# AI Assignment 2.

# Penguin Classification Analysis.

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In [1]:

```
# Importing libraries.

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
# Loading the dataset.

from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving penguins_size.csv to penguins_size.csv
```

In [3]:

```
# Reading the dataset

df = pd.read_csv('penguins_size.csv')

df.head()
```

Out[3]:

| | species | island | culmen_length_mm | culmen_depth_mm | flipper_length_mm | body_mass_g | sex |
|---|---|---|---|---|---|---|---|
| **0** | Adelie | Torgersen | 39.1 | 18.7 | 181.0 | 3750.0 | MALE |
| **1** | Adelie | Torgersen | 39.5 | 17.4 | 186.0 | 3800.0 | FEMALE |
| **2** | Adelie | Torgersen | 40.3 | 18.0 | 195.0 | 3250.0 | FEMALE |
| **3** | Adelie | Torgersen | NaN | NaN | NaN | NaN | NaN |
| **4** | Adelie | Torgersen | 36.7 | 19.3 | 193.0 | 3450.0 | FEMALE |

## Performing Data Cleaning & Preprocessing.

In [4]:

```
df.isnull().sum()
```

Out[4]:

```
species              0
island               0
culmen_length_mm     2
culmen_depth_mm      2
flipper_length_mm    2
```

```
body_mass_g           2
sex                  10
dtype: int64
```

In [5]:
```
# Total percentage of missing data

missing_data = df.isnull().sum()

total_percentage = (missing_data.sum()/df.shape[0]) * 100

print(f'The total percentage of missing data is {round(total_percentage,2)}%')
```

```
The total percentage of missing data is 5.23%
```

In [6]:
```
# Percentage of missing data per category

total = df.isnull().sum().sort_values(ascending=False)

percent_total = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)*10

missing = pd.concat([total, percent_total], axis=1, keys=["Total", "Percentage"])

missing_data = missing[missing['Total']>0]
missing_data
```

Out[6]:

| | Total | Percentage |
|---|---|---|
| **sex** | 10 | 2.906977 |
| **culmen_length_mm** | 2 | 0.581395 |
| **culmen_depth_mm** | 2 | 0.581395 |
| **flipper_length_mm** | 2 | 0.581395 |
| **body_mass_g** | 2 | 0.581395 |

In [7]:
```
# Replace missing values using fillna() function

# For numerical columns, replace with median

numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns

df[numerical_columns] = df[numerical_columns].fillna(df[numerical_columns].median())
```

In [8]:
```
# For categorical columns, replace with mode (most common value)

categorical_columns = df.select_dtypes(include=['object']).columns

for column in categorical_columns:
    df[column] = df[column].fillna(df[column].mode()[0])
```

In [9]:
```
df.isnull().sum()
```

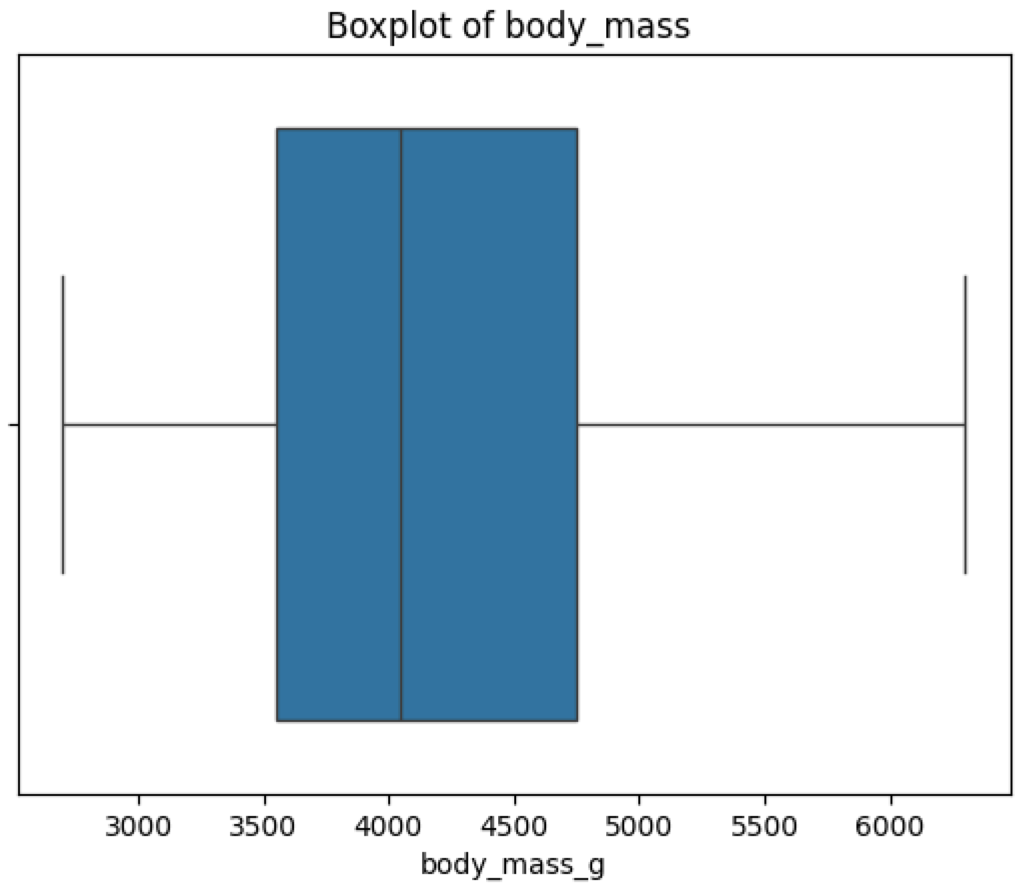
Out[9]:
```
species              0
island               0
culmen_length_mm     0
culmen_depth_mm      0
flipper_length_mm    0
body_mass_g          0
sex                  0
dtype: int64
```

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 344 entries, 0 to 343
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   species            344 non-null    object 
 1   island             344 non-null    object 
 2   culmen_length_mm   344 non-null    float64
 3   culmen_depth_mm    344 non-null    float64
 4   flipper_length_mm  344 non-null    float64
 5   body_mass_g        344 non-null    float64
 6   sex                344 non-null    object 
dtypes: float64(4), object(3)
memory usage: 18.9+ KB
```

In [11]:
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.boxplot(data=df,x=df["body_mass_g"])
plt.title("Boxplot of body_mass ")
```

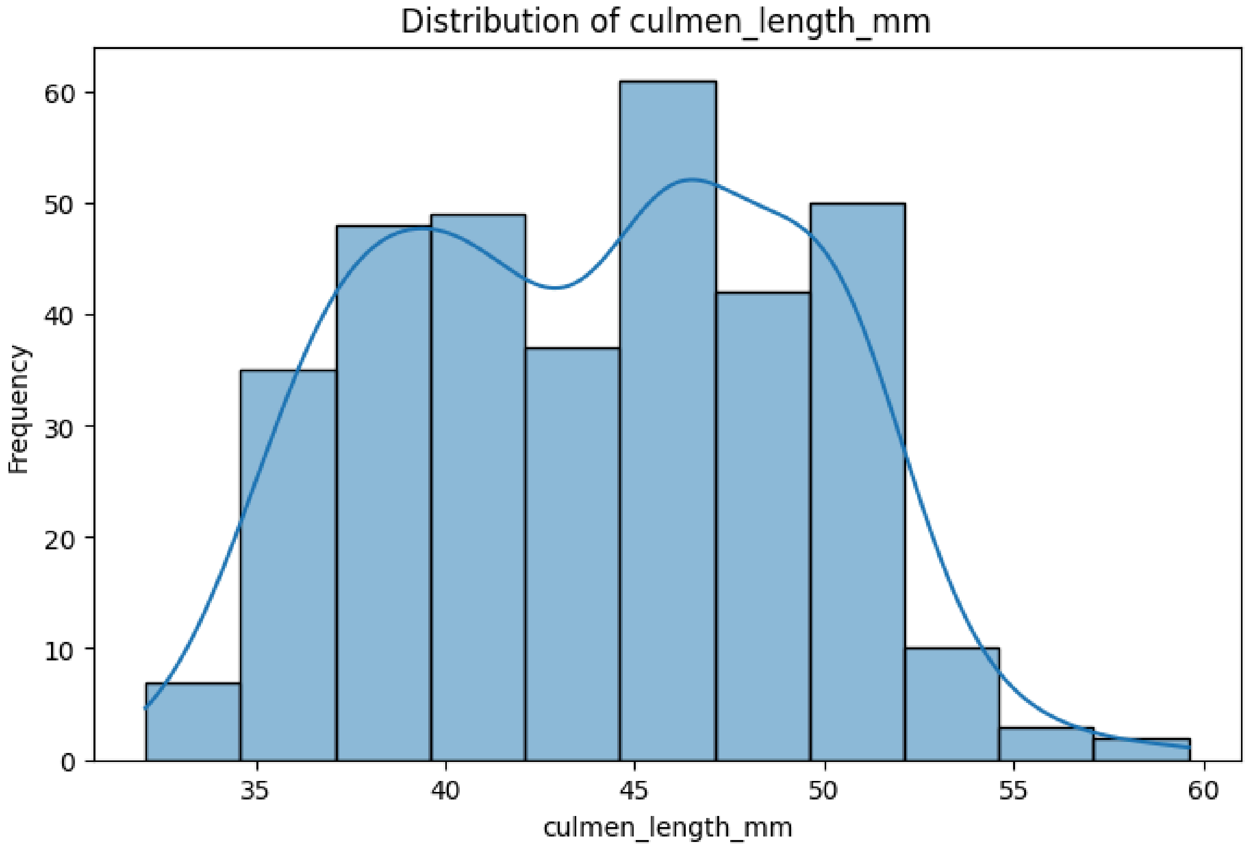
Out[11]:
```
Text(0.5, 1.0, 'Boxplot of body_mass ')
```

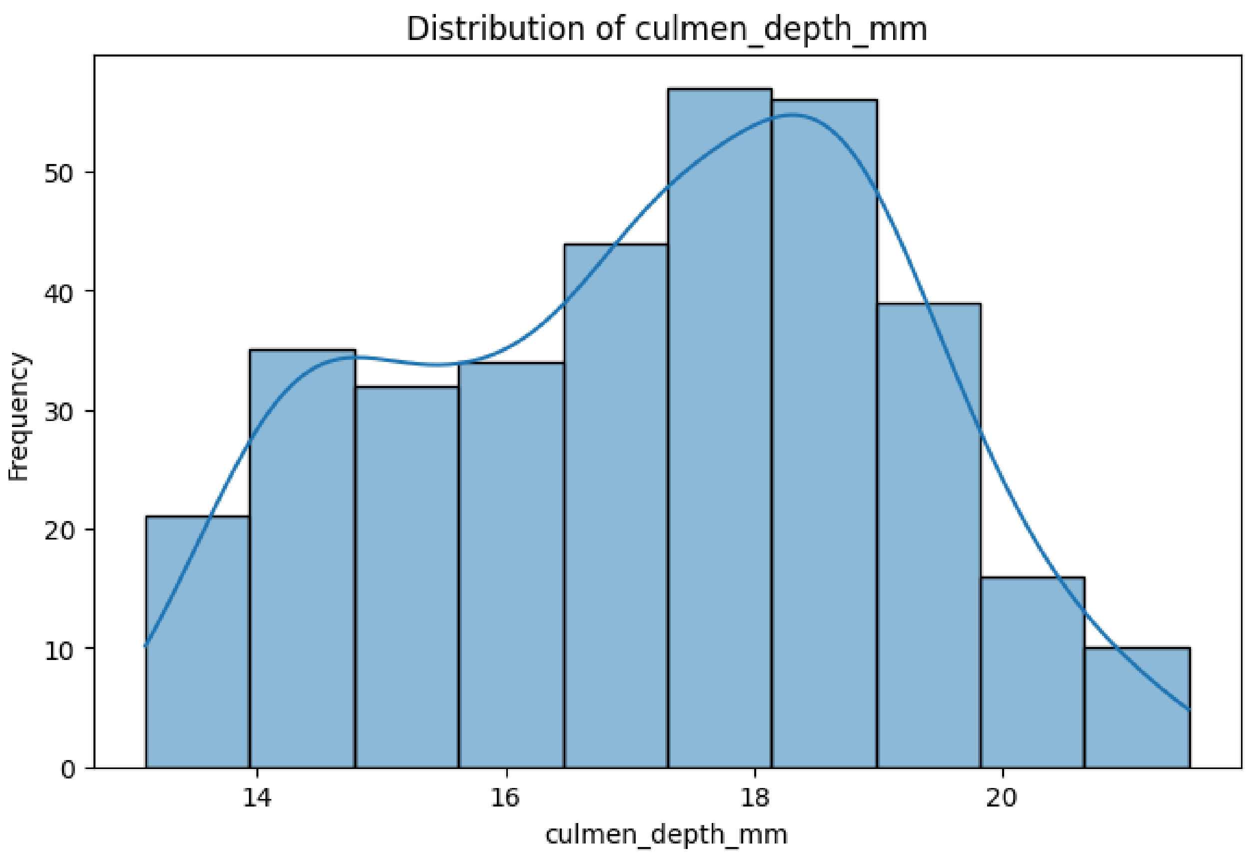


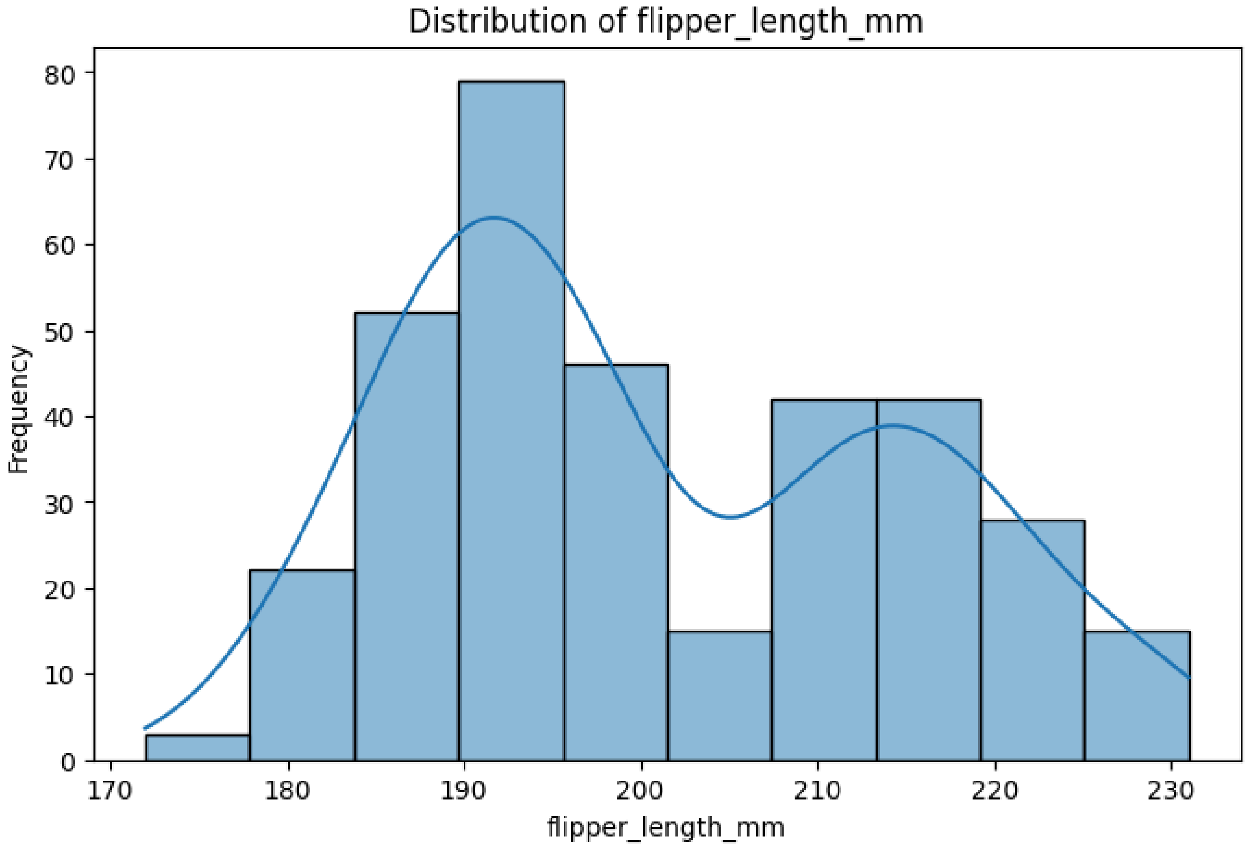

# Univariate Analysis.

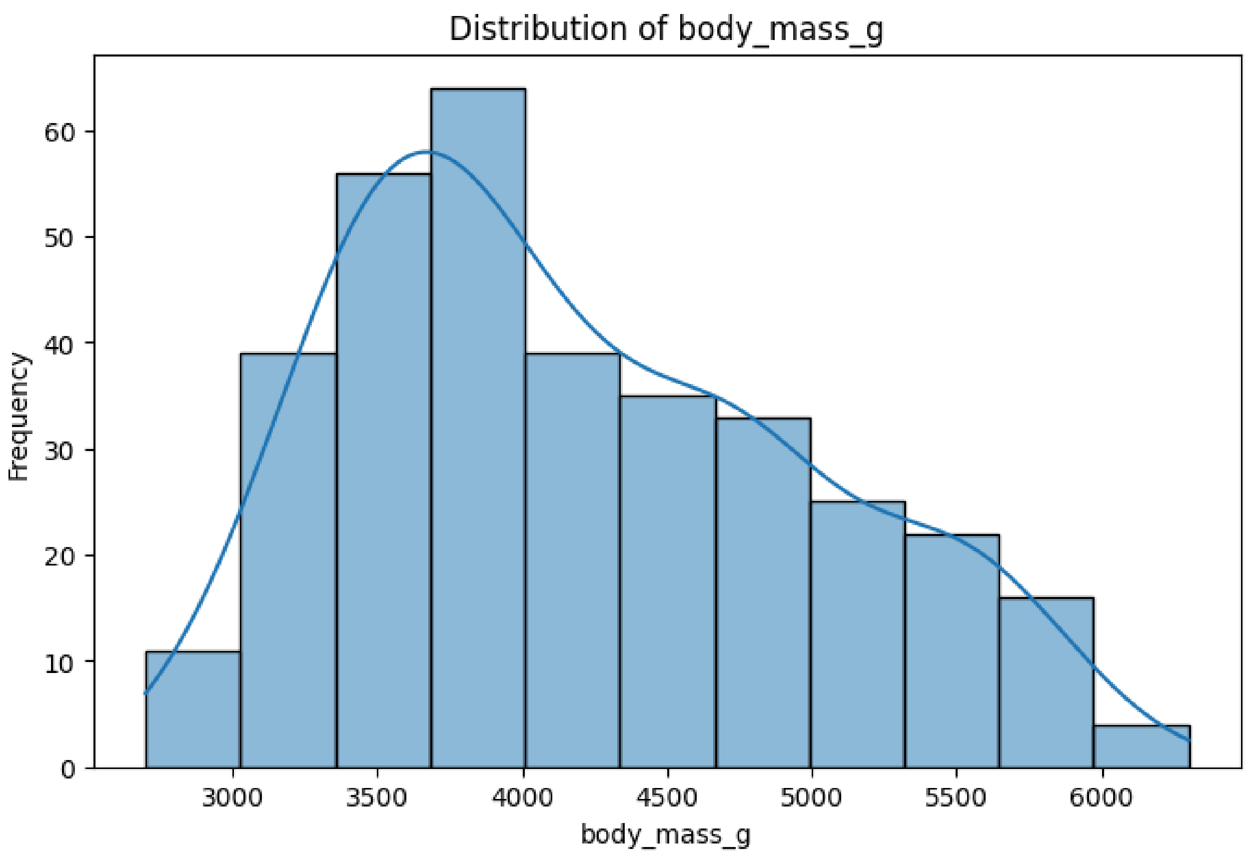
In [12]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Univariate Analysis
def univariate_analysis(data, column):
    plt.figure(figsize=(8, 5))
    sns.histplot(data[column], kde=True)
    plt.title(f"Distribution of {column}")
    plt.xlabel(column)
    plt.ylabel("Frequency")
    plt.show()

# Perform univariate analysis for each numerical column
numerical_columns = ['culmen_length_mm', 'culmen_depth_mm', 'flipper_length_mm', 'body_
for column in numerical_columns:
    univariate_analysis(df, column)
```


Distribution of culmen_length_mm
Frequency
0
10
20
30
40
50
60
35
40
45
50
55
60
culmen_length_mm

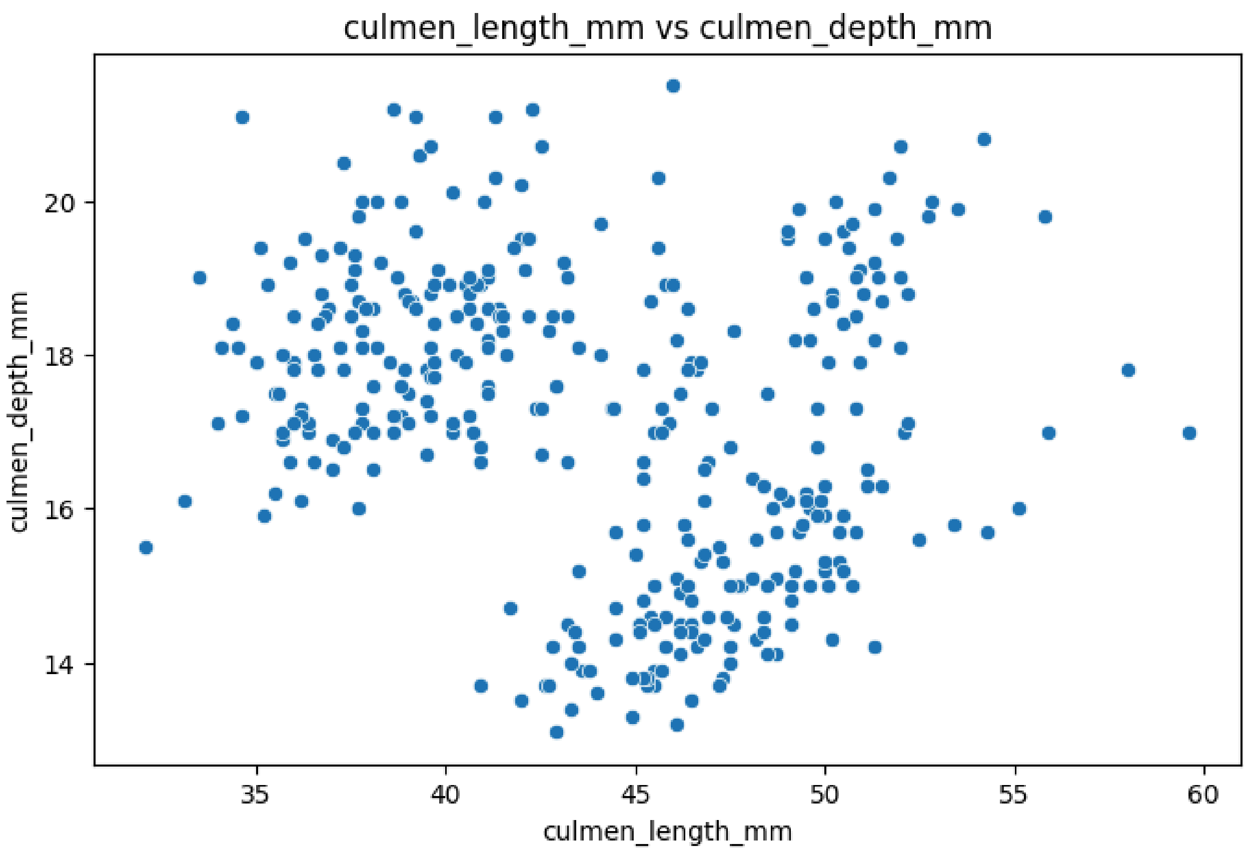

Distribution of culmen_depth_mm
Frequency
0
10
20
30
40
50
14
16
18
20
culmen_depth_mm

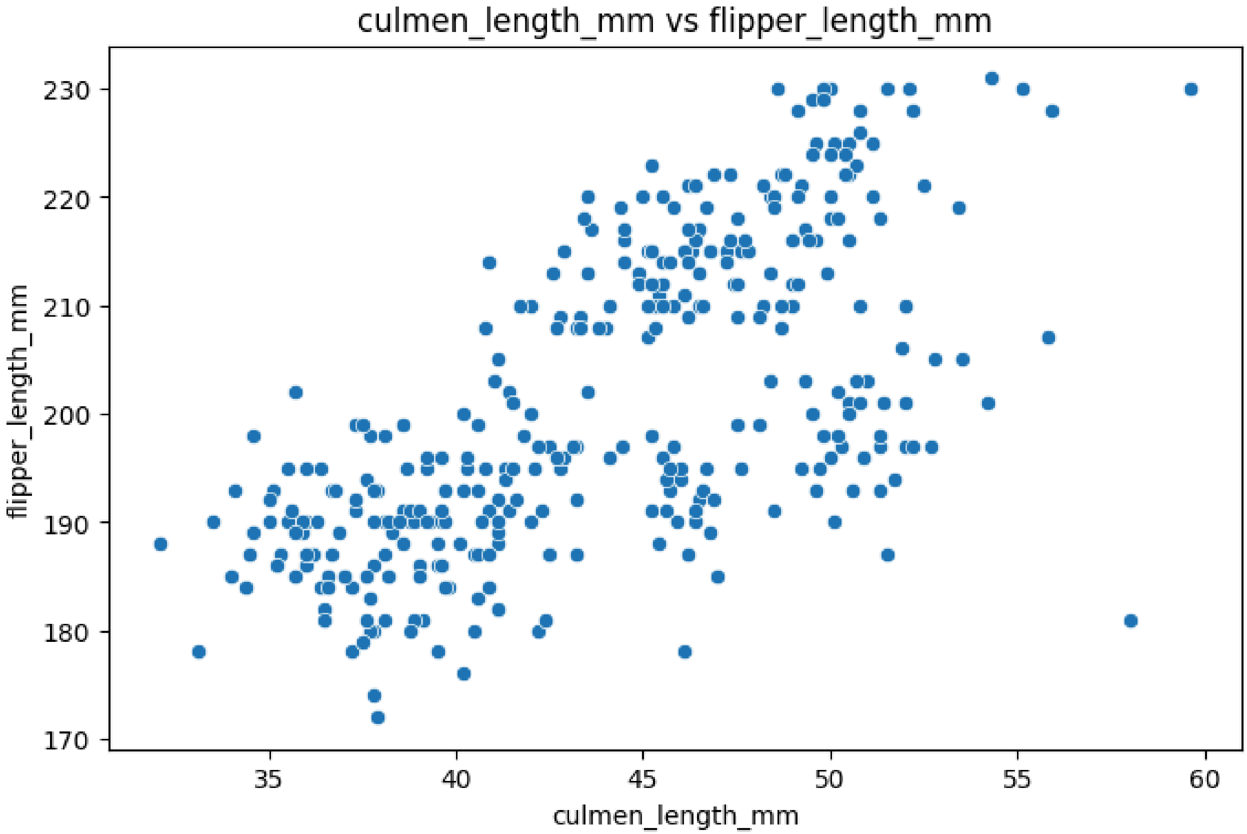


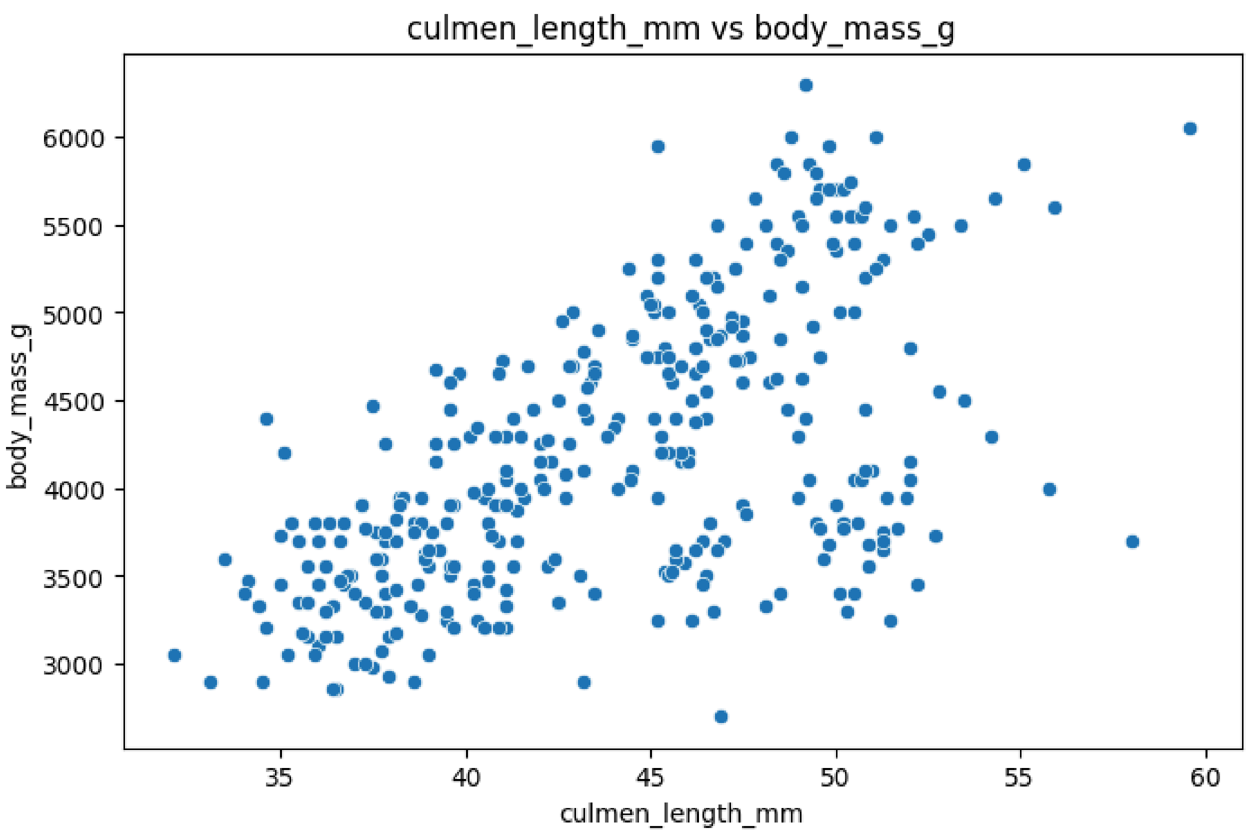



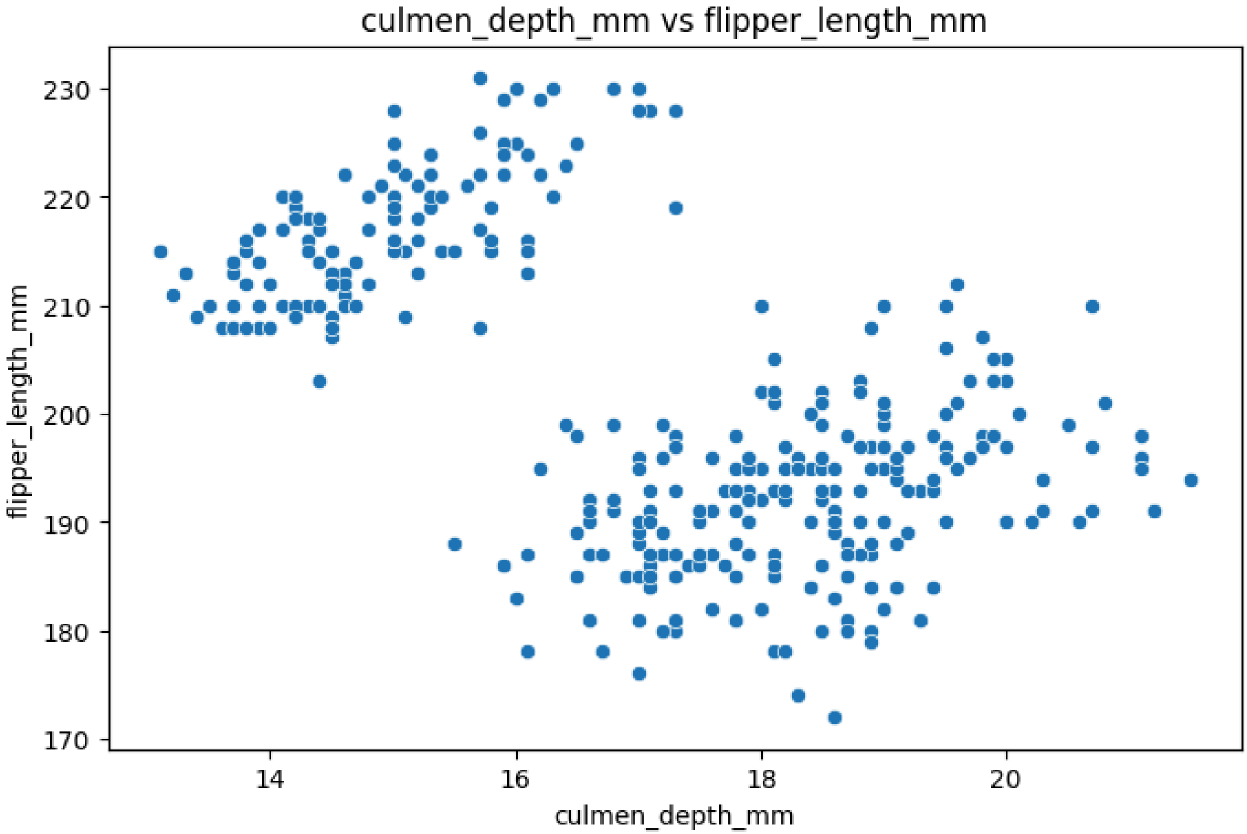

# BiVariate Analysis.

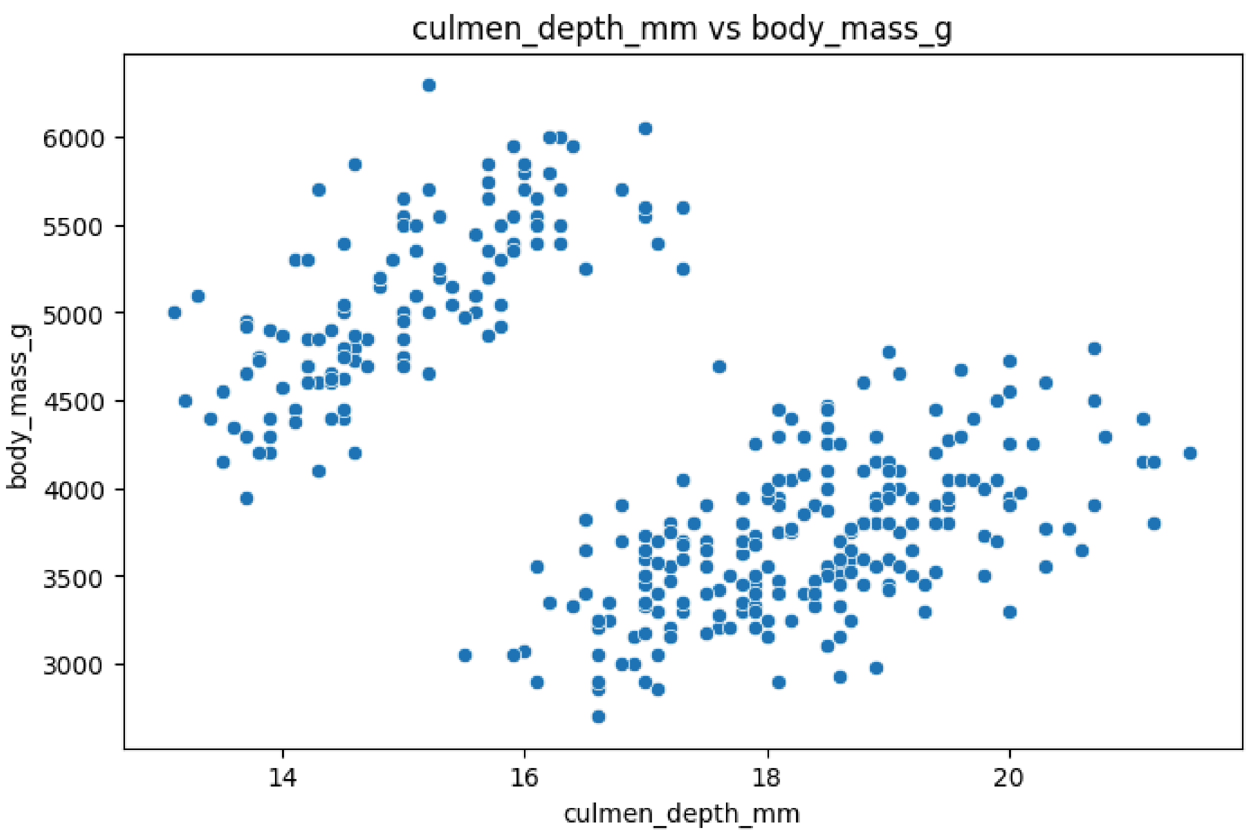
In [13]:
```
# Bivariate Analysis
def bivariate_analysis(data, x_column, y_column):
    plt.figure(figsize=(8, 5))
    sns.scatterplot(data=data, x=x_column, y=y_column)
    plt.title(f"{x_column} vs {y_column}")
    plt.xlabel(x_column)
    plt.ylabel(y_column)
    plt.show()

# Perform bivariate analysis for pairs of numerical columns
for i in range(len(numerical_columns)):
    for j in range(i+1, len(numerical_columns)):
        bivariate_analysis(df, numerical_columns[i], numerical_columns[j])

# Calculate and visualize correlation matrix
correlation_matrix = df[numerical_columns].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title("Correlation Matrix")
plt.show()
```

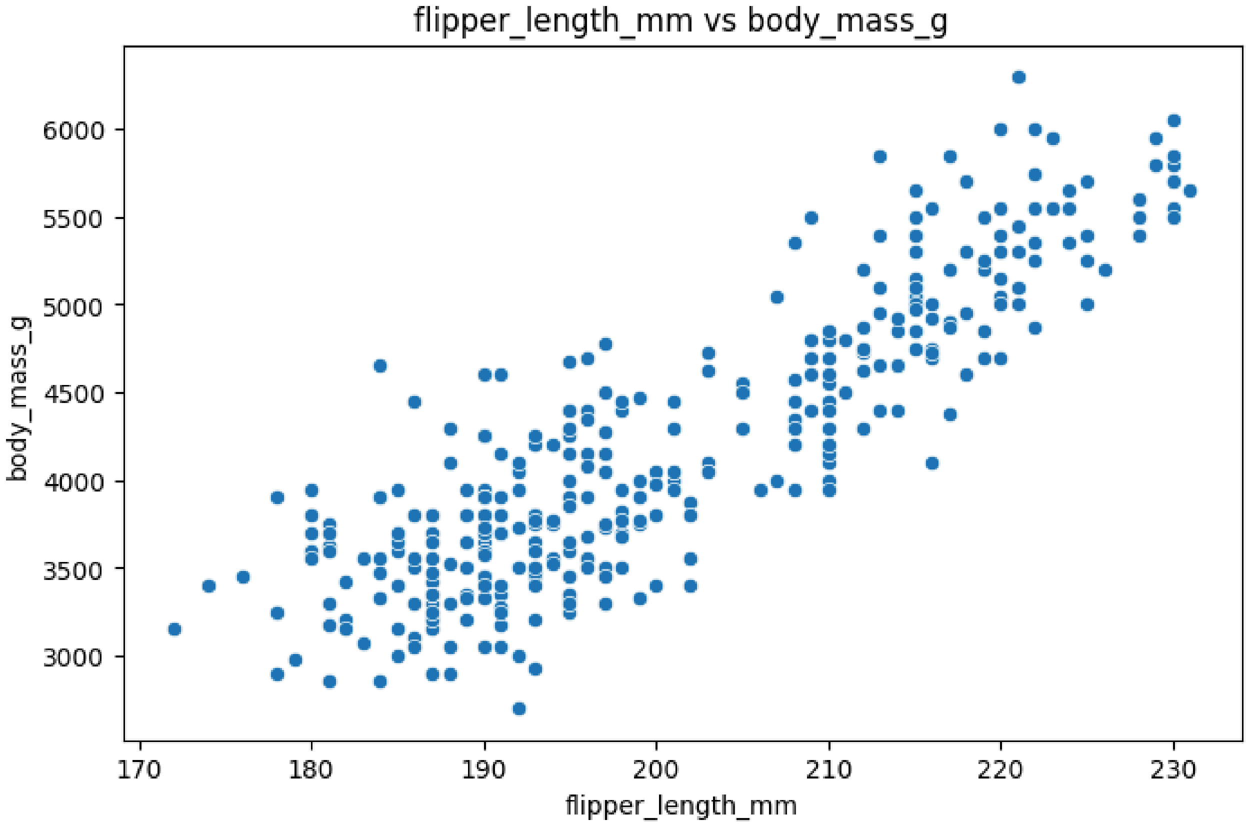


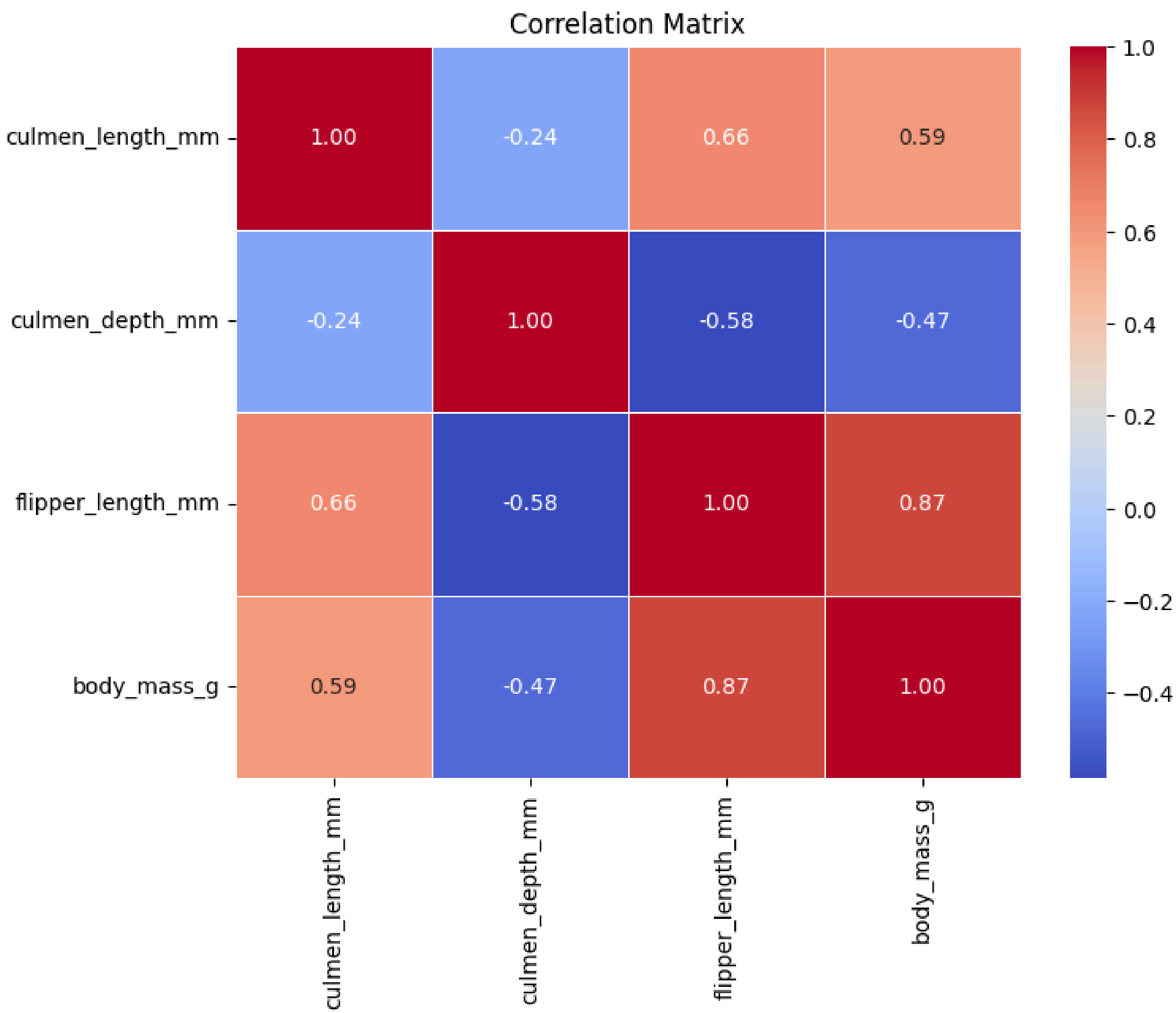

culmen_length_mm vs flipper_length_mm
flipper_length_mm
170
180
190
200
210
220
230
35
40
45
50
55
60
culmen_length_mm


culmen_length_mm vs body_mass_g
body_mass_g
3000
3500
4000
4500
5000
5500
6000
35
40
45
50
55
60
culmen_length_mm


culmen_depth_mm vs flipper_length_mm
flipper_length_mm
culmen_depth_mm
170
180
190
200
210
220
230
14
16
18
20


culmen_depth_mm vs body_mass_g
body_mass_g
culmen_depth_mm
3000
3500
4000
4500
5000
5500
6000
14
16
18
20


flipper_length_mm vs body_mass_g
body_mass_g
flipper_length_mm
6000
5500
5000
4500
4000
3500
3000
170
180
190
200
210
220
230

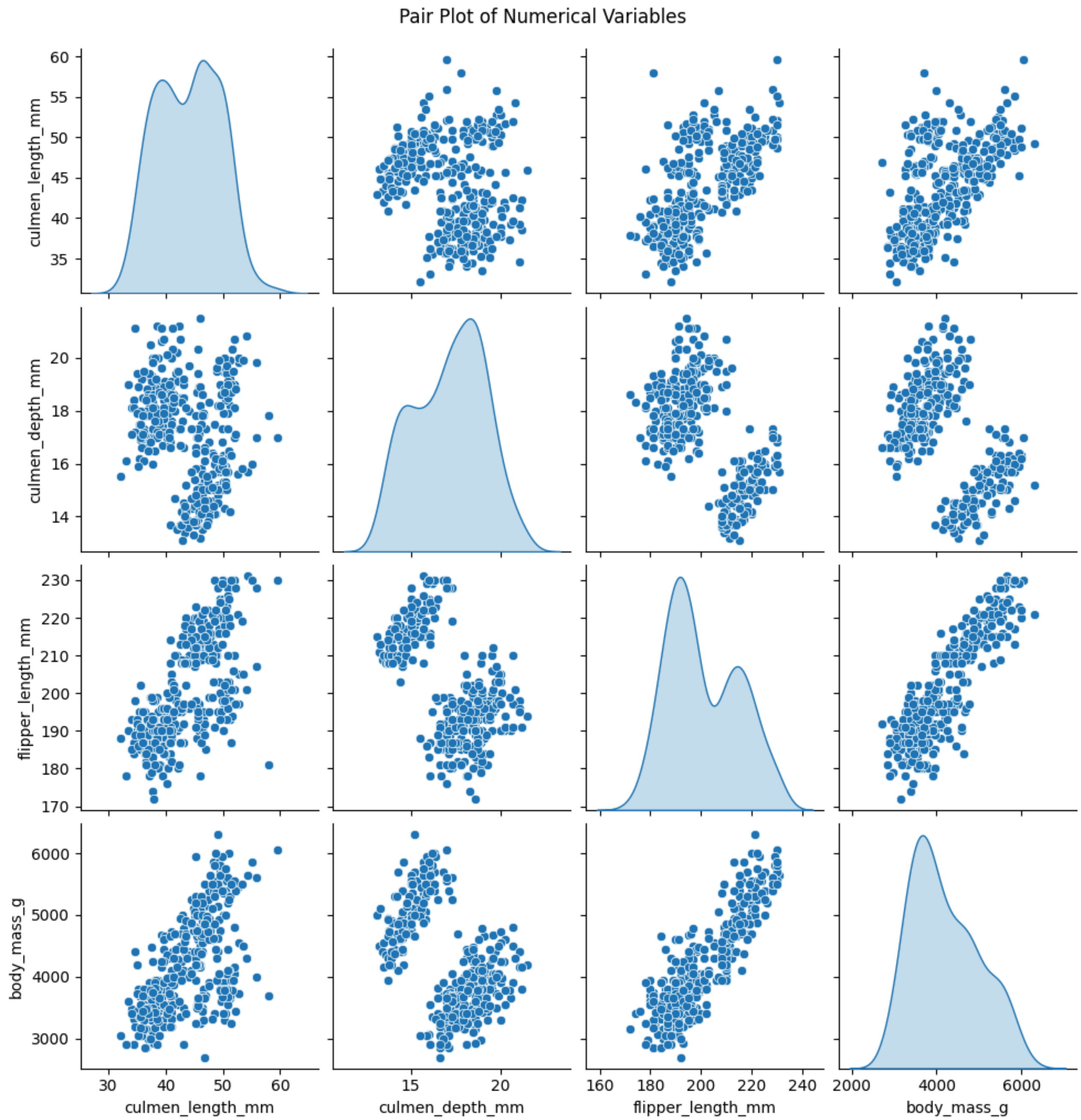

Correlation Matrix
culmen_length_mm
culmen_depth_mm
flipper_length_mm
body_mass_g
1.00
-0.24
0.66
0.59
-0.24
1.00
-0.58
-0.47
0.66
-0.58
1.00
0.87
0.59
-0.47
0.87
1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

# Multi-Variate Analysis.

In [14]:

```
# Multivariate Analysis
plt.figure(figsize=(10, 8))
sns.pairplot(df[numerical_columns], diag_kind='kde')
plt.suptitle("Pair Plot of Numerical Variables", y=1.02)
plt.show()
```

<Figure size 1000x800 with 0 Axes>




# Performing Encoding on Categorical Columns.

In [15]:

```
from sklearn.preprocessing import LabelEncoder

# Identify categorical columns
```

```
categorical_columns = df.select_dtypes(include=['object']).columns
print("\nCategorical Columns:")
print(categorical_columns)

# Perform encoding using LabelEncoder
label_encoder = LabelEncoder()
for column in categorical_columns:
    df[column] = label_encoder.fit_transform(df[column])

# Display the updated dataset
print("\nUpdated Dataset Preview:")
print(df.head())
```

```
Categorical Columns:
Index(['species', 'island', 'sex'], dtype='object')

Updated Dataset Preview:
   species  island  culmen_length_mm  culmen_depth_mm  flipper_length_mm  \
0        0       2             39.10             18.7              181.0
1        0       2             39.50             17.4              186.0
2        0       2             40.30             18.0              195.0
3        0       2             44.45             17.3              197.0
4        0       2             36.70             19.3              193.0

   body_mass_g  sex
0       3750.0    2
1       3800.0    1
2       3250.0    1
3       4050.0    2
4       3450.0    1
```

In [16]:

```
df.head()
```

Out[16]:

| | species | island | culmen_length_mm | culmen_depth_mm | flipper_length_mm | body_mass_g | sex |
|---|---|---|---|---|---|---|---|
| **0** | 0 | 2 | 39.10 | 18.7 | 181.0 | 3750.0 | 2 |
| **1** | 0 | 2 | 39.50 | 17.4 | 186.0 | 3800.0 | 1 |
| **2** | 0 | 2 | 40.30 | 18.0 | 195.0 | 3250.0 | 1 |
| **3** | 0 | 2 | 44.45 | 17.3 | 197.0 | 4050.0 | 2 |
| **4** | 0 | 2 | 36.70 | 19.3 | 193.0 | 3450.0 | 1 |

In [17]:

```
df.species.unique()
```

Out[17]:

```
array([0, 1, 2])
```

In [18]:

```
df.island.unique()
```

Out[18]:

```
array([2, 0, 1])
```

# Split the data into Dependent and Independent variables.

In [19]:

```
# Define the target variable
target_column = 'species'

# Split the dataset into dependent and independent variables

X = df.drop(columns=[target_column])  # Independent variables (features)
y = df[target_column]  # Dependent variable (target)

# Display the shape of the independent and dependent variables
print("\nShape of Independent Variables (Features):", X.shape)
print("Shape of Dependent Variable (Target):", y.shape)
```

```
Shape of Independent Variables (Features): (344, 6)
Shape of Dependent Variable (Target): (344,)
```

# Scaling the data.

In [20]:

```
from sklearn.preprocessing import StandardScaler

# Initialize StandardScaler
scaler = StandardScaler()

# Fit and transform the features
X_scaled = scaler.fit_transform(X)

# Convert the scaled features back to a DataFrame
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

# Display the scaled features
print("\nScaled Features (First 5 rows):")
print(X_scaled_df.head())
```

```
Scaled Features (First 5 rows):
     island  culmen_length_mm  culmen_depth_mm  flipper_length_mm  \
0  1.844076         -0.887622         0.787289          -1.420541
1  1.844076         -0.814037         0.126114          -1.063485
2  1.844076         -0.666866         0.431272          -0.420786
3  1.844076          0.096581         0.075255          -0.277964
4  1.844076         -1.329133         1.092447          -0.563608

   body_mass_g       sex
0    -0.564625  0.960230
1    -0.502010 -1.017729
2    -1.190773 -1.017729
3    -0.188936  0.960230
4    -0.940314 -1.017729
```

# Training, Testing, Modelling and Evaluating the metrices.

In [21]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4

# Choose a machine learning model (Random Forest Classifier)
model = RandomForestClassifier(n_estimators=100, random_state=40)

# Train the model on the training data
model.fit(X_train, y_train)

# Test the trained model on the testing data
y_pred = model.predict(X_test)

# Measure the performance using evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

# Display the evaluation metrics
print("Accuracy:", accuracy)
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(class_report)
```

```
Accuracy: 0.9710144927536232

Confusion Matrix:
[[33  1  0]
 [ 1 11  0]
 [ 0  0 23]]

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.97      0.97        34
           1       0.92      0.92      0.92        12
           2       1.00      1.00      1.00        23

    accuracy                           0.97        69
   macro avg       0.96      0.96      0.96        69
weighted avg       0.97      0.97      0.97        69
```

# Comparing Performance Evaluation of Models.

In [22]:

```
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
```

In [48]:

```
# list of models
models = [SVC(), KNeighborsClassifier(), RandomForestClassifier()]
```

In [46]:

```
def compare_models_train_test():

  for model in models:

    # training the model
    model.fit(X_train, y_train)

    # evaluating the model
    test_data_prediction = model.predict(X_test)

    accuracy = accuracy_score(y_test, test_data_prediction)

    print('Accuracy score of the ', model, ' = ', accuracy)

    conf_matrix = confusion_matrix(y_test, test_data_prediction)
    class_report = classification_report(y_test, test_data_prediction)
    print("\nConfusion Matrix:")
    print(conf_matrix)
    print("\nClassification Report:")
    print(class_report)
```

In [47]:

```
compare_models_train_test()
```

```
Accuracy score of the  SVC()  =  0.7971014492753623

Confusion Matrix:
[[32  0  2]
 [12  0  0]
 [ 0  0 23]]

Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.94      0.82        34
           1       0.00      0.00      0.00        12
           2       0.92      1.00      0.96        23

    accuracy                           0.80        69
   macro avg       0.55      0.65      0.59        69
weighted avg       0.67      0.80      0.72        69

Accuracy score of the  KNeighborsClassifier()  =  0.782608695652174

Confusion Matrix:
[[30  4  0]
 [ 8  4  0]
 [ 3  0 20]]

Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.88      0.80        34
           1       0.50      0.33      0.40        12
           2       1.00      0.87      0.93        23

    accuracy                           0.78        69
   macro avg       0.74      0.70      0.71        69
```

```
weighted avg       0.78      0.78      0.77        69

Accuracy score of the  RandomForestClassifier()  =  0.9855072463768116

Confusion Matrix:
[[34  0  0]
 [ 1 11  0]
 [ 0  0 23]]

Classification Report:
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        34
           1       1.00      0.92      0.96        12
           2       1.00      1.00      1.00        23

    accuracy                           0.99        69
   macro avg       0.99      0.97      0.98        69
weighted avg       0.99      0.99      0.99        69

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels wi
th no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels wi
th no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels wi
th no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [ ]: