             2111 non-null   object 
 9   SMOKE                           2111 non-null   object 
 10  CH2O                            2111 non-null   float64
 11  family_history_with_overweight  2111 non-null   object 
 12  FAF                             2111 non-null   float64
 13  TUE                             2111 non-null   float64
 14  CAEC                            2111 non-null   object 
 15  MTRANS                          2111 non-null   object 
 16  NObeyesdad                      2111 non-null   object 
dtypes: float64(8), object(9)
memory usage: 280.5+ KB
```

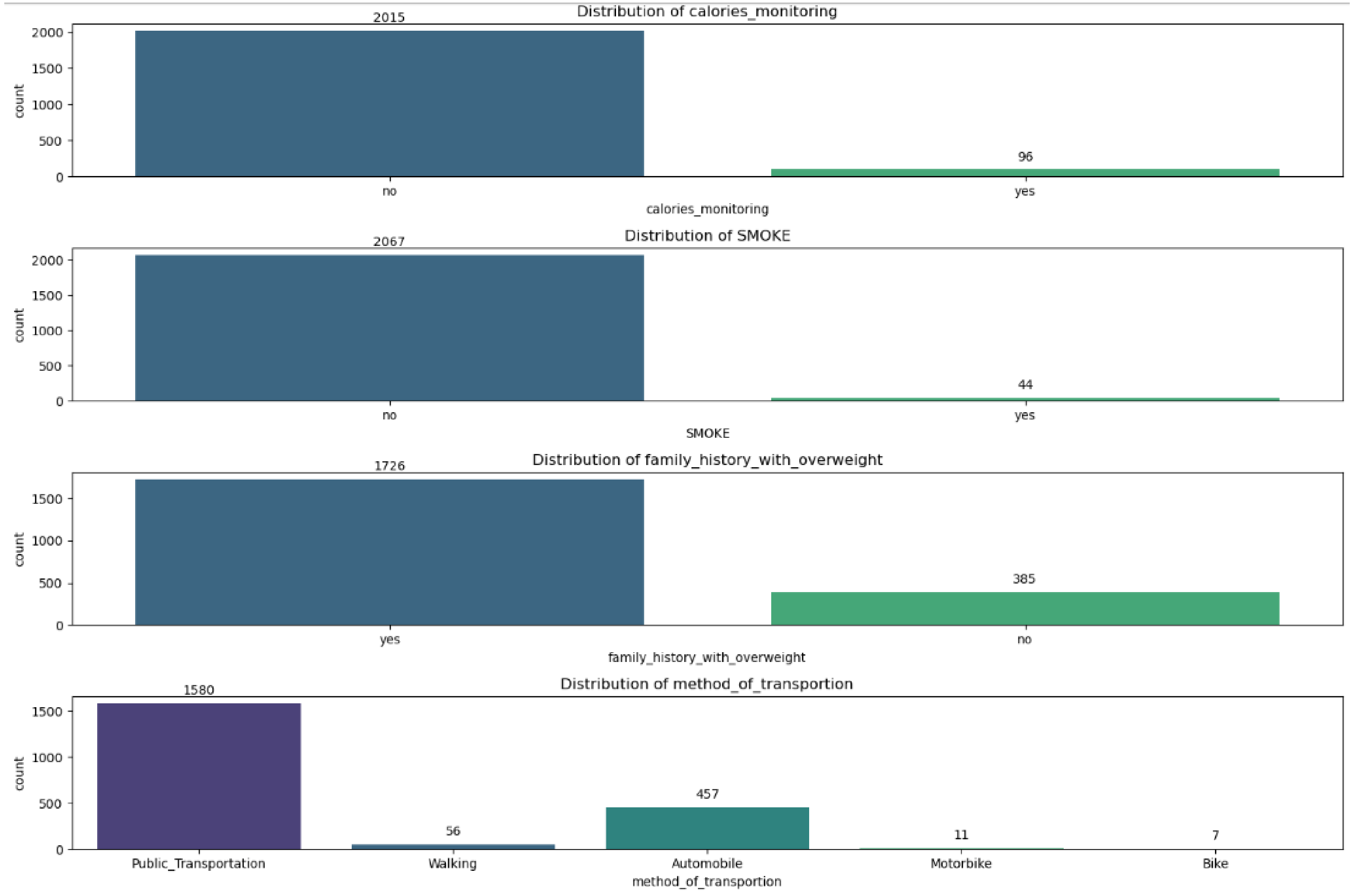
Exploratory Data Analysis – distribution of instances for every class



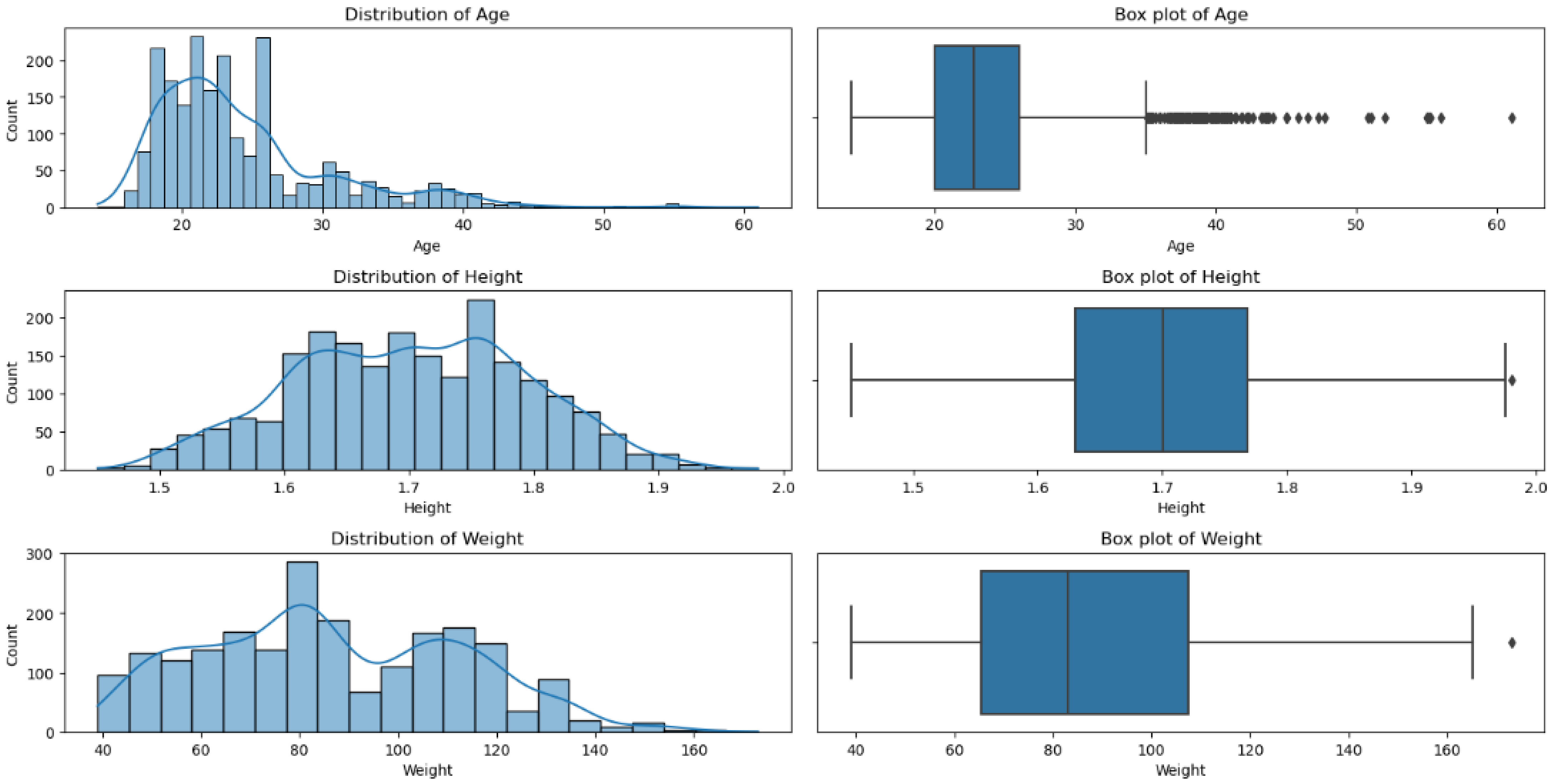
Exploratory Data Analysis – distribution of categorical features



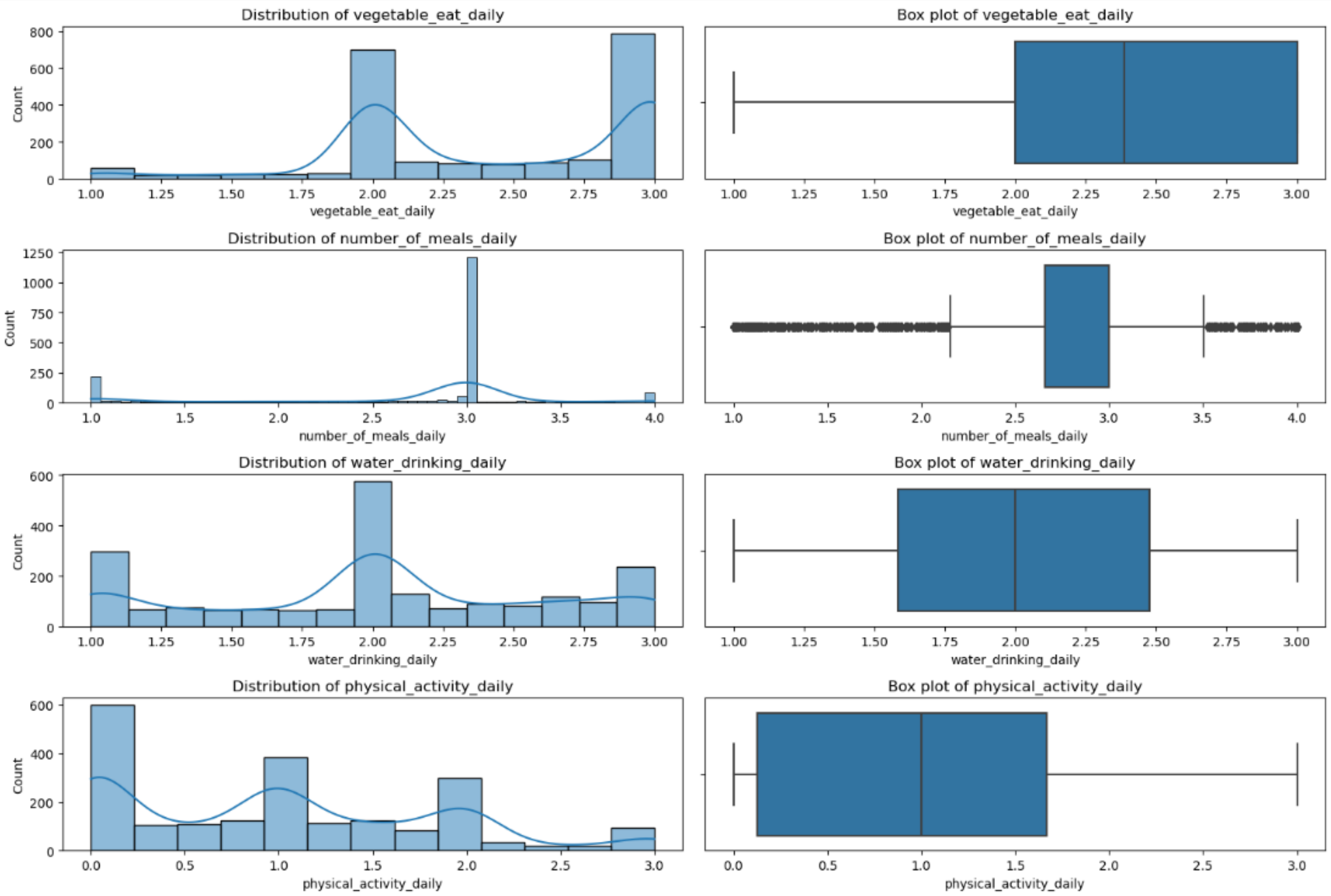
Exploratory Data Analysis – distribution of categorical features



Exploratory Data Analysis – distribution of continuous features



Exploratory Data Analysis – distribution of continuous features



Data Preprocessing

Now, we need to encode our categorical variables and scale continuous values.

The categorical variables that need encoding: gender, alcohol_drinking_frequency, high_calorie_food_eat, food_between_meals, calories_monitoring, calories_monitoring, SMOKE, family_history_with_overweight, method_of_transportatio NObeyesdad(our target variable).

```
label_encoders = {}

for col in categorical_features:
    le = LabelEncoder()
    obesity_df[col] = le.fit_transform(obesity_df[col])
    label_encoders[col] = le

# Encoding the target variable
target_le = LabelEncoder()
obesity_df['NObeyesdad'] = target_le.fit_transform(obesity_df['NObeyesdad'])
label_encoders['NObeyesdad'] = target_le

# Scaling continuous variables
scaler = StandardScaler()
obesity_df[continuous_features] = scaler.fit_transform(obesity_df[continuous_features])
```

The continuous variables that need scaling: Age, Height, Weight, vegetable_eat_daily, number_of_meals_daily, water_drinking_daily, physical_activity_daily, electronics_usage_daily.

Model training

For the training, I picked the following models

- Logistic Regression
- Decision Tree Classifier
- Random Forest Classifier
- Support Vector Machine
- K-Nearest Neighbors

For each model we will:

1) Train the model
2) Evaluate the model and prepare a classification report along with confusion matrix
3) Perform cross-validation to validate the model performance

```python
# Function to evaluate model
def evaluate_model(model, X_train, X_test, y_train, y_test):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(classification_report(y_test, y_pred))
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot()
    plt.show()
```

Model training

```python
# Initialize variables to store the best classifier and its performance
best_classifier = None
best_classifier_name = ""
best_cv_score = 0

# Classifier names and their instances
classifiers = {
    "Logistic Regression": LogisticRegression(max_iter=10000, random_state=42),
    "Decision Tree Classifier": DecisionTreeClassifier(random_state=42),
    "Random Forest Classifier": RandomForestClassifier(random_state=42),
    "Support Vector Machine (SVM)": SVC(random_state=42),
    "K-Nearest Neighbors (KNN)": KNeighborsClassifier()
}

# Define a function to evaluate each model
def evaluate_and_cross_validate(model, X_train, X_test, y_train, y_test, model_name):
    # Train the model
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Classification report and confusion matrix
    print(f"{model_name} Classification Report:")
    print(classification_report(y_test, y_pred))
    print(f"{model_name} Confusion Matrix:")
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot()
    plt.title(f"Confusion Matrix for {model_name}")
    plt.show()

    # Cross-validation
    cv_scores = cross_val_score(model, X, y, cv=10)
    mean_cv_score = cv_scores.mean()
    print(f"{model_name} Cross-Validation Scores: {cv_scores}")
    print(f"Mean CV Score: {mean_cv_score}\n")

    return mean_cv_score
```

```python
# Evaluate each classifier and store the best one
for name, clf in classifiers.items():
    mean_cv_score = evaluate_and_cross_validate(clf, X_train, X_test, y_train, y_test, name)

    # Check if this is the best classifier
    if mean_cv_score > best_cv_score:
        best_cv_score = mean_cv_score
        best_classifier = clf
        best_classifier_name = name
```

Evaluation

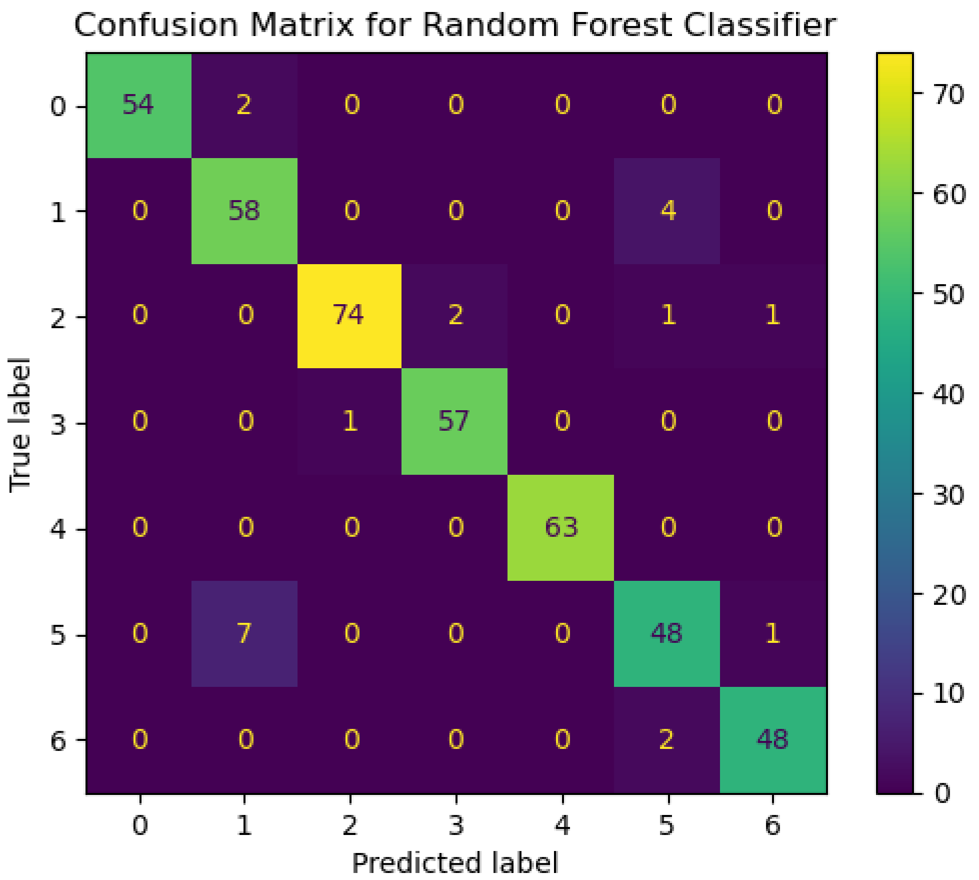
```
print(f"Best classifier: {best_classifier_name}\nAverage accuracy:{best_cv_score}")
```

```
Best classifier: Random Forest Classifier
Average accuracy:0.9470446213001876
```

Random Forest Classifier Classification Report:

	precision	recall	f1-score	support
0	1.00	0.96	0.98	56
1	0.87	0.94	0.90	62
2	0.99	0.95	0.97	78
3	0.97	0.98	0.97	58
4	1.00	1.00	1.00	63
5	0.87	0.86	0.86	56
6	0.96	0.96	0.96	50
accuracy			0.95	423
macro avg	0.95	0.95	0.95	423
weighted avg	0.95	0.95	0.95	423

Random Forest Classifier Confusion Matrix:




```
Random Forest Classifier Cross-Validation Scores: [0.73584906 0.83412322 0.99052133 0.99526066 0.98578199 0.97630332
 0.98578199 0.98578199 0.99052133 0.99052133]
Mean CV Score: 0.9470446213001876
```

Thank You for Your Attention