ECS784P_CW01_ChaitanyaIngle_220754482_Final

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1 1. Importing Libraries

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
```

2 2. Reading Dataset

[2]:
```
df = pd.read_csv('/content/sample_data/onlinefoods.csv')
```

A) Looking at top 10 records

[3]:
```
df.head(10)
```

[3]:
```
   Age  Gender Marital Status Occupation   Monthly Income  \
0   20  Female         Single    Student        No Income
1   24  Female         Single    Student   Below Rs.10000
2   22    Male         Single    Student   Below Rs.10000
3   22  Female         Single    Student        No Income
4   22    Male         Single    Student   Below Rs.10000
5   27  Female        Married   Employee  More than 50000
6   22    Male         Single    Student        No Income
7   24  Female         Single    Student        No Income
8   23  Female         Single    Student        No Income
9   23  Female         Single    Student        No Income

  Educational Qualifications  Family size  latitude  longitude  Pin code  \
0              Post Graduate            4   12.9766    77.5993    560001
1                   Graduate            3   12.9770    77.5773    560009
2              Post Graduate            3   12.9551    77.6593    560017
3                   Graduate            6   12.9473    77.5616    560019
4              Post Graduate            4   12.9850    77.5533    560010
5              Post Graduate            2   12.9299    77.6848    560103
6                   Graduate            3   12.9770    77.5773    560009
7              Post Graduate            3   12.9828    77.6131    560042
```

```
8             Post Graduate           2   12.9766    77.5993    560001
9             Post Graduate           4   12.9854    77.7081    560048

  Output   Feedback Unnamed: 12
0    Yes   Positive         Yes
1    Yes   Positive         Yes
2    Yes  Negative          Yes
3    Yes   Positive         Yes
4    Yes   Positive         Yes
5    Yes   Positive         Yes
6    Yes   Positive         Yes
7    Yes   Positive         Yes
8    Yes   Positive         Yes
9    Yes   Positive         Yes
```

B) Understanding our dataset, by looking at the number of Rows & Columns and the Datatype and record count of each Column

[4]:
```python
df.shape
```

[4]:
```
(388, 13)
```

[5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 388 entries, 0 to 387
Data columns (total 13 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Age                         388 non-null    int64
 1   Gender                      388 non-null    object
 2   Marital Status              388 non-null    object
 3   Occupation                  388 non-null    object
 4   Monthly Income              388 non-null    object
 5   Educational Qualifications  388 non-null    object
 6   Family size                 388 non-null    int64
 7   latitude                    388 non-null    float64
 8   longitude                   388 non-null    float64
 9   Pin code                    388 non-null    int64
 10  Output                      388 non-null    object
 11  Feedback                    388 non-null    object
 12  Unnamed: 12                 388 non-null    object
dtypes: float64(2), int64(3), object(8)
memory usage: 39.5+ KB
```

3 3. Data Preprocessing

A) Checking Null values, if any

[6]:
```
null_values = df.isnull().sum()

# To display the count of null values for each column
print(null_values)
```

```
Age                           0
Gender                        0
Marital Status                0
Occupation                    0
Monthly Income                0
Educational Qualifications    0
Family size                   0
latitude                      0
longitude                     0
Pin code                      0
Output                        0
Feedback                      0
Unnamed: 12                   0
dtype: int64
```

B) Dropping unwanted columns

[7]:
```
df = df.drop(['Unnamed: 12'], axis=1)
```

4 4. Exploratory Data Analysis

A) Summary statistics of our dataset

[8]:
```
df.describe()
```

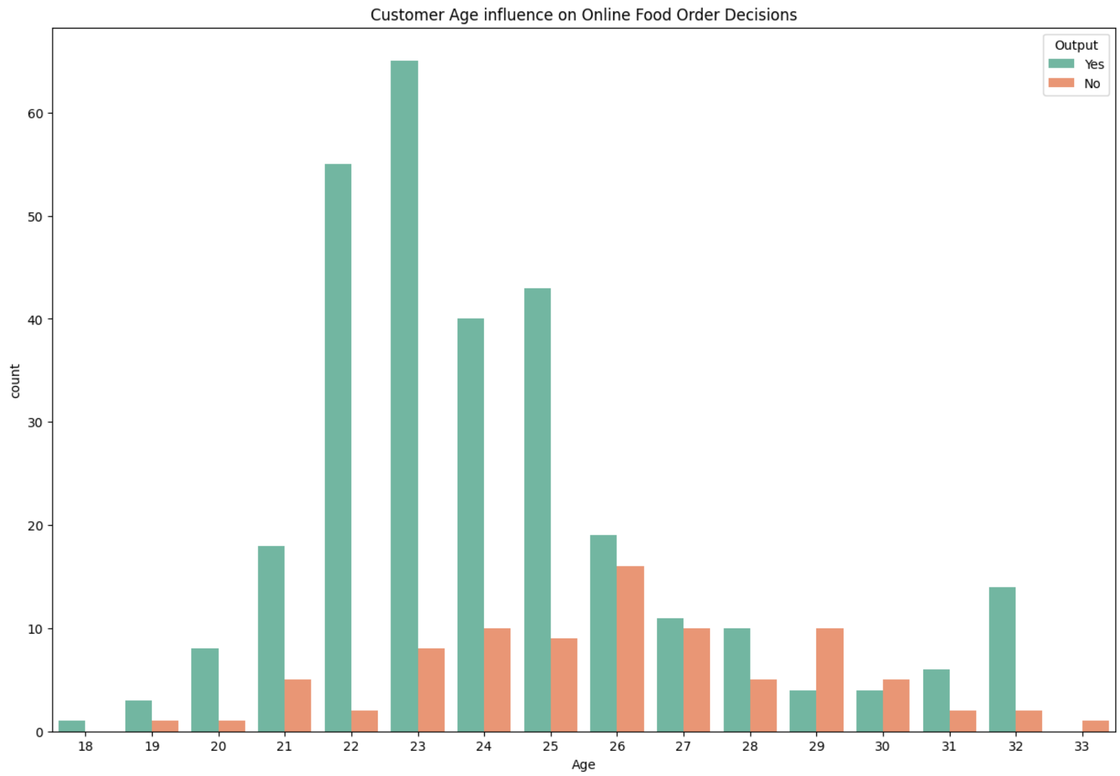
[8]:

	Age	Family size	latitude	longitude	Pin code
count	388.000000	388.000000	388.000000	388.000000	388.000000
mean	24.628866	3.280928	12.972058	77.600160	560040.113402
std	2.975593	1.351025	0.044489	0.051354	31.399609
min	18.000000	1.000000	12.865200	77.484200	560001.000000
25%	23.000000	2.000000	12.936900	77.565275	560010.750000
50%	24.000000	3.000000	12.977000	77.592100	560033.500000
75%	26.000000	4.000000	12.997025	77.630900	560068.000000
max	33.000000	6.000000	13.102000	77.758200	560109.000000

B) Creating plots to analyze our Dataset

[9]:
```
plt.figure(figsize=(15, 10))
plt.title("Customer Age influence on Online Food Order Decisions")
```

```
sns.countplot(x='Age',data=df,hue='Output',palette="Set2")
plt.show()
```



C) Extracting subset of data who have Ordered food, to analyze with various features in our dataset

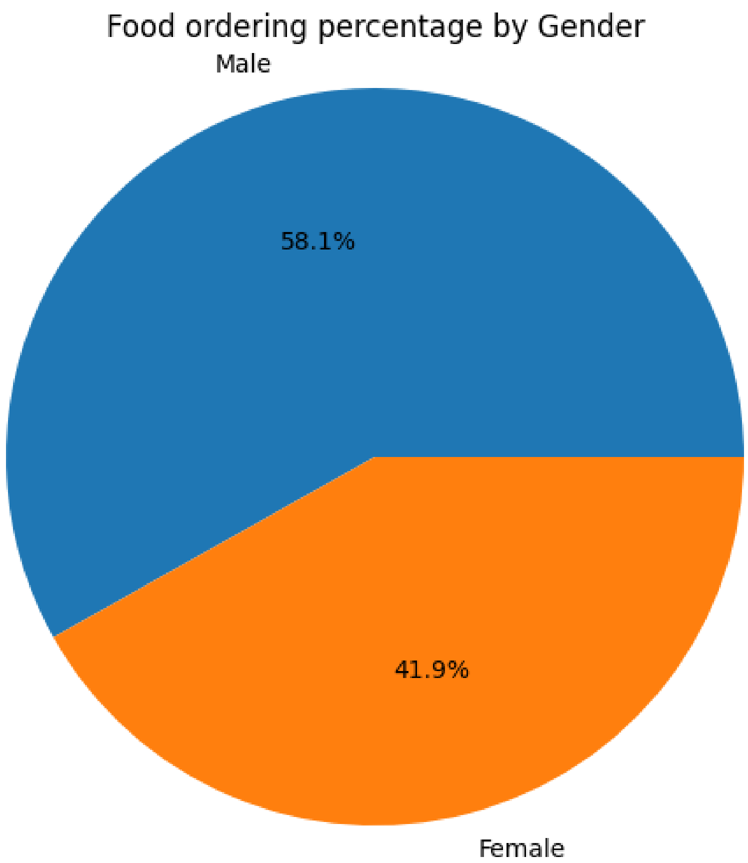
[10]:
```
ordered_food = df.query("Output == 'Yes'")
ordered_food.head()
```

[10]:
```
   Age  Gender Marital Status Occupation  Monthly Income  \
0   20  Female         Single    Student       No Income
1   24  Female         Single    Student  Below Rs.10000
2   22    Male         Single    Student  Below Rs.10000
3   22  Female         Single    Student       No Income
4   22    Male         Single    Student  Below Rs.10000

  Educational Qualifications  Family size  latitude  longitude  Pin code  \
0              Post Graduate            4   12.9766    77.5993    560001
1                   Graduate            3   12.9770    77.5773    560009
2              Post Graduate            3   12.9551    77.6593    560017
3                   Graduate            6   12.9473    77.5616    560019
4              Post Graduate            4   12.9850    77.5533    560010
```

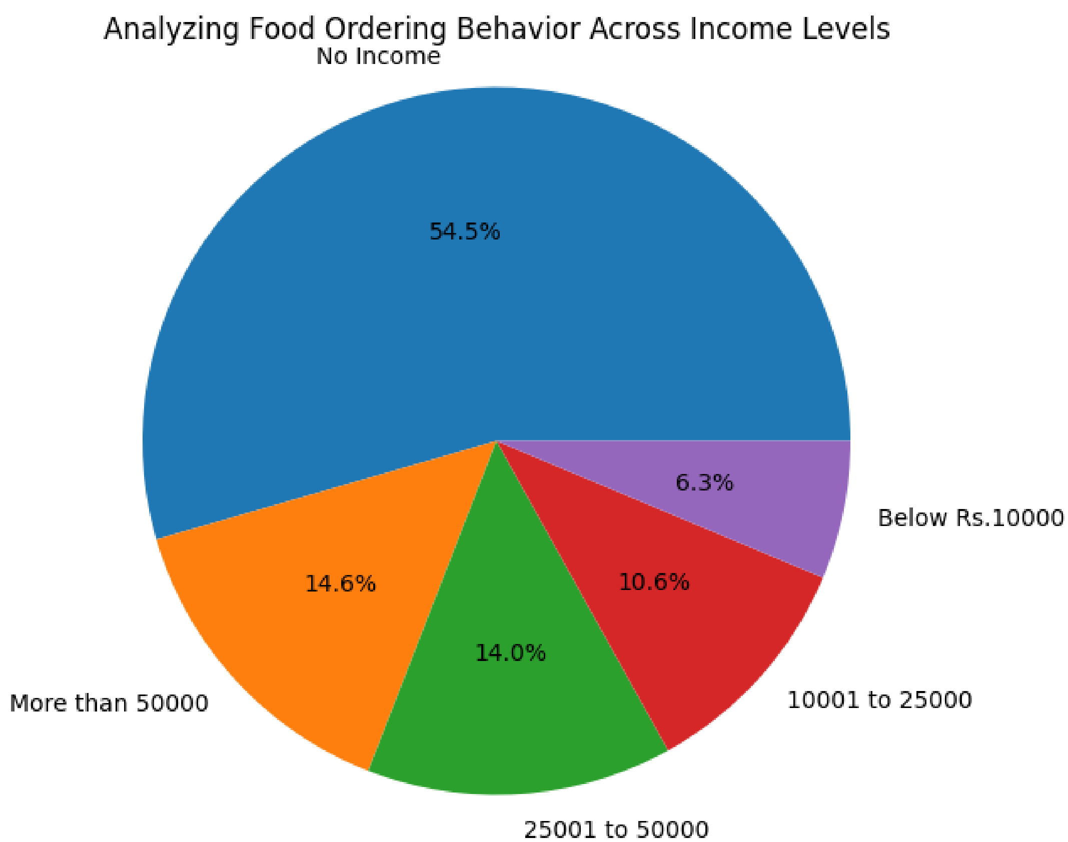
```
  Output   Feedback
0    Yes   Positive
1    Yes   Positive
2    Yes  Negative
3    Yes   Positive
4    Yes   Positive
```

D) Creating Pie charts to understand influence of key features on Food ordering

[11]:
```
OrderCountByGender = ordered_food["Gender"].value_counts()

# Create pie chart
plt.figure(figsize=(8, 6))  # Set figure size
plt.pie(OrderCountByGender, labels=OrderCountByGender.index, autopct='%1.1f%%')
plt.title('Food ordering percentage by Gender')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle
plt.show()
```



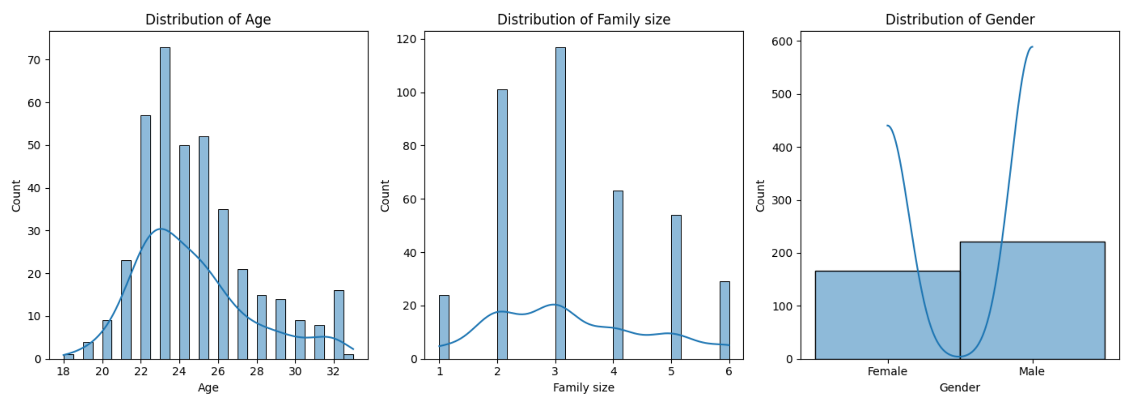
[12]:
```
# Calculate monthly income counts
monthly_income_counts = ordered_food["Monthly Income"].value_counts()

# Create pie chart
plt.figure(figsize=(8, 6))  # Set figure size
plt.pie(monthly_income_counts, labels=monthly_income_counts.index, autopct='%1.
↪1f%%')
plt.title('Analyzing Food Ordering Behavior Across Income Levels')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle
plt.show()
```



E) Creating Histograms to understand the data distribution among few features

[13]:
```
# Let's visualize the distribution of some key features

# List of features for EDA
features_to_plot = ['Age', 'Family size','Gender']

# Plotting the distribution of features
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(14, 5))
```

```
for i, col in enumerate(features_to_plot):
    sns.histplot(df[col], kde=True, bins=30, ax=axes[i]).
 ↪set_title(f'Distribution of {col}')

# Adjust the layout
plt.tight_layout()
plt.show()
```




```
[14]: df.dtypes
```

```
[14]: Age                              int64
      Gender                          object
      Marital Status                  object
      Occupation                      object
      Monthly Income                  object
      Educational Qualifications      object
      Family size                      int64
      latitude                       float64
      longitude                      float64
      Pin code                         int64
      Output                          object
      Feedback                        object
      dtype: object
```

D) Checking various Categorical column's unique labels record counts, to understand the distribution and help in converting those values to numerical data

```
[15]: print('Gender Counts: ', df['Gender'].value_counts())
print('-----------')
print('Marital Status Counts: ', df['Marital Status'].value_counts())
print('-----------')
print('Occupation counts: ', df['Occupation'].value_counts())
```

```python
print('-----------')
print('Monthly Income counts: ', df['Monthly Income'].value_counts())
print('-----------')
print('Educational Qualifications counts: ', df['Educational Qualifications'].
 ↪value_counts())
print('-----------')
print('Feedback counts: ', df['Feedback'].value_counts())
```

```
Gender Counts:  Male      222
Female    166
Name: Gender, dtype: int64
-----------
Marital Status Counts:  Single               268
Married              108
Prefer not to say     12
Name: Marital Status, dtype: int64
-----------
Occupation counts:  Student           207
Employee          118
Self Employeed     54
House wife          9
Name: Occupation, dtype: int64
-----------
Monthly Income counts:  No Income          187
25001 to 50000      69
More than 50000     62
10001 to 25000      45
Below Rs.10000      25
Name: Monthly Income, dtype: int64
-----------
Educational Qualifications counts:  Graduate         177
Post Graduate    174
Ph.D              23
School            12
Uneducated         2
Name: Educational Qualifications, dtype: int64
-----------
Feedback counts:  Positive     317
Negative     71
Name: Feedback, dtype: int64
```

5 5. Data Preparation - Converting categorical data to numerical data

[16]:
```
df["Gender"] = df["Gender"].map({"Male":0,"Female":1}) # male or female

df["Marital Status"] = df["Marital Status"].map({"Married":0,"Single":1,"Prefer␣
↪not to say":2})


df["Occupation"] = df["Occupation"].replace(to_replace=["Employee","Self␣
↪Employeed"], value=1) # employed
df["Occupation"] = df["Occupation"].replace(to_replace=["Student","House␣
↪wife"], value=0) # unemployed


df["Educational Qualifications"] = df["Educational Qualifications"].
↪map({"Graduate": 1,
                                                                                ␣
↪"Post Graduate": 2,
                                                                                ␣
↪"Ph.D": 3, "School": 4,
                                                                                ␣
↪"Uneducated": 5})


df["Monthly Income"] = df["Monthly Income"].replace(to_replace=["No Income"],␣
↪value=0) # no income
df["Monthly Income"] = df["Monthly Income"].replace(to_replace=["Below Rs.
↪10000",
                                                                "More than␣
↪50000",
                                                                "25001 to␣
↪50000",
                                                                "10001 to␣
↪25000"], value=1)  # has an income

df["Feedback"] = df["Feedback"].map({"Negative ":0,"Positive":1}) # negative or␣
↪positive

df["Output"] = df["Output"].map({"No":0,"Yes":1}) # no or yes
```

[17]:
```
df.head(10)
```

[17]:
```
   Age  Gender  Marital Status  Occupation  Monthly Income  \
0   20       1               1           0               0
1   24       1               1           0               1
```

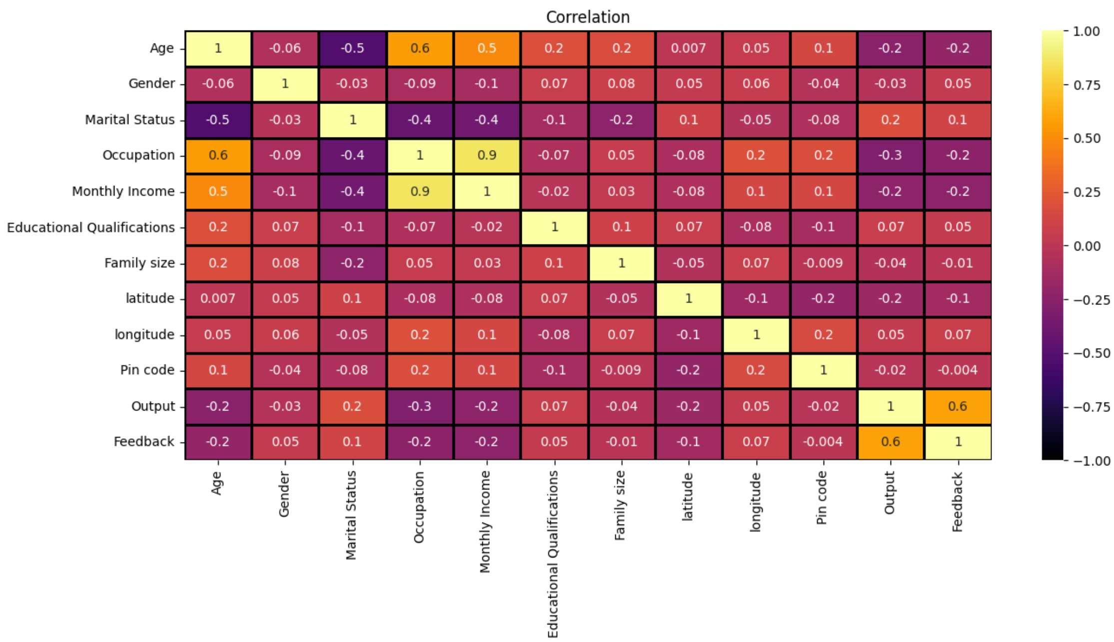
```
2   22       0                1            0                1
3   22       1                1            0                0
4   22       0                1            0                1
5   27       1                0            1                1
6   22       0                1            0                0
7   24       1                1            0                0
8   23       1                1            0                0
9   23       1                1            0                0

   Educational Qualifications  Family size  latitude  longitude  Pin code  \
0                           2            4   12.9766    77.5993    560001
1                           1            3   12.9770    77.5773    560009
2                           2            3   12.9551    77.6593    560017
3                           1            6   12.9473    77.5616    560019
4                           2            4   12.9850    77.5533    560010
5                           2            2   12.9299    77.6848    560103
6                           1            3   12.9770    77.5773    560009
7                           2            3   12.9828    77.6131    560042
8                           2            2   12.9766    77.5993    560001
9                           2            4   12.9854    77.7081    560048

   Output  Feedback
0       1         1
1       1         1
2       1         0
3       1         1
4       1         1
5       1         1
6       1         1
7       1         1
8       1         1
9       1         1
```

A) Creating Correlation matix to understand the relationship between various variables in our dataset and also its influence on out target variable

[18]:
```
corr_df = df.corr(method="pearson")

plt.figure(figsize=(14, 6))
heatmap = sns.heatmap(corr_df, annot=True, fmt=".1g", vmin=-1, vmax=1,␣
 ↪center=0, cmap="inferno", linewidths=1, linecolor="black")
heatmap.set_title("Correlation")
heatmap.set_xticklabels(heatmap.get_xticklabels(), rotation=90)
```

[18]:
```
[Text(0.5, 0, 'Age'),
 Text(1.5, 0, 'Gender'),
 Text(2.5, 0, 'Marital Status'),
```

```
 Text(3.5, 0, 'Occupation'),
 Text(4.5, 0, 'Monthly Income'),
 Text(5.5, 0, 'Educational Qualifications'),
 Text(6.5, 0, 'Family size'),
 Text(7.5, 0, 'latitude'),
 Text(8.5, 0, 'longitude'),
 Text(9.5, 0, 'Pin code'),
 Text(10.5, 0, 'Output'),
 Text(11.5, 0, 'Feedback')]
```



6 6. Model Training

[19]:
```python
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
```

A) Splitting data into Train and Test sets

[20]:
```python
X = df.drop('Output',axis=1)
y = df['Output']

X_train,X_test, y_train, y_test = train_test_split(X,y, test_size=0.25,
                                                    random_state=101)
```

```python
print("Shape of train dataset : ", X_train.shape)
print("Shape of test dataset : ", X_test.shape)
```

```
Shape of train dataset :  (291, 11)
Shape of test dataset :  (97, 11)
```

B) Random Forest Classifier model

[21]:
```python
rfc = RandomForestClassifier(n_estimators=100)
rfc.fit(X_train, y_train)

RandomForestAccuracy = rfc.score(X_test, y_test)
print("Accuracy:", RandomForestAccuracy)
```

```
Accuracy: 0.8865979381443299
```

C) Logistic Regression model

[22]:
```python
# Initialize and train Logistic Regression classifier
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)

# Evaluate the classifier
LogisticRegressionAccuracy = log_reg.score(X_test, y_test)
print("Accuracy:", LogisticRegressionAccuracy)
```

```
Accuracy: 0.7731958762886598
```

7 7. Comparing Test results

A) Confusion matrix created based on Predictions made using Random Forest classifier model

[23]:
```python
# Optionally, print confusion matrix
y_pred = rfc.predict(X_test)
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix Random Forest classifier:")
print(conf_matrix)
```

```
Confusion Matrix Random Forest classifier:
[[16  6]
 [ 5 70]]
```

B) Confusion matrix created based on Predictions made using Logistic Regression model

[24]:
```python
# Optionally, print confusion matrix
y_pred1 = log_reg.predict(X_test)
conf_matrix = confusion_matrix(y_test, y_pred1)
```

```
print("Confusion Matrix Logistic Regression:")
print(conf_matrix)
```

```
Confusion Matrix Logistic Regression:
[[ 0 22]
 [ 0 75]]
```

C) Evaluating score by cross-validation

[25]:
```
# Evaluating a score by cross-validation
# cv determines the cross-validation splitting strategy
scores = cross_val_score(rfc, X_train, y_train,cv=5)

# average score
print("Accuracy: ", scores.mean(), scores.std() * 2)
```

```
Accuracy:  0.9037405026300409 0.047047021260004554
```

[26]:
```
# Evaluating a score by cross-validation
# cv determines the cross-validation splitting strategy
scores = cross_val_score(log_reg, X_train, y_train,cv=5)

# average score
print("Accuracy: ", scores.mean(), scores.std() * 2)
```

```
Accuracy:  0.7766218585622443 0.0030391583869082694
```

8 ———————————— END ————————————-

[26]:
```

```