Obesity Insight Prediction

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Project Description: Predicting Obesity Risk Based on Lifestyle & Demographic Factors Using Machine Learning Techniques
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Instructor: Professor Zhaochen Gu

Load Necessary Libraries

Below are the libraries required for this project

Pandas: For data manipulation and numerical computations.
Scikit-learn: For data preprocessing and splitting, machine learning models, evaluation metrics, and workflow utilities.
Machine Learning Models: GaussianNB, SVC, Random Forest.
Evaluation Metrics: Accuracy, classification report, and confusion matrix.
Matplotlib and Seaborn: For creating visualizations to visually explore and understand the data.

In [58]:
```
# Data manipulation and analysis
import pandas as pd

# Data preprocessing and splitting
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler, OneHotEncoder

# Machine Learning models
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, Vo

# Evaluation metrics
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Workflow utilities
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer
```

1st Approach: Naive Bayes

Step 1. Load the dataset

In [59]:
```
# Load dataset
data = pd.read_csv('ObesityDataSet.csv')
```

Step 2. Load the dataset and display basic information

In [31]:
```
data.head()
```

Out[31]:

	Gender	Age	Height	Weight	family_history_with_overweight	FAVC	FCVC	NCP	CAEC
0	Female	21.0	63.8	141.1	1	0	2.0	3.0	1
1	Female	21.0	59.8	123.5	1	0	3.0	3.0	1
2	Male	23.0	70.9	169.8	1	0	2.0	3.0	1
3	Male	27.0	70.9	191.8	0	0	3.0	3.0	1
4	Male	22.0	70.1	198.0	0	0	2.0	1.0	1

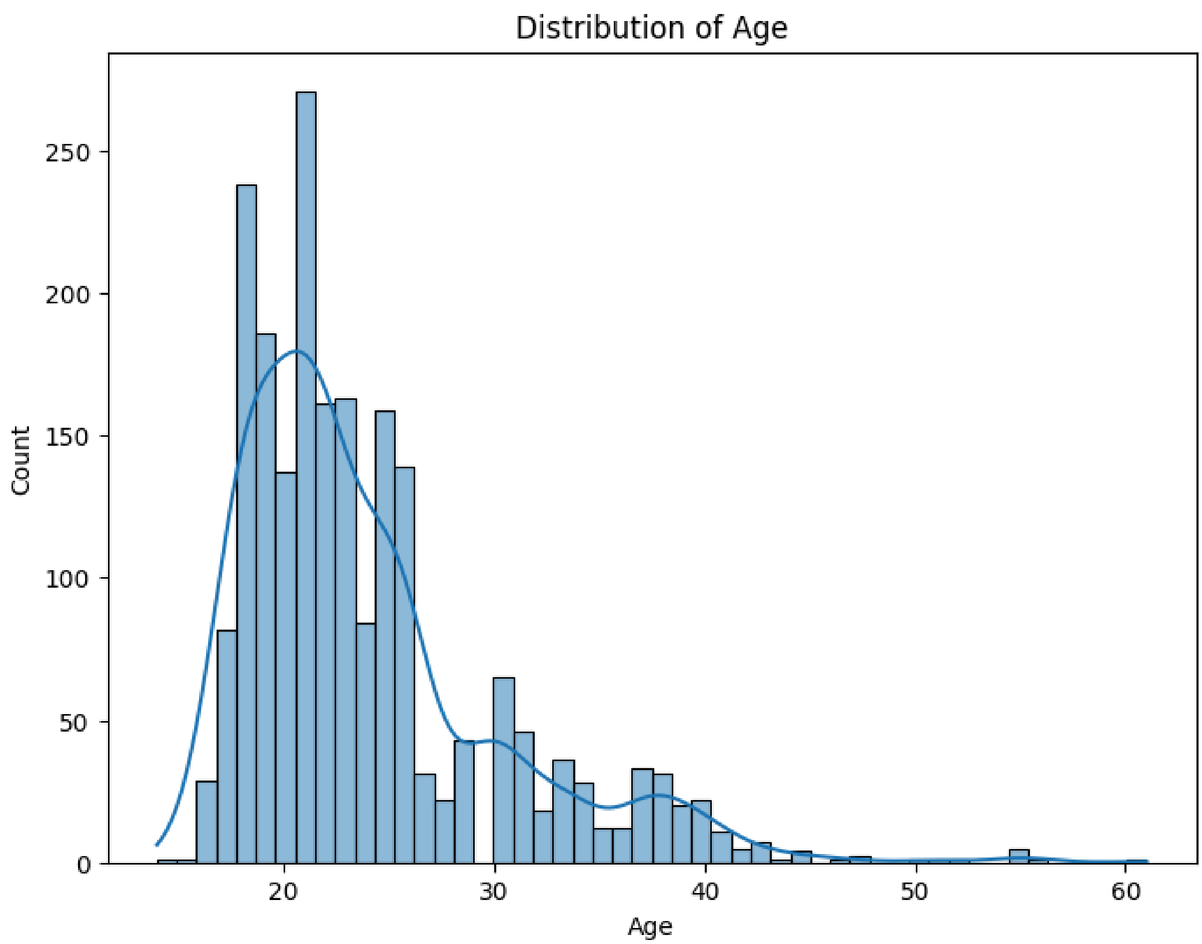
In [32]:
```
data.shape
```

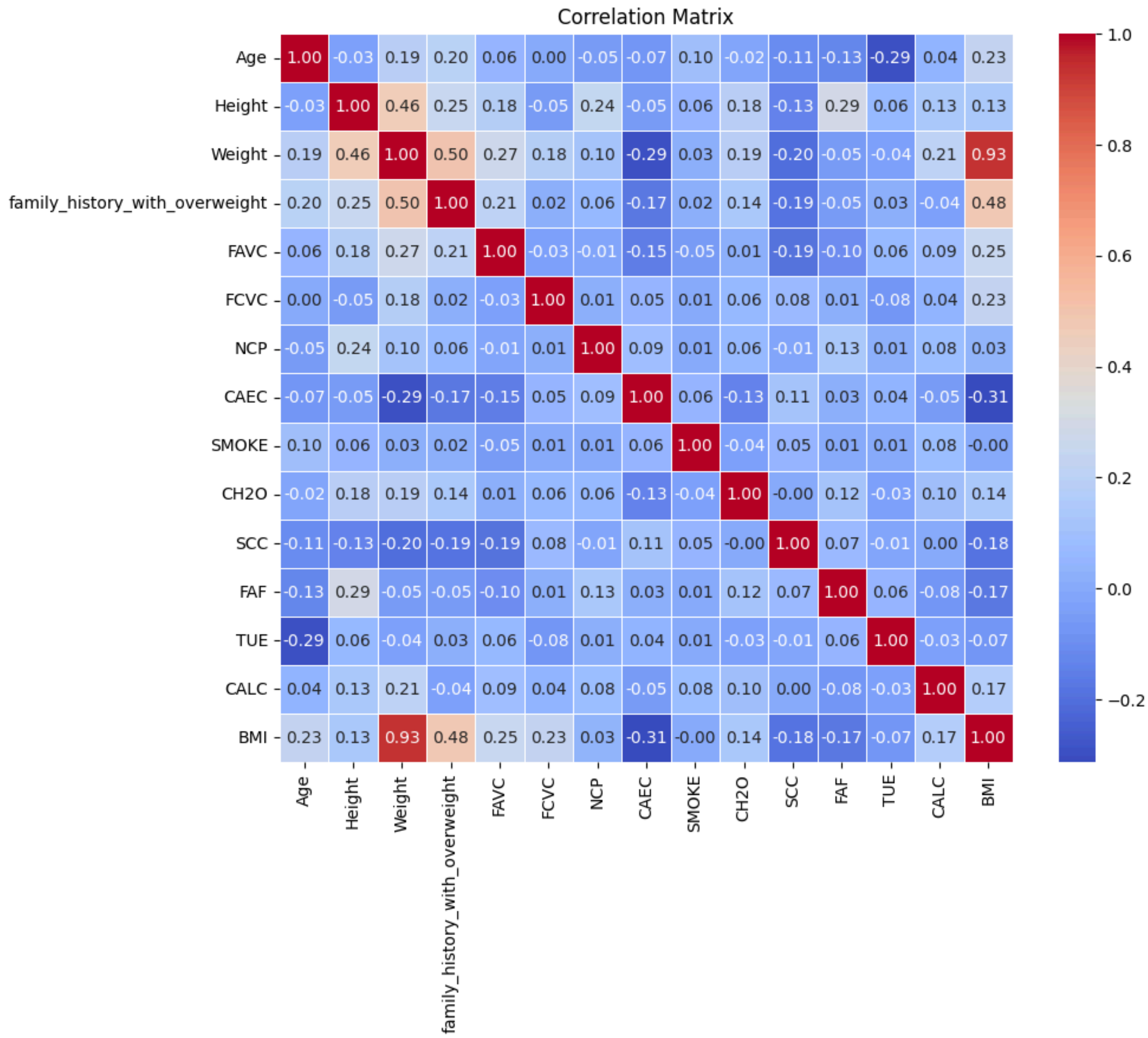
Out[32]:
```
(2111, 18)
```

In [33]:
```
# Basic statistics
print(data.describe())

# Basic statistics
print("# Basic Statistics:")
print(data.describe())

# Distribution of a numerical column (example: 'Age' if available)
plt.figure(figsize=(8, 6))
sns.histplot(data=data, x='Age', bins=50, kde=True)
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()

# Correlation matrix for numeric data
plt.figure(figsize=(10, 8))
numeric_data = data.select_dtypes(include='number')
correlation_matrix = numeric_data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=
plt.title('Correlation Matrix')
plt.show()
```

```
               Age       Height       Weight  family_history_with_overweight  \
count  2111.000000  2111.000000  2111.000000                     2111.000000   
mean     23.972525    66.995216   190.890857                        0.817622   
std       6.308664     3.673707    57.742270                        0.386247   
min      14.000000    57.100000    86.000000                        0.000000   
25%      19.000000    64.200000   144.350000                        1.000000   
50%      22.000000    66.900000   183.000000                        1.000000   
75%      26.000000    69.600000   236.850000                        1.000000   
max      61.000000    78.000000   381.400000                        1.000000   

              FAVC         FCVC          NCP         CAEC        SMOKE  \
count  2111.000000  2111.000000  2111.000000  2111.000000  2111.000000   
mean      0.883941     2.423496     2.687826     1.140692     0.020843   
std       0.320371     0.583905     0.809680     0.468543     0.142893   
min       0.000000     1.000000     1.000000     0.000000     0.000000   
25%       1.000000     2.000000     3.000000     1.000000     0.000000   
50%       1.000000     2.000000     3.000000     1.000000     0.000000   
75%       1.000000     3.000000     3.000000     1.000000     0.000000   
max       1.000000     3.000000     4.000000     3.000000     1.000000   

              CH2O          SCC          FAF          TUE         CALC  \
count  2111.000000  2111.000000  2111.000000  2111.000000  2111.000000   
mean      2.014685     0.045476     1.006632     0.664614     0.731407   
std       0.688616     0.208395     0.895462     0.674009     0.515498   
min       1.000000     0.000000     0.000000     0.000000     0.000000   
25%       2.000000     0.000000     0.000000     0.000000     0.000000   
50%       2.000000     0.000000     1.000000     1.000000     1.000000   
75%       2.000000     0.000000     2.000000     1.000000     1.000000   
max       3.000000     1.000000     3.000000     2.000000     3.000000   

               BMI  
count  2111.000000  
mean     29.697205  
std       8.011096  
min      13.000000  
25%      24.300000  
50%      28.700000  
75%      36.000000  
max      50.800000  
# Basic Statistics:
               Age       Height       Weight  family_history_with_overweight  \
count  2111.000000  2111.000000  2111.000000                     2111.000000   
mean     23.972525    66.995216   190.890857                        0.817622   
std       6.308664     3.673707    57.742270                        0.386247   
min      14.000000    57.100000    86.000000                        0.000000   
25%      19.000000    64.200000   144.350000                        1.000000   
50%      22.000000    66.900000   183.000000                        1.000000   
75%      26.000000    69.600000   236.850000                        1.000000   
max      61.000000    78.000000   381.400000                        1.000000   

              FAVC         FCVC          NCP         CAEC        SMOKE  \
count  2111.000000  2111.000000  2111.000000  2111.000000  2111.000000   
mean      0.883941     2.423496     2.687826     1.140692     0.020843   
std       0.320371     0.583905     0.809680     0.468543     0.142893   
min       0.000000     1.000000     1.000000     0.000000     0.000000   
25%       1.000000     2.000000     3.000000     1.000000     0.000000   
```

```
50%         1.000000     2.000000     3.000000     1.000000     0.000000
75%         1.000000     3.000000     3.000000     1.000000     0.000000
max         1.000000     3.000000     4.000000     3.000000     1.000000

              CH2O          SCC          FAF          TUE         CALC  \
count  2111.000000  2111.000000  2111.000000  2111.000000  2111.000000
mean      2.014685     0.045476     1.006632     0.664614     0.731407
std       0.688616     0.208395     0.895462     0.674009     0.515498
min       1.000000     0.000000     0.000000     0.000000     0.000000
25%       2.000000     0.000000     0.000000     0.000000     0.000000
50%       2.000000     0.000000     1.000000     1.000000     1.000000
75%       2.000000     0.000000     2.000000     1.000000     1.000000
max       3.000000     1.000000     3.000000     2.000000     3.000000

               BMI
count  2111.000000
mean     29.697205
std       8.011096
min      13.000000
25%      24.300000
50%      28.700000
75%      36.000000
max      50.800000
```





Step 3. Prepare the data

In [34]:
```python
# Specify the feature matrix X and the target vector y
X = data.drop('NObeyesdad', axis=1)
y = data['NObeyesdad']

# Encode categorical variables if any
le = LabelEncoder()
for col in X.columns:
    if X[col].dtype == 'object':
        X[col] = le.fit_transform(X[col])
```

Step 4. Split the data into training and testing sets

In [35]:
```python
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

Step 5. Initialize and train the Naive Bayes classifier

In [36]:
```python
# Initialize the Naive Bayes classifier
model = GaussianNB()

# Train the model
model.fit(X_train, y_train)
```

Out[36]:
```
GaussianNB

GaussianNB()
```

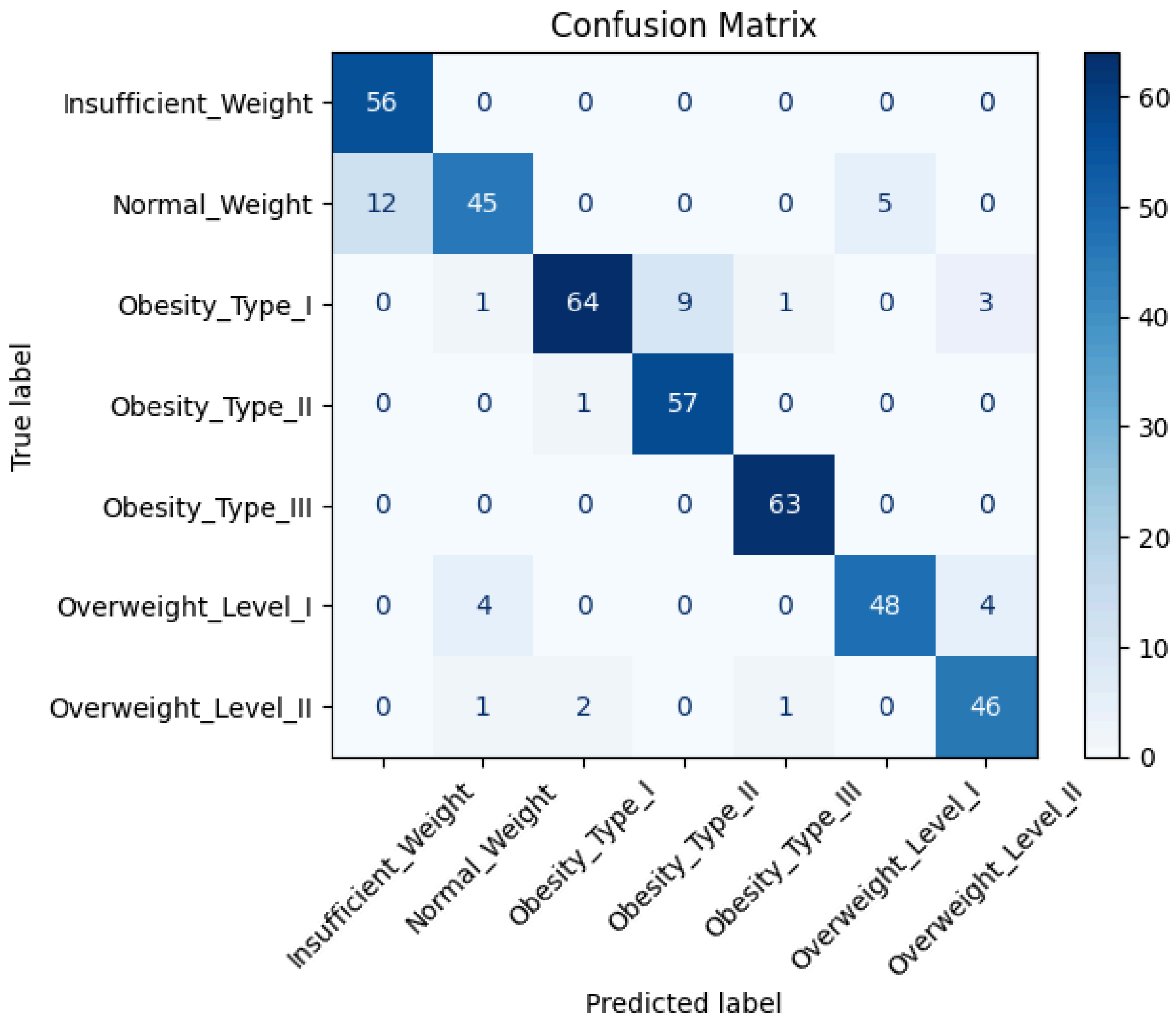
Step 6. Make predictions and calculate accuracy

In [37]:
```python
# Make predictions
predictions = model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, predictions)
print(f'Accuracy: {accuracy}')

report = classification_report(y_test, predictions)
print(report)
```

```
Accuracy: 0.8959810874704491
                     precision    recall  f1-score   support

Insufficient_Weight       0.82      1.00      0.90        56
      Normal_Weight       0.88      0.73      0.80        62
     Obesity_Type_I       0.96      0.82      0.88        78
    Obesity_Type_II       0.86      0.98      0.92        58
   Obesity_Type_III       0.97      1.00      0.98        63
 Overweight_Level_I       0.91      0.86      0.88        56
Overweight_Level_II       0.87      0.92      0.89        50

           accuracy                           0.90       423
          macro avg       0.90      0.90      0.89       423
       weighted avg       0.90      0.90      0.89       423
```

In [38]:
```python
# Confusion matrix
conf_matrix = confusion_matrix(y_test, predictions)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=model.cl

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
disp.plot(cmap='Blues', values_format='d')
plt.xticks(rotation=45)  # Rotate x-axis labels for readability
plt.title('Confusion Matrix')
plt.show()
```

```
<Figure size 1000x700 with 0 Axes>
```



2nd Approach: SVC

Step 1. Load the dataset

In [39]:
```
data = pd.read_csv('ObesityDataSet.csv')
```

Step 2. Define categorical and continuous features

In [40]:
```
categorical_features = ['Gender', 'CALC', 'FAVC', 'SCC', 'SMOKE', 'family_history_w
continuous_features = ['Age', 'Height', 'Weight', 'FCVC', "NCP", 'CH2O', 'FAF', 'TU
```

Step 3. Encode target and categorical features

In [41]:
```
label_encoder = LabelEncoder()

# Encoding the target variable
data['NObeyesdad'] = label_encoder.fit_transform(data['NObeyesdad'])
```

```
# Encoding categorical variables
data[categorical_features] = data[categorical_features].apply(label_encoder.fit_tra
```

Step 4. Prepare feature matrix X and target vector y

In [42]:
```
X = data.drop('NObeyesdad', axis=1)
y = data['NObeyesdad']
```

Step 5. Split the data into training and testing sets

In [43]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_sta
```

Step 6. Scale the features

In [44]:
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Step 7. Initialize and train the SVM classifier

In [45]:
```
classifier = SVC(kernel='linear', random_state=0)
classifier.fit(X_train, y_train)
```

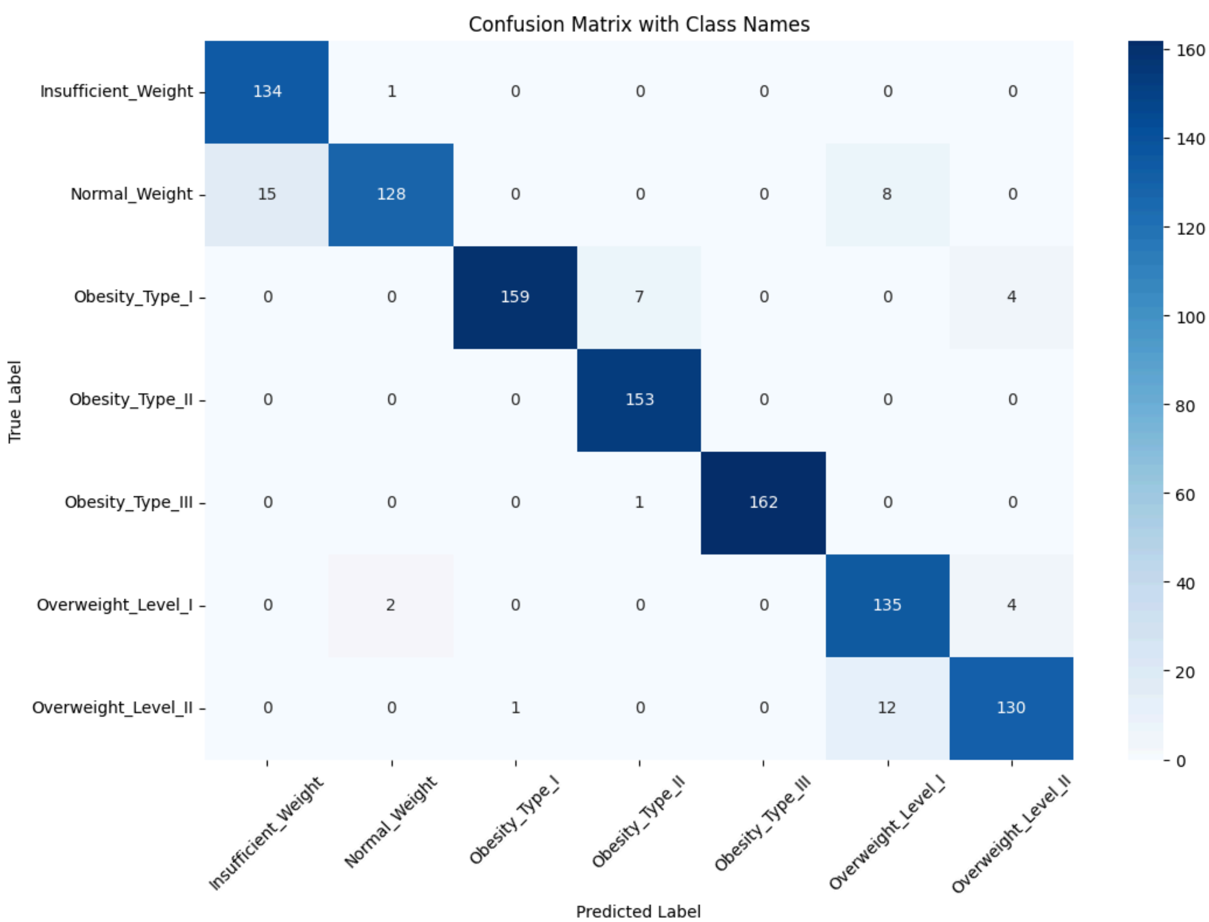
Out[45]:
```
SVC
SVC(kernel='linear', random_state=0)
```

Step 8. Make predictions and evaluate the model

In [46]:
```
predictions = classifier.predict(X_test)

report = classification_report(y_test, predictions)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.90      0.99      0.94       135
           1       0.98      0.85      0.91       151
           2       0.99      0.94      0.96       170
           3       0.95      1.00      0.97       153
           4       1.00      0.99      1.00       163
           5       0.87      0.96      0.91       141
           6       0.94      0.91      0.93       143

    accuracy                           0.95      1056
   macro avg       0.95      0.95      0.95      1056
weighted avg       0.95      0.95      0.95      1056
```

In [47]:
```
# Manually specify the correct class names
class_names = [
    "Insufficient_Weight",
    "Normal_Weight",
    "Obesity_Type_I",
    "Obesity_Type_II",
    "Obesity_Type_III",
    "Overweight_Level_I",
    "Overweight_Level_II"
]

# Generate the confusion matrix
conf_matrix = confusion_matrix(y_test, predictions)

# Plot confusion matrix
plt.figure(figsize=(12, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=class_names
plt.title('Confusion Matrix with Class Names')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.yticks(rotation=0)  # Keep y-axis labels horizontal
plt.show()

# Calculate and print the accuracy
accuracy = accuracy_score(y_test, predictions)
print(f"Accuracy: {accuracy}")
```



```
Accuracy: 0.9479166666666666
```

Best Approach: Ensemble Method with Support Vector, Random Forest and Gradient Boosting Classifier

Step 1. Load the dataset

In [48]:
```python
data = pd.read_csv('ObesityDataSet.csv')
```

Step 2. Select categorical and numerical columns

In [49]:
```python
categorical_cols = data.select_dtypes(include=['object']).columns.tolist()
categorical_cols.remove('NObeyesdad')  # Remove the target column from the list
numerical_cols = data.select_dtypes(include=['float64', 'int64']).columns.tolist()
```

Step 3. Create a preprocessing transformer

In [50]:
```python
preprocessor = ColumnTransformer(
    transformers=[
        ('num', 'passthrough', numerical_cols),
        ('cat', OneHotEncoder(), categorical_cols)
    ])
```

Step 4. Define individual classifiers and the ensemble model

In [51]:
```python
rf = RandomForestClassifier(random_state=42)
svc = SVC(probability=True, random_state=42)
gb = GradientBoostingClassifier(random_state=42)

ensemble_model = VotingClassifier(
    estimators=[
        ('rf', rf),
        ('svc', svc),
        ('gb', gb)
    ],
    voting='soft'  # Using 'soft' voting
)
```

Step 5. Create the pipeline with preprocessing and ensemble model

In [52]:
```python
ensemble_pipeline = make_pipeline(preprocessor, ensemble_model)
```

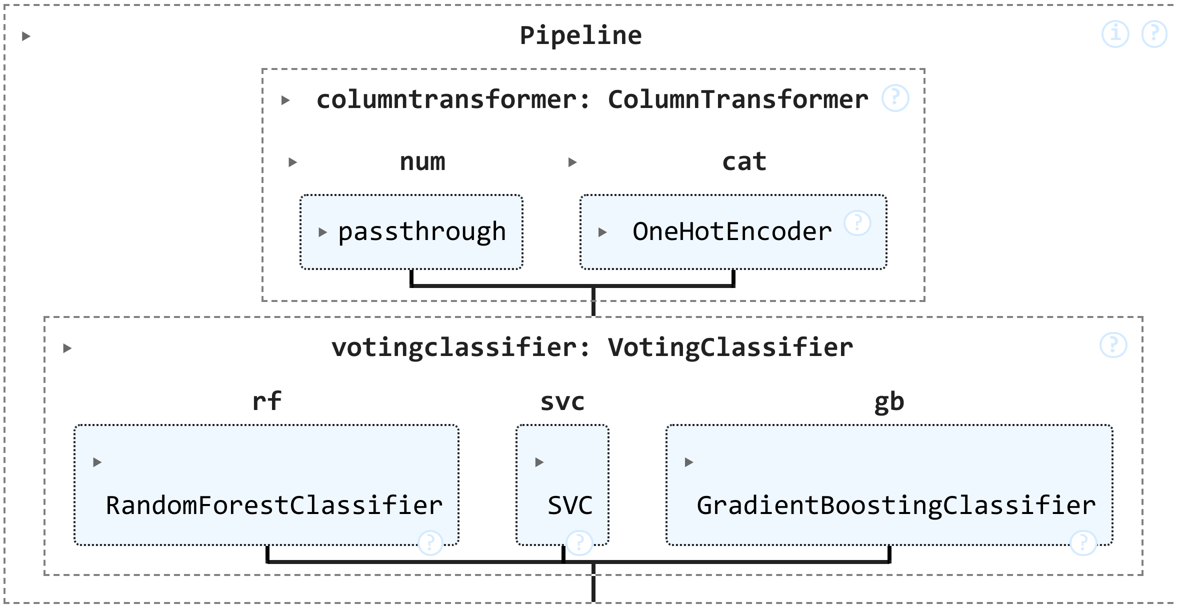
Step 6. Split the data into training and testing sets

In [53]:
```
X = data.drop('NObeyesdad', axis=1)
y = data['NObeyesdad']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

Step 7. Train the ensemble model

In [54]:
```
ensemble_pipeline.fit(X_train, y_train)
```

Out[54]:



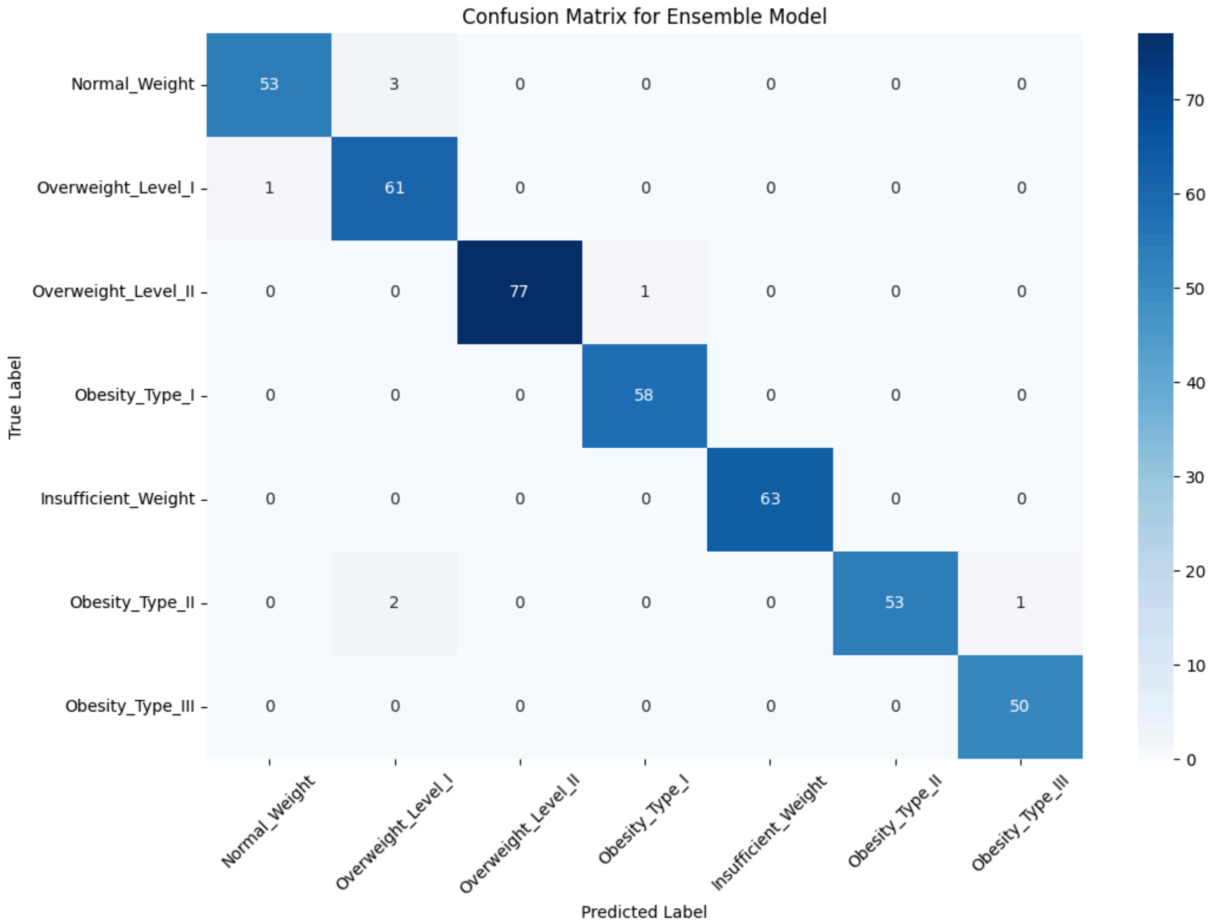
Step 8. Predict and evaluate the ensemble model

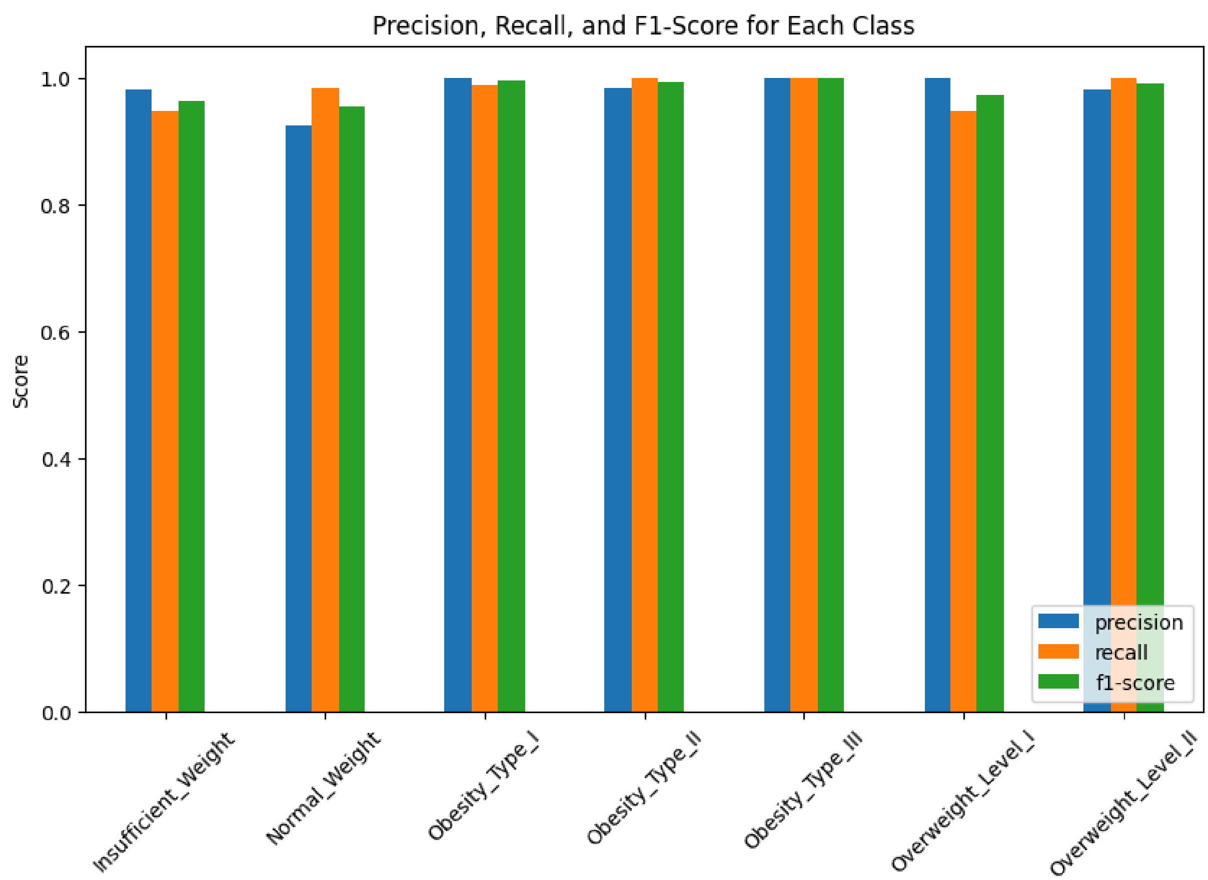
In [55]:
```
y_pred = ensemble_pipeline.predict(X_test)
report = classification_report(y_test, y_pred)
print(report)
```

```
                     precision    recall  f1-score   support

Insufficient_Weight       0.98      0.95      0.96        56
      Normal_Weight       0.92      0.98      0.95        62
     Obesity_Type_I       1.00      0.99      0.99        78
    Obesity_Type_II       0.98      1.00      0.99        58
   Obesity_Type_III       1.00      1.00      1.00        63
 Overweight_Level_I       1.00      0.95      0.97        56
Overweight_Level_II       0.98      1.00      0.99        50

           accuracy                           0.98       423
          macro avg       0.98      0.98      0.98       423
       weighted avg       0.98      0.98      0.98       423
```

In [56]:
```
# Generate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Manually specify class names (or fetch them if needed)
```

```
class_names = y.unique()  # Unique class names from the dataset

# Plot confusion matrix
plt.figure(figsize=(12, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=class_names
plt.title('Confusion Matrix for Ensemble Model')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.yticks(rotation=0)  # Keep y-axis labels horizontal
plt.show()

# Classification Report Metrics Visualization
report_dict = classification_report(y_test, y_pred, output_dict=True)
scores = pd.DataFrame(report_dict).T

# Bar chart for precision, recall, and F1-score
scores = scores[:-3]  # Remove accuracy, macro avg, and weighted avg
scores[['precision', 'recall', 'f1-score']].plot(kind='bar', figsize=(10, 6))
plt.title('Precision, Recall, and F1-Score for Each Class')
plt.ylabel('Score')
plt.xlabel('Classes')
plt.xticks(rotation=45)
plt.legend(loc='lower right')
plt.show()

# Print overall accuracy
accuracy = report_dict['accuracy']
print(f"Overall Accuracy: {accuracy:.2f}")
```


Confusion Matrix for Ensemble Model
True Label
Predicted Label
Normal_Weight
Overweight_Level_I
Overweight_Level_II
Obesity_Type_I
Insufficient_Weight
Obesity_Type_II
Obesity_Type_III
53 3 0 0 0 0 0
1 61 0 0 0 0 0
0 0 77 1 0 0 0
0 0 0 58 0 0 0
0 0 0 0 63 0 0
0 2 0 0 0 53 1
0 0 0 0 0 0 50
0
10
20
30
40
50
60
70


Precision, Recall, and F1-Score for Each Class
Score
Classes
0.0
0.2
0.4
0.6
0.8
1.0
Insufficient_Weight
Normal_Weight
Obesity_Type_I
Obesity_Type_II
Obesity_Type_III
Overweight_Level_I
Overweight_Level_II
precision
recall
f1-score

```
Overall Accuracy: 0.98
```

In [57]:

```python
# Define model accuracies (replace these with the actual calculated values)
model_accuracies = {
    'Naive Bayes': 0.8959810874704491,  # Example accuracy, replace with actual val
    'SVC': 0.9479166666666666,          # Example accuracy, replace with actual val
    'Ensemble Method': 0.98  # Example accuracy, replace with actual value
}

# Extract model names and their accuracies
models = list(model_accuracies.keys())
accuracies = list(model_accuracies.values())

# Plot the bar chart
plt.figure(figsize=(8, 6))
plt.bar(models, accuracies, color=['blue', 'green', 'orange'])
plt.ylim(0, 1.0)
plt.title('Accuracy Comparison of Models')
plt.ylabel('Accuracy')
plt.xlabel('Models')
for i, v in enumerate(accuracies):
    plt.text(i, v + 0.01, f"{v:.2f}", ha='center', fontweight='bold')  # Add accura
plt.show()
```