Super Market Sales Analytics

1) Data Science Proposal

1. The Team
Group Number: 49

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2. Problem Statement and Background
To Analyze and Build models for the sales of different products in a supermarket located in different cities using machine learning techniques

3. The Data Source
The dataset is Supermarket_Sales_Dataset.csv. This dataset contains various attributes of supermarkets like Invoice Id, Branch, City, Customer Type, Gender, Product Type, Unit Price, Quantity, Tax, Selling Price, Date, Time, Payment Type, Cost Price, Gross Income, Rating.

4. Goals of Your Analysis

- Get maximum insights from a data set
- Uncover Underlying structure
- Extract important features from the data set
- Train a Machine Learning model for predicting Customer Rating
- Validation of Predicted Model
- Visualization of results with Graphical representations

5. Description of Data Analysis Tools You Plan to Use

- numpy
- pandas

- seaborn
- matplotlib
- sklearn
- scipy

6. Describe the Data Products Your Project Will Produce

- Performance of 3 clustering techniques - AHC, K-Means, K-Medoids
- Comparison of performance of the two classifiers – Logistic regression and Decision tree to predict

In [1]:
```
#Import Libraries
import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
from scipy.stats import skew
from prettytable import PrettyTable
from datetime import datetime

# For feature selections and Feature Engineering
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectKBest, chi2, mutual_info_classif
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from sklearn.linear_model import LinearRegression
from collections import Counter
from sklearn.decomposition import PCA
from imblearn.combine import SMOTETomek
from sklearn.ensemble import RandomForestClassifier

# Clustering
from sklearn.cluster import KMeans
from sklearn_extra.cluster import KMedoids
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score
import silhouetteplot
import scipy.cluster.hierarchy as sch
from sklearn.datasets import make_moons
from sklearn.metrics import adjusted_rand_score

# Importing the DecisionTreeClassifier and LogisticRegressionClassifier for model building
from sklearn import tree
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn import model_selection

# For Analyzing the models
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
```

```python
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import (accuracy_score, classification_report, confusion_matrix)
from sklearn.model_selection import cross_val_score

import warnings
warnings.simplefilter(action="ignore", category=FutureWarning)
pd.options.mode.chained_assignment = None
```

In [2]:

```python
#Read Data from the csv file
df = pd.read_csv('Supermarket_Sales_Dataset.csv')
df.head(2)
```

Out[2]:

	Invoice ID	Branch	City	Customer Type	Gender	Product Type	Unit Price	Quantity	Tax	Selling Price	Date	Time	Payment Type	Cost Price	Gross Income	Ratin
0	750-67-8428	A	Bangalore	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Debit card	522.83	26.1415	9.
1	226-31-3081	C	Mysore	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	3.8200	9.

In [3]:

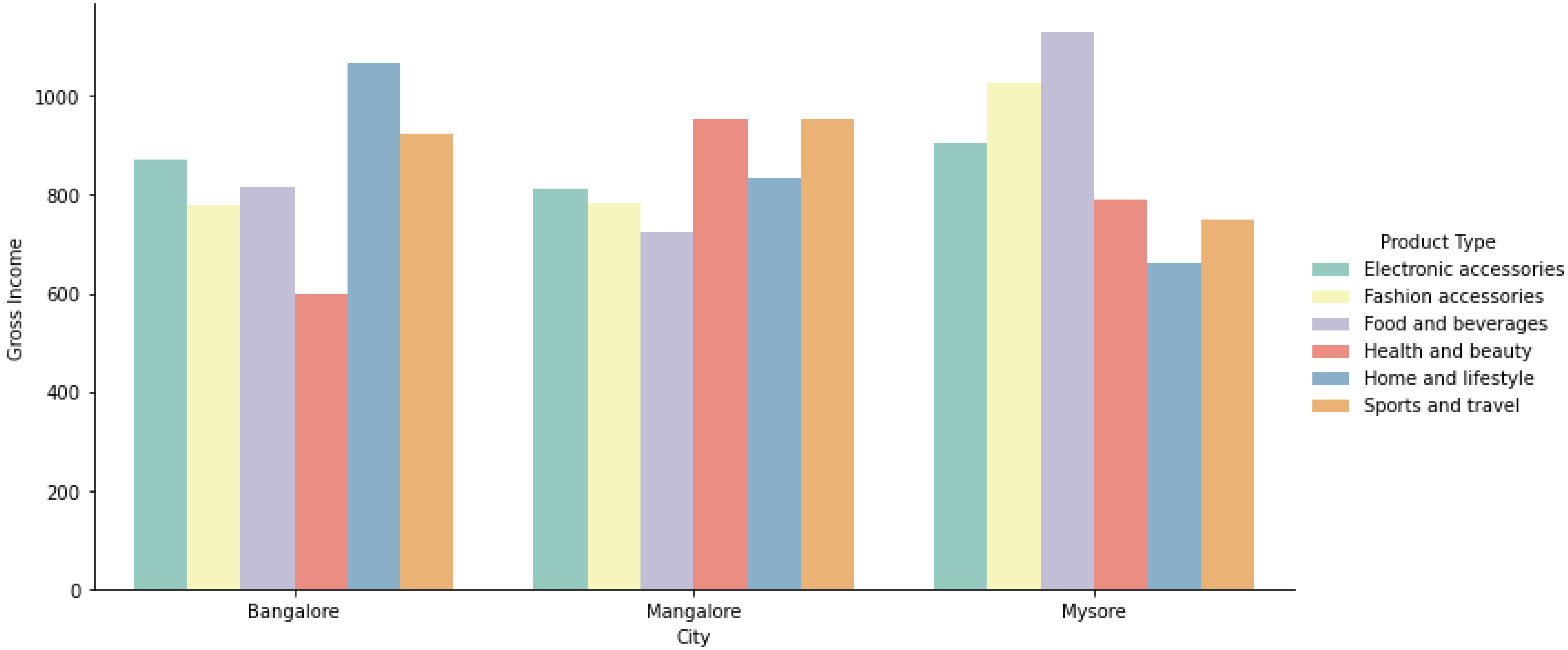
```python
#Defining class colour
class color:
   BLUE = '\033[94m'
   BOLD = '\033[1m'
   END = '\033[0m'
```

Objectives

1) Which city has a better sale for products in the Electronic Accessories product line?

In [4]:

```
dfCat=df[['City','Product Type','Gross Income']].groupby(['City','Product Type'],as_index=False).sum()
sns.catplot(data=dfCat, y='Gross Income', x='City',kind='bar', hue='Product Type',height=5,aspect=2,palette="Set3")
plt.show()

dfCat[dfCat['Product Type'] == 'Electronic accessories'].nlargest(1,'Gross Income')
```



Out[4]:

	City	Product Type	Gross Income
12	Mysore	Electronic accessories	903.2845

2) Which payment method is used more often at a particular city, branch and for which product type ?

In [5]:

```
dfpm=df[['City','Product Type','Payment Type','Invoice ID']].groupby(['City','Product Type','Payment Type'],as_index
dfpm.sort_values(by = ['City', 'Invoice ID'], ascending = [True, False],inplace = True)
dfpm.drop_duplicates(subset="City",inplace = True)
dfpm.head()
```

Out[5]:

	City	Product Type	Payment Type	Invoice ID
14	Bangalore	Home and lifestyle	Debit card	26
33	Mangalore	Sports and travel	Cash	26
42	Mysore	Food and beverages	Cash	31

3) Which Product type has been more purchased by female customers?

In [6]:

```
dfgender=df[['Gender','Product Type','Quantity']].groupby(['Gender','Product Type'],as_index=False).sum()
dfgender[dfgender['Gender'] == 'Female'].nlargest(1,'Quantity')
```

Out[6]:

	Gender	Product Type	Quantity
1	Female	Fashion accessories	530

4) In which month does the highest number of home and lifestyle products have been sold ?

In [7]:
```
dfm = df[df['Product Type'] == 'Home and lifestyle']
dfm['Date'] = pd.to_datetime(dfm['Date'])
dfm['Month'] = dfm['Date'].dt.month_name(locale = 'English')
dfmtrend = dfm[['Month','Quantity']].groupby([dfm['Month']]).sum()
dfmtrend.sort_values(by = ['Quantity'], ascending = [False],inplace = True)
dfmtrend.head(1)
```

Out[7]:

	Quantity
Month	
March	364

5) At what time most of the female customers are purchasing products ?

In [8]:
```
dff = df[df['Gender'] == 'Female']
dfft = dff[['Gender','Time','Invoice ID']]
dfft['Invoice ID Count'] = dfft['Invoice ID']
dfff=dfft[['Gender','Time','Invoice ID Count']].groupby(['Gender','Time'],as_index=False).count()
dfff.sort_values(by = ['Invoice ID Count'], ascending = False,inplace = True)
dfff.drop_duplicates(subset="Time",inplace = True)
dfff.head(1)
```

Out[8]:

	Gender	Time	Invoice ID Count
168	Female	14:42	6

2) Exploratory Data Analysis

In [9]:
```
#Size of the Dataset
print(color.BLUE + color.BOLD + "\nSize of Dataset:" + color.END)
print(df.shape)
```

Size of Dataset:
```
(1000, 16)
```

In [10]:
```
# Attribute and its datatype
ptbl = PrettyTable()

for attribute in df.columns:
    ptbl.field_names = ["Attribute Name", "Data Type"]
    ptbl.add_row([attribute, df[attribute].dtype])

print(ptbl)
```

```
+----------------+-----------+
| Attribute Name | Data Type |
+----------------+-----------+
|   Invoice ID   |   object  |
|     Branch     |   object  |
|      City      |   object  |
| Customer Type  |   object  |
|     Gender     |   object  |
|  Product Type  |   object  |
|   Unit Price   |  float64  |
|    Quantity    |   int64   |
|      Tax       |  float64  |
| Selling Price  |  float64  |
|      Date      |   object  |
|      Time      |   object  |
|  Payment Type  |   object  |
|   Cost Price   |  float64  |
|  Gross Income  |  float64  |
|     Rating     |  float64  |
+----------------+-----------+
```

In [11]:
```
#Distribution Of Data
distTxt = color.BLUE + color.BOLD + "Data Distribution" + color.END
print(distTxt.center(100))
df.describe()
```

```
                                         Data Distribution
```

Out[11]:

	Unit Price	Quantity	Tax	Selling Price	Cost Price	Gross Income	Rating
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	1000.00000
mean	55.672130	5.510000	15.379369	322.966749	307.58738	15.379369	6.97270
std	26.494628	2.923431	11.708825	245.885335	234.17651	11.708825	1.71858
min	10.080000	1.000000	0.508500	10.678500	10.17000	0.508500	4.00000
25%	32.875000	3.000000	5.924875	124.422375	118.49750	5.924875	5.50000
50%	55.230000	5.000000	12.088000	253.848000	241.76000	12.088000	7.00000
75%	77.935000	8.000000	22.445250	471.350250	448.90500	22.445250	8.50000
max	99.960000	10.000000	49.650000	1042.650000	993.00000	49.650000	10.00000

In [12]:
```
columnsList = list(df)
categoricalList = list(df.select_dtypes(include=['object']).columns)
numericalList = list(set(columnsList) - set(categoricalList))

#Character or Numerical Data
print(color.BLUE + color.BOLD + "Categorical Data:" + color.END)
print(categoricalList)
print(color.BLUE + color.BOLD + "\nNumerical Data:" + color.END)
print(numericalList)
```

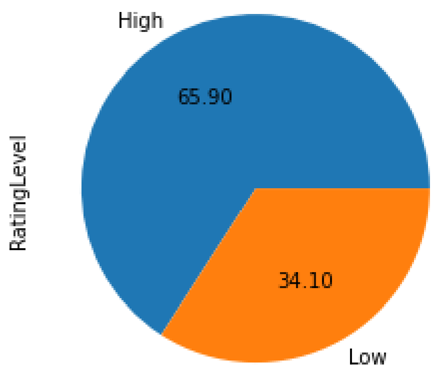
```
Categorical Data:
['Invoice ID', 'Branch', 'City', 'Customer Type', 'Gender', 'Product Type', 'Date', 'Time', 'Payment Type']

Numerical Data:
['Tax ', 'Quantity', 'Selling Price', 'Cost Price', 'Gross Income', 'Unit Price', 'Rating']
```

In [13]:

```
df['RatingLevel'] = pd.cut(x=df['Rating'],
                           bins=[1, 6, 10],
                           labels=['Low', 'High'])

#Balanced or Imbalanced Dataset
print(color.BLUE + color.BOLD + "Classification of Rating Level:" + color.END)
count = df['RatingLevel'].value_counts()
print(count)
count.plot.pie(autopct='%.2f')
```

```
Classification of Rating Level:
High    659
Low     341
Name: RatingLevel, dtype: int64
```

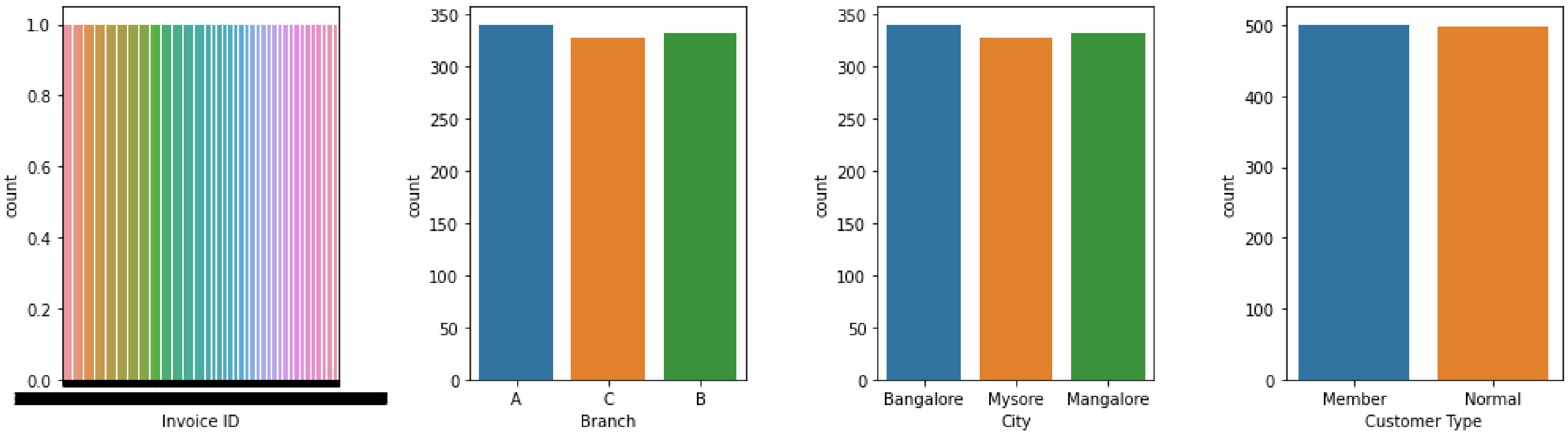
Out[13]: <AxesSubplot:ylabel='RatingLevel'>

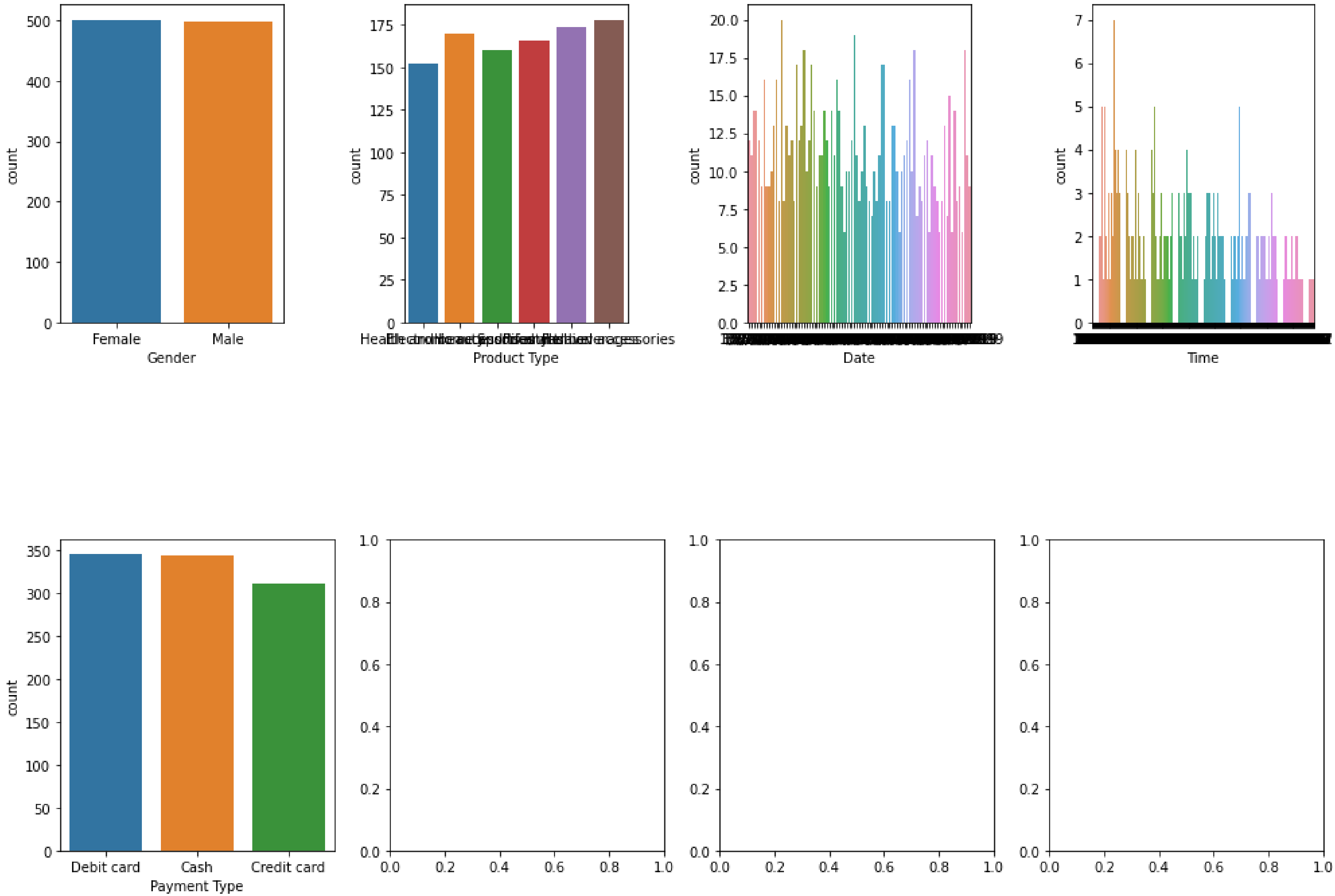


Data Visualization

In [14]:

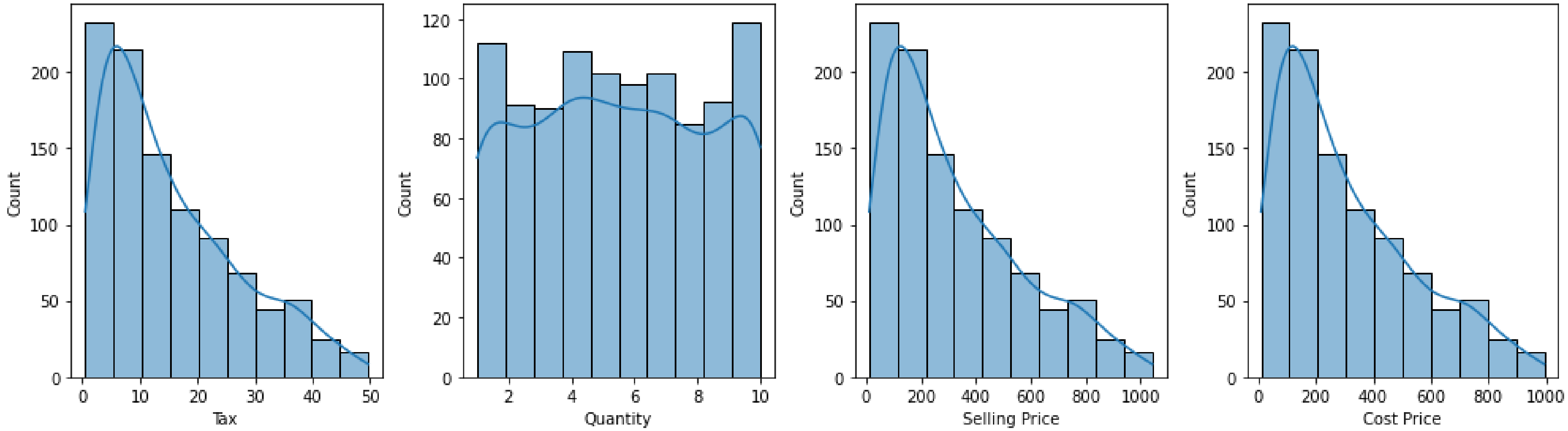
```python
#Count Plots (for categorical attributes)

plt.rcParams["figure.figsize"] = [14.00, 4.0]
plt.rcParams["figure.autolayout"] = True

index = 0
graphsInARow = 4

for attr in categoricalList:

    if (index % graphsInARow == 0):
        f, ax = plt.subplots(1, graphsInARow)

    sns.countplot(x=attr, data=df, ax = ax[index % graphsInARow])
    index = index + 1

    if (index % graphsInARow == 0):
        plt.show()
```

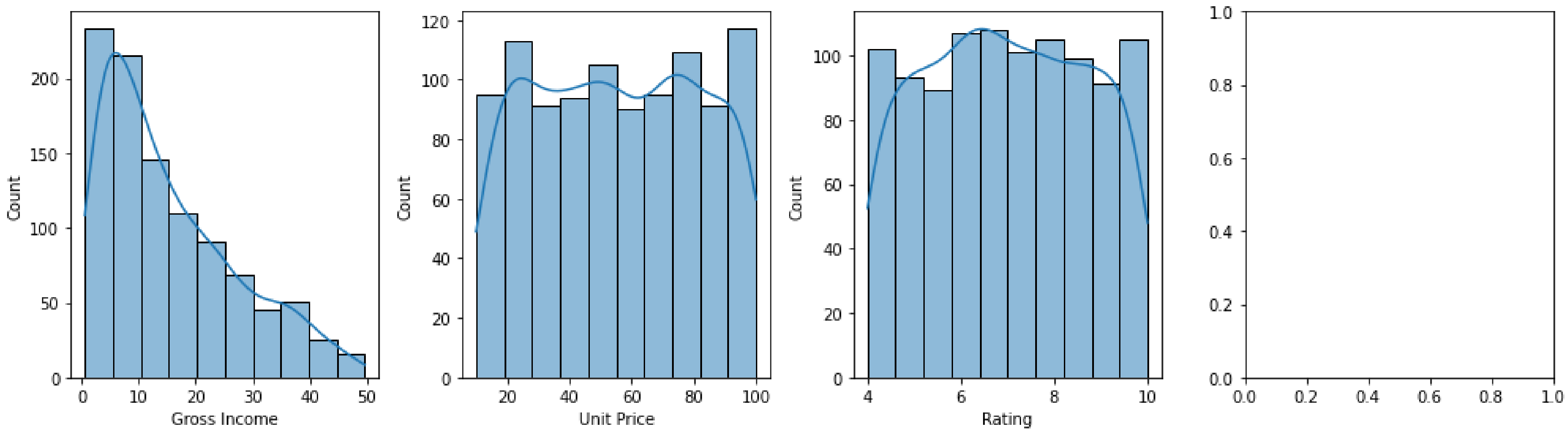



count
Female
Male
Gender
count
Product Type
count
Date
count
Time
count
Debit card
Cash
Credit card
Payment Type

In [15]:

```
#Histogram Distribution (for Continuous Attributes)
plt.rcParams["figure.figsize"] = [14.00, 4.0]
plt.rcParams["figure.autolayout"] = True

index = 0
graphsInARow = 4

for attr in numericalList:
    if (index % graphsInARow == 0):
        f, ax = plt.subplots(1, graphsInARow)
    sns.histplot(data=df[attr], bins=10, kde=True, ax = ax[index % graphsInARow])
    index = index + 1
    if (index % graphsInARow == 0):
        plt.show()
```




Count
Gross Income
Count
Unit Price
Count
Rating

In [16]:

```python
#Correlation of the features in the dataset
corr = df.corr()

corrTxt = color.BLUE + color.BOLD + "Correlation Using HeatMap" + color.END
print(corrTxt.center(120))

#Visualizing correlation using Heatmap
plt.figure(figsize=(10,7.5))
sns.heatmap(corr, annot=True, cmap='GnBu')
```

Correlation Using HeatMap

Out[16]:

```
<AxesSubplot:>
```

3) Data Wrangling

In [17]:
```
#Count of NaN/Null values from dataset
print(color.BLUE + color.BOLD + "\nCount of NaN/Null values for each feature:" + color.END)
print(df.isna().sum())
```

```
Count of NaN/Null values for each feature:
Invoice ID       0
Branch           0
City             0
Customer Type    0
Gender           0
Product Type     0
Unit Price       0
Quantity         0
Tax              0
Selling Price    0
Date             0
Time             0
Payment Type     0
Cost Price       0
Gross Income     0
Rating           0
RatingLevel      0
dtype: int64
```

In [18]:
```
# Checking for duplicates
df.duplicated().sum()
```

Out[18]: 0

In [19]:
```
# Dropping the attributes that has a unique number(number assignment) for all the rows or attributes derivable from
df=df.drop(['Invoice ID','Branch', 'Date', 'Time'], axis=1)
```

In [20]:
```
df.shape
```

Out[20]: (1000, 13)

In [21]:
```
df.head(2)
```

Out[21]:

	City	Customer Type	Gender	Product Type	Unit Price	Quantity	Tax	Selling Price	Payment Type	Cost Price	Gross Income	Rating	RatingLevel
0	Bangalore	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	Debit card	522.83	26.1415	9.1	High
1	Mysore	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	Cash	76.40	3.8200	9.6	High

4) Clustering

In [22]:
```
#Copy of df
dfCopy = df.copy()

for column in dfCopy.columns:
    #If Column data type is int or float continue
    if dfCopy[column].dtype == 'int64' or dfCopy[column].dtype == 'float64':
        continue
        #If Column data type is object, encode and transform it
    dfCopy[column] = LabelEncoder().fit_transform(dfCopy[column].astype(str))
```

In [23]:
```
dfCopy.head(2)
```

Out[23]:

	City	Customer Type	Gender	Product Type	Unit Price	Quantity	Tax	Selling Price	Payment Type	Cost Price	Gross Income	Rating	RatingLevel
0	0	0	0	3	74.69	7	26.1415	548.9715	2	522.83	26.1415	9.1	0
1	2	1	0	0	15.28	5	3.8200	80.2200	0	76.40	3.8200	9.6	0

In [24]:
```
# Scaling is done
scaler = StandardScaler()
scaled_features = scaler.fit_transform(dfCopy)
scaled_features.shape
```

Out[24]: (1000, 13)

In [25]:
```
scaled_features_df = pd.DataFrame(scaled_features)
scaled_features_df.columns = ['City', 'Customer Type', 'Gender', 'Product Type', 'Unit Price',
       'Quantity', 'Tax ', 'Selling Price', 'Payment Type', 'Cost Price',
       'Gross Income', 'Rating', 'RatingLevel']
scaled_features_df.head()
```

Out[25]:

	City	Customer Type	Gender	Product Type	Unit Price	Quantity	Tax	Selling Price	Payment Type	Cost Price	Gross Income	Rating	RatingLevel
0	-1.208970	-0.998002	-0.998002	0.319617	0.718160	0.509930	0.919607	0.919607	1.203528	0.919607	0.919607	1.238443	-0.719340
1	1.238338	1.002002	-0.998002	-1.430109	-1.525303	-0.174540	-0.987730	-0.987730	-1.205937	-0.987730	-0.987730	1.529527	-0.719340
2	-1.208970	1.002002	1.002002	0.902859	-0.352781	0.509930	0.071446	0.071446	-0.001205	0.071446	0.071446	0.248760	-0.719340
3	-1.208970	-0.998002	1.002002	0.319617	0.096214	0.852165	0.675780	0.675780	1.203528	0.675780	0.675780	0.830927	-0.719340
4	-1.208970	1.002002	1.002002	1.486101	1.156959	0.509930	1.267125	1.267125	1.203528	1.267125	1.267125	-0.973790	1.390162

1. K-Means Clustering

In [26]:
```
range_n_clusters = [2, 3, 4]
silhouette_avg_mean = []
for num_clusters in range_n_clusters:

    # intialise kmeans
    kmeans1 = KMeans(n_clusters = num_clusters, max_iter = 50)
    kmeans1.fit(dfCopy)

    cluster_labels = kmeans1.labels_

    # silhouette score
    silhouette_avg = silhouette_score(dfCopy, cluster_labels).round(3)
    silhouette_avg_mean.append(silhouette_avg)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, silhouette_avg))
```

```
For n_clusters=2, the silhouette score is 0.644
For n_clusters=3, the silhouette score is 0.591
For n_clusters=4, the silhouette score is 0.548
```

2. K-Medoids Clustering

In [27]:
```
range_n_clusters = [2, 3, 4]
silhouette_avg_med = []
for num_clusters in range_n_clusters:

    kmedoids1 = KMedoids(num_clusters).fit(dfCopy)
    cluster_labels = kmedoids1.labels_

    # silhouette score
    silhouette_avg = silhouette_score(dfCopy, cluster_labels).round(3)
    silhouette_avg_med.append(silhouette_avg)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, silhouette_avg))
```

```
For n_clusters=2, the silhouette score is 0.631
For n_clusters=3, the silhouette score is 0.582
For n_clusters=4, the silhouette score is 0.535
```

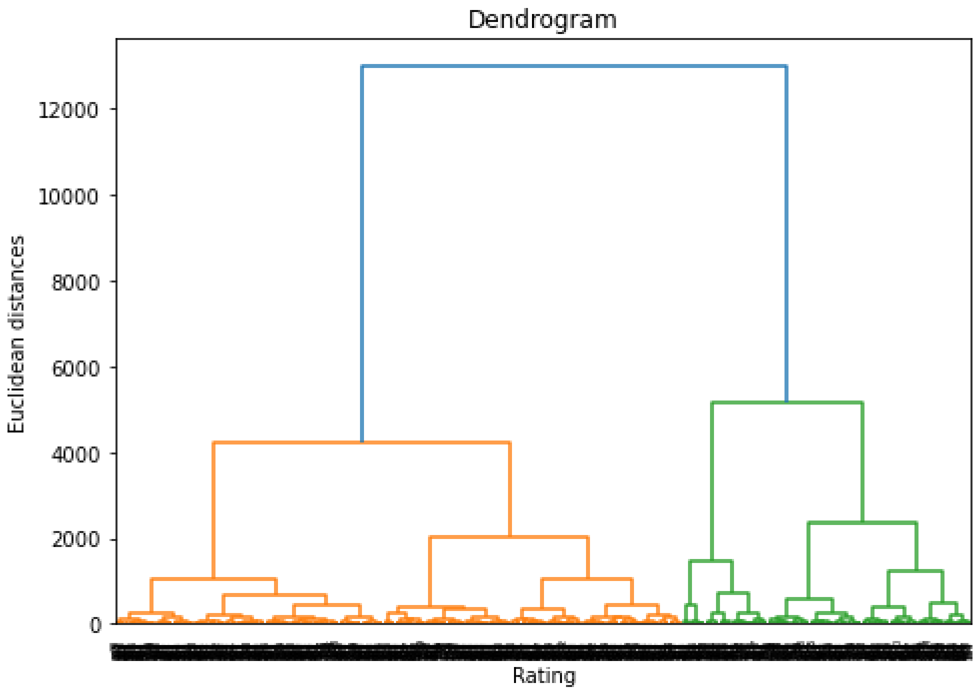
3. Agglomerative Hierarchical Clustering (AHC)

In [28]:

```
range_n_clusters = [2, 3, 4]
silhouette_avg_clust = []
for num_clusters in range_n_clusters:
    cluster1 = AgglomerativeClustering(n_clusters = num_clusters, affinity='euclidean', linkage='ward')
    cluster1.fit_predict(dfCopy)
    cluster_labels = cluster1.labels_

    # silhouette score
    silhouette_avg = silhouette_score(dfCopy, cluster_labels).round(3)
    silhouette_avg_clust.append(silhouette_avg)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, silhouette_avg))
```

```
For n_clusters=2, the silhouette score is 0.639
For n_clusters=3, the silhouette score is 0.59
For n_clusters=4, the silhouette score is 0.518
```

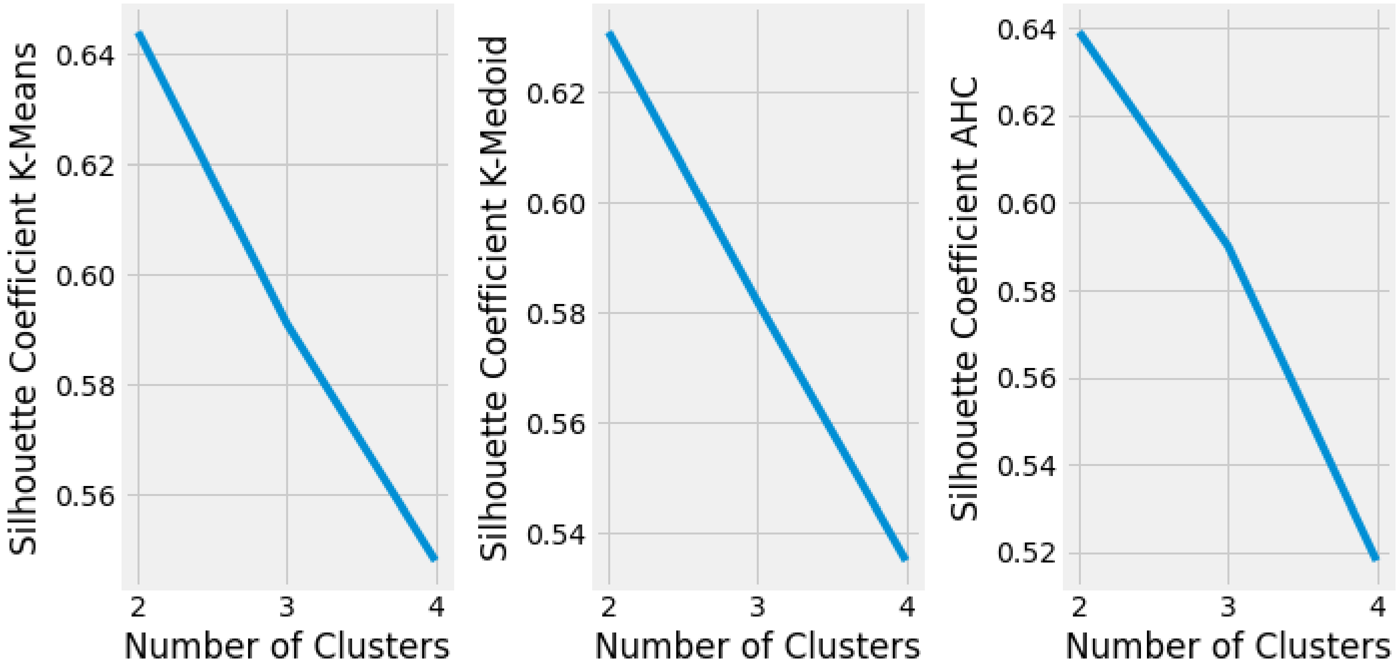
In [29]:
```
plt.figure(figsize=(7, 5))

dendrogram = sch.dendrogram(sch.linkage(dfCopy, method  = "ward"))
plt.title('Dendrogram')
plt.xlabel('Rating')
plt.ylabel('Euclidean distances')
plt.show()
```



Comparison of 3 Clustering methods using Elbow Method

In [30]:

```
plt.figure(figsize=(10, 5))

plt.style.use("fivethirtyeight")
plt.subplot(1,3,1)
plt.plot(range(2, 5), silhouette_avg_mean)
plt.xticks(range(2, 5))
plt.xlabel("Number of Clusters")
plt.ylabel("Silhouette Coefficient K-Means")

plt.style.use("fivethirtyeight")
plt.subplot(1,3,2)
plt.plot(range(2, 5), silhouette_avg_med)
plt.xticks(range(2, 5))
plt.xlabel("Number of Clusters")
plt.ylabel("Silhouette Coefficient K-Medoid")

plt.style.use("fivethirtyeight")
plt.subplot(1,3,3)
plt.plot(range(2, 5), silhouette_avg_clust)
plt.xticks(range(2, 5))
plt.xlabel("Number of Clusters")
plt.ylabel("Silhouette Coefficient AHC")

plt.subplots_adjust(left=1,
                    bottom=0.1,
                    right=2,
                    top=0.9,
                    wspace=1,
                    hspace=1)
plt.show()
```



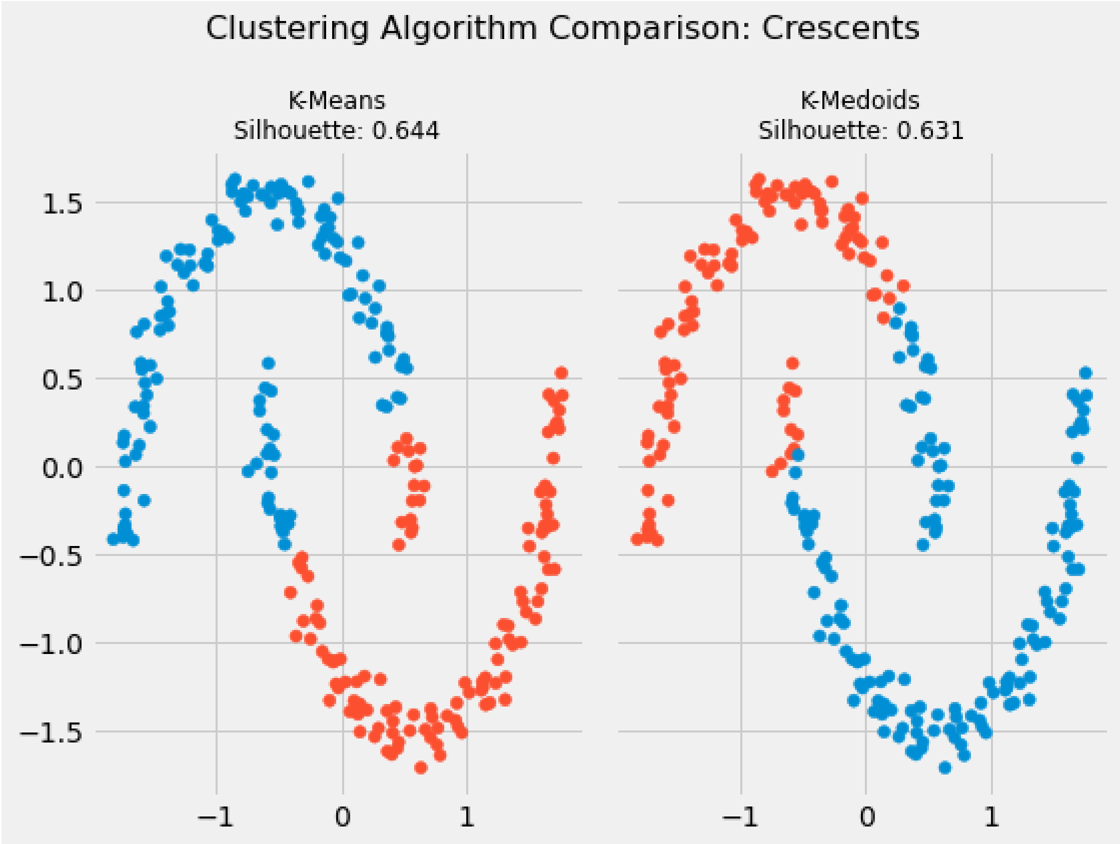
Best Silhouette Score

In [31]:
```
features, true_labels = make_moons(
    n_samples=250, noise=0.05, random_state=42
)
scaled_features1 = scaler.fit_transform(features)
```

In [32]:

```
# Best score is for k = 2
kmeans1 = KMeans(n_clusters=2)
kmedoids1 = KMedoids(n_clusters=2)
ahc1 = AgglomerativeClustering(n_clusters=2)

# Fit the algorithms to the features
kmeans1.fit(scaled_features1)
kmedoids1.fit(scaled_features1)
ahc1.fit_predict(scaled_features1)

# Compute the silhouette scores for each algorithm
kmeans_silhouette1 = silhouette_score(
    scaled_features1, kmeans1.labels_).round(3)
kmedoids_silhouette1 = silhouette_score(
   scaled_features1, kmedoids1.labels_).round (3)
ahc_silhouette1 = silhouette_score(
   scaled_features1, ahc1.labels_).round (3)
```

In [33]:
```
# Plot the data and cluster silhouette comparison
fig, (ax1, ax2) = plt.subplots(
    1, 2, figsize=(8, 6), sharex=True, sharey=True
)
fig.suptitle(f"Clustering Algorithm Comparison: Crescents", fontsize=16)
fte_colors = {
    0: "#008fd5",
    1: "#fc4f30",
}
# The k-means plot
kd_colors = [fte_colors[label] for label in kmeans1.labels_]
ax1.scatter(scaled_features1[:, 0], scaled_features1[:, 1], c=kd_colors)
ax1.set_title(
    f"K-Means\nSilhouette: {silhouette_avg_mean[0]}", fontdict={"fontsize": 12}
)

# The ahc plot
ahc_colors = [fte_colors[label] for label in kmedoids1.labels_]
ax2.scatter(scaled_features1[:, 0], scaled_features1[:, 1], c=ahc_colors)
ax2.set_title(
    f"K-Medoids\nSilhouette: {silhouette_avg_med[0]}", fontdict={"fontsize": 12}
)
plt.show()
```



5) Feature Selection Engineering

Feature Selection 1 - Filter Method (Removing Higher Correlated features)

In [34]:
```
def featSelectFilter(dfFeat1):
    # Create correlation matrix
    corr_matrix = corr.abs()

    # Select upper triangle of correlation matrix
    upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype('bool'))

    # Get features with correlation greater than 0.75
    to_drop = [column for column in upper.columns if any(upper[column] > 0.75)]

    print(color.BLUE + color.BOLD + 'Features removed since correlation is higher:' + color.END)
    print(to_drop)

    # Drop features
    dfFeat1.drop(list(to_drop), axis=1, inplace=True)

    #Size of the Dataset
    print(color.BLUE + color.BOLD + "\nSize of Dataset:" + color.END)
    print(dfFeat1.shape)

    return dfFeat1
```

In [35]:
```
#Transform the non numerical data into numerical
def transformToNumerical(dfFeat1):
    for column in dfFeat1.columns:
        #If Column data type is Int i.e, numerical continue
        if dfFeat1[column].dtype == 'int64' or dfFeat1[column].dtype == 'float64':
            continue
        #If Column data type is not Int, encode and transform to Numerical
        dfFeat1[column] = LabelEncoder().fit_transform(dfFeat1[column].astype(str))

    return dfFeat1
```

In [36]:

```python
def minMaxScaler(dfFeat1):
    # Using Min Max Scaler
    min_max_scaler = MinMaxScaler()
    min_max_scaled = min_max_scaler.fit_transform(dfFeat1)

    # Creating new Data frame with the scaled value
    FE1_Norm = pd.DataFrame(min_max_scaled, columns = dfFeat1.columns)

    return FE1_Norm
```

In [37]:

```python
#Split the entire dataset to Train and Test
def splitTrainTest(dfFeat1, dfFeat2):
    #Splitting the dataset
    X = dfFeat1.iloc[:, 0:dfFeat2.shape[1]]
    X = X.drop(['RatingLevel','Rating'], axis=1)
    Y = dfFeat1.iloc[:, -1]

    #Split the data into 75% training and 25% testing
    return train_test_split(X, Y, test_size = 0.25, random_state = 0)
```

In [38]:

```python
#Dimensionality Reduction using PCA
def dimReductionPCA(X_train, X_test):
    # Make an instance of the Model
    pca = PCA(.95)

    pca.fit(X_train)

    X_train = pca.transform(X_train) #PCA transformation on Train Set
    X_test = pca.transform(X_test) #PCA transformation on Test Set

    #How much information (variance) attributed to each of the principal components
    explained_variance = pca.explained_variance_ratio_
    print(color.BLUE + color.BOLD + 'Variance attributed to each of the principal components:' + color.END)
    print(explained_variance)

    return X_train, X_test
```

In [39]:

```
#Handling the Dataset Imbalance Using Hybridization: SMOTE + Tomek Links
def handleClassImbalance(X_train, Y_train):

    counter = Counter(Y_train) #Before Sampling, count of Y_train
    print(color.BLUE + color.BOLD + 'Before Sampling:' + color.END)
    print(counter)

    #Oversampling the train dataset using SMOTE + Tomek
    #To get better class clusters, Tomek links are applied to oversampled minority class samples done by SMOTE
    smtom = SMOTETomek(random_state=0)
    X_train_smtom, y_train_smtom = smtom.fit_resample(X_train, Y_train) #Fit the resampled model

    counter = Counter(y_train_smtom) #After Sampling, Count of y_train_smtom
    print(color.BLUE + color.BOLD + 'After Sampling:' + color.END)
    print(counter)

    return X_train_smtom, y_train_smtom
```

In [40]:

```
# Train the model using Random Forest classifier
# This meta estimator fits a number of decision tree classifiers on sub-samples of the
# dataset and uses averaging to improve the predictive accuracy and control over-fitting

def randomForestModel(X_train_smtom, y_train_smtom):
    #Number of trees given as '10' with criterion 'entropy' and seed for random generator is set as '0'
    randomforest = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state = 0)
    randomforest.fit(X_train_smtom, y_train_smtom)

    return randomforest
```

In [41]:
```python
#Plotting top features that help in predicting using the Random Forest Built-in Feature Importance

def importantFeatures(randomforest, dfFeat1):
    #Determine the feature importance values
    importances = randomforest.feature_importances_

    #Create a dictionary with the importances values
    important_features_dict = {}
    for idx, val in enumerate(importances):
        important_features_dict[idx] = val

    #Sort the feature importances in descending order
    important_features_list = sorted(important_features_dict,
                                     key=important_features_dict.get,
                                     reverse=True)[1:]

    important_features = dfFeat1.columns[important_features_list]

    #Visualize the top 6 feature importance using bar chart
    feat_importances = pd.Series(importances[important_features_list], index=important_features)
    feat_importances.nlargest(6).plot(kind='barh')
    plt.xlabel('Feature Importance')
    plt.title('Top Features With Higher Random Forest Feature Importance')
    plt.show()
```

In [42]:
```
# Create Machine Learning models - Logistic regression and Decision tree to predict

def mlPredict(X_train_smtom, y_train_smtom, Y_test):
    cv_dataFrames = []

    # Prepare Machine Learning models - Logistic regression and Decision tree
    models = []

    #Parametric Supervised learning model based on probability
    models.append(('Logistic Regression(LR)', LogisticRegression()))
    #Non-Parametric Supervised learning model by learning simple decision rules inferred from the data features
    models.append(('Decision Tree(CART)', DecisionTreeClassifier()))

    results = []
    mNames = [] #List for collecting model names

    #List of scoring metrics for comparison of models
    scoring = ['accuracy', 'precision_weighted', 'recall_weighted', 'f1_weighted', 'roc_auc']

    targ_names = ['Low', 'High'] #List of target values

    for mName, model in models: #Looping through each of the models

            #Split the dataset into '5' folds and Each fold is used once as a validation while the '5 - 1'
            #remaining folds form the training set
            #Shuffle is set to 'True' to shuffle the data before splitting into batches
            #Random_state affects the ordering of the indices, which controls the randomness of each fold
            kfold = model_selection.KFold(n_splits=5, shuffle=True, random_state=90210)

            #Evaluate metrics by cross-validation
            cv_res = model_selection.cross_validate(model, X_train_smtom, y_train_smtom, cv=kfold, scoring=scoring)

            #Fit the model and predict the label of test set
            ml = model.fit(X_train_smtom, y_train_smtom)
            y_pred = ml.predict(X_test)

            print(color.BLUE + color.BOLD + mName + color.END)

            #Number of correct and incorrect predictions compared wih Actual class and Predicted class
            cm = confusion_matrix(Y_test, y_pred)

```

```
            TN = cm[0][0] #True Negative(Predicted No, Actual No, classifier is getting things right)
            TP = cm[1][1] #True Positive(Predicted Yes, Actual Yes, classifier is getting things right)
            FN = cm[1][0] #False Negative(Predicted No, Actual Yes, classifier is getting things wrong i.e, mislabel
            FP = cm[0][1] #False Positive(Predicted Yes, Actual No, classifier is getting things wrong i.e, mislabel

            print(color.BOLD + "\nConfusion Matrix:" + color.END)

            column_names = ['Predicted Low', 'High']
            row_names    = ['Actual Low', 'High']

            cm_df = pd.DataFrame(cm, columns=column_names, index=row_names)

            print(cm_df)

            #Accuracy determines how often is classifier correct, (TP+TN)/Total
            print(color.BOLD + "\nAccuracy:" + color.END)
            print(round(accuracy_score(Y_test, y_pred) * 100, 2),"%")

            #Return the list of scores calculated for each cv='10' folds, estimator object
            #implementing ‘fit’ and n_jobs='-1' means using all processors
            cross_val_lr = cross_val_score(estimator = model, X = X_train_smtom, y = y_train_smtom, cv = 10, n_jobs
            print(color.BOLD + "\nCross Validation Accuracy:" + color.END)
            print(round(cross_val_lr.mean() * 100 , 2),"%")

            #Report showing the main classification metrics with the target names 'Yes' and 'No'
            print(color.BOLD + "\nClassification Report:" + color.END)
            print(classification_report(Y_test, y_pred, target_names=targ_names))

            #Get False Positive Rates and True Postive rates for the Classifiers
            #By roc_curve module by passing the test dataset and the predicted data through it
            print(color.BOLD + "\nReceiver Operating Characteristic(ROC):" + color.END)
            false_positive_rate1, true_positive_rate1, threshold1 = roc_curve(Y_test, y_pred)

            #Ploting ROC Curves with False Positive Rate on X-axis and True Positive Rate on Y-axis
            title = 'Receiver Operating Characteristic(ROC) - ' + mName
            plt.subplots(1, figsize=(7,5))
            plt.title(title)
            plt.plot(false_positive_rate1, true_positive_rate1)
            plt.plot([0, 1], ls="--")
            plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
            plt.ylabel('True Positive Rate')
            plt.xlabel('False Positive Rate')
```

```python

            results.append(cv_res) #Appending the cross validation metrics
            mNames.append(mName) #Appending each of the model names

            dataFrame = pd.DataFrame(cv_res) #Create data frame of cross validation results
            dataFrame['model'] = mName #Add the model name to dataframe
            cv_dataFrames.append(dataFrame) #Append each of the data frames

            result = pd.concat(cv_dataFrames, ignore_index=True) #Concatenate the the dataframes object ingnoring in
    return result
```

In [43]:
```
#Comparison of Performance of Logistic Regression and Decision tree models

def ml_ModelsComparison(result):
    mlValues = []

    #Iterating through result values and append the values of each models to mlValues[]
    for model in list(set(result.model.values)):
        m_dataFrame = result.loc[result.model == model]
        mlValue = m_dataFrame.sample(n=30, replace=True)
        mlValues.append(mlValue)

    m_dataFrame = pd.concat(mlValues, ignore_index=True) #Concatenate the the dataframes object ingnoring index

    #Massage a DataFrame into a format where identifier variable is 'model', variable column 'metrics'
    #and value column 'values'
    perf_results = pd.melt(m_dataFrame,id_vars=['model'],var_name='metrics', value_name='values')

    tym_metrics = ['fit_time','score_time'] # Fit time Metrics

    #Performance Metrics
    perf_results_nofit = perf_results.loc[~perf_results['metrics'].isin(tym_metrics)] # Get dataframe without fit da
    perf_results_nofit = perf_results_nofit.sort_values(by='values') #Sort the performance result on its values

    #Visualization of Comparison of LR and CART Model using BoxPlot
    plt.figure(figsize=(10, 7))
    sns.set(font_scale=1)
    g = sns.boxplot(x="model", y="values", hue="metrics", data=perf_results_nofit, palette="Set3")
    plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
    plt.title('Comparison of LR and CART Model by Classification Metric')

    return perf_results_nofit, m_dataFrame
```

Feature Selection 2 - Chi-Square and Mutual Info

In [44]:
```
def select_featureschi(X_train, y_train):
    fs = SelectKBest(score_func=chi2, k=5)
    fs.fit_transform(X_train, y_train)
    return fs

def selected_features_chi2(dfFeat2):
    #Splitting the dataset
    X = dfFeat2.iloc[:, 0:dfFeat2.shape[1]]
    X = X.drop(['RatingLevel','Rating'], axis=1)
    y = dfFeat2.iloc[:, -1]

    fs = select_featureschi(X, y)

    selected_features_chi2 = list(X.columns[fs.get_support(indices=True)])
    return selected_features_chi2
```

In [45]:
```
def select_featuresinfo(X_train, y_train):
    fs = SelectKBest(score_func=mutual_info_classif, k=5)
    fs.fit_transform(X_train, y_train)
    return fs

def selected_features_mutual_info(dfFeat2):
    #Splitting the dataset
    X = dfFeat2.iloc[:, 0:dfFeat2.shape[1]]
    X = X.drop(['RatingLevel','Rating'], axis=1)
    y = dfFeat2.iloc[:, -1]

    fs = select_featuresinfo(X, y)

    selected_features_mutual_info = list(X.columns[fs.get_support(indices=True)])
    return selected_features_mutual_info
```

Calling the functions

In [65]:
```
#Feature Selection 1 - Filter Method(Removing Higher Correlated features)
dfFeature1 = df.copy() #Create a copy of dataset
dfFeature1 = featSelectFilter(dfFeature1)
```

```
Features removed since correlation is higher:
['Selling Price', 'Cost Price', 'Gross Income']

Size of Dataset:
(1000, 10)
```

In [66]:
```
#Feature Encoding (To Numerical)
dfFeature1 = transformToNumerical(dfFeature1)
dfFeature1.head(2)
```

Out[66]:

	City	Customer Type	Gender	Product Type	Unit Price	Quantity	Tax	Payment Type	Rating	RatingLevel
0	0	0	0	3	74.69	7	26.1415	2	9.1	0
1	2	1	0	0	15.28	5	3.8200	0	9.6	0

In [67]:
```
dfFeature1 = minMaxScaler(dfFeature1)
dfFeature1.head(2)
```

Out[67]:

	City	Customer Type	Gender	Product Type	Unit Price	Quantity	Tax	Payment Type	Rating	RatingLevel
0	0.0	0.0	0.0	0.6	0.718847	0.666667	0.521616	1.0	0.850000	0.0
1	1.0	1.0	0.0	0.0	0.057855	0.444444	0.067387	0.0	0.933333	0.0

In [68]:
```
#Splitting the Dataset to Train and Test
X_train, X_test, Y_train, Y_test = splitTrainTest(dfFeature1, dfFeature1)
```

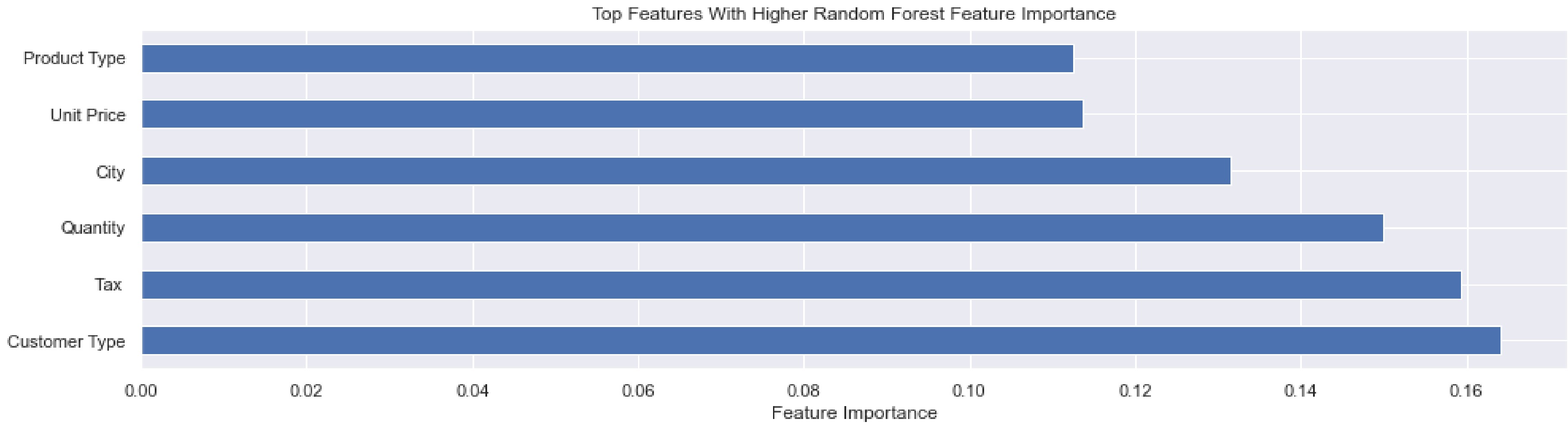
In [69]:
```
#PCA Dimensionality Reduction
X_train, X_test = dimReductionPCA(X_train, X_test)
```

```
Variance attributed to each of the principal components:
[0.22059842 0.19658315 0.14265224 0.14076454 0.12170646 0.0977056
 0.07657132]
```

In [70]:
```
#Handling Imbalanced Dataset
X_train_smtom, y_train_smtom = handleClassImbalance(X_train, Y_train)
```

```
Before Sampling:
Counter({0.0: 510, 1.0: 240})
After Sampling:
Counter({1.0: 465, 0.0: 465})
```

In [71]:
```
#RandomForest Model for important features
randomforest = randomForestModel(X_train_smtom, y_train_smtom)
importantFeatures(randomforest, dfFeature1)
```

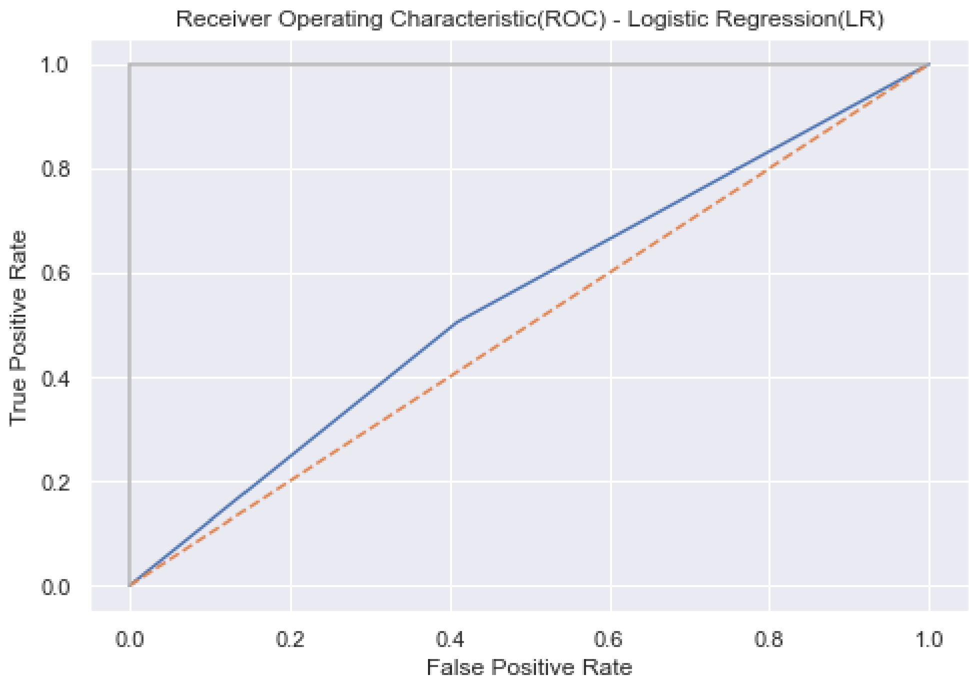


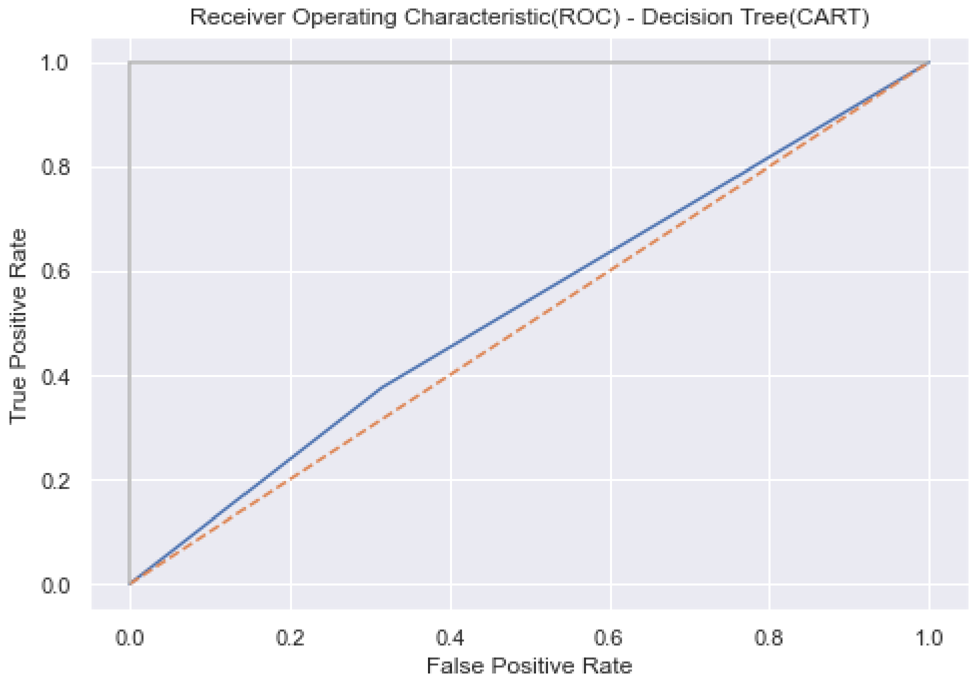
In [72]:
```
result = mlPredict(X_train_smtom, y_train_smtom, Y_test)
```

```
Logistic Regression(LR)

Confusion Matrix:
            Predicted Low  High
Actual Low             88    61
High                   50    51

Accuracy:
55.6 %

Cross Validation Accuracy:
52.26 %

Classification Report:
              precision    recall  f1-score   support

         Low       0.64      0.59      0.61       149
        High       0.46      0.50      0.48       101

    accuracy                           0.56       250
   macro avg       0.55      0.55      0.55       250
weighted avg       0.56      0.56      0.56       250


Receiver Operating Characteristic(ROC):
Decision Tree(CART)

Confusion Matrix:
            Predicted Low  High
Actual Low            102    47
High                   63    38

Accuracy:
56.0 %

Cross Validation Accuracy:
66.45 %

Classification Report:
```

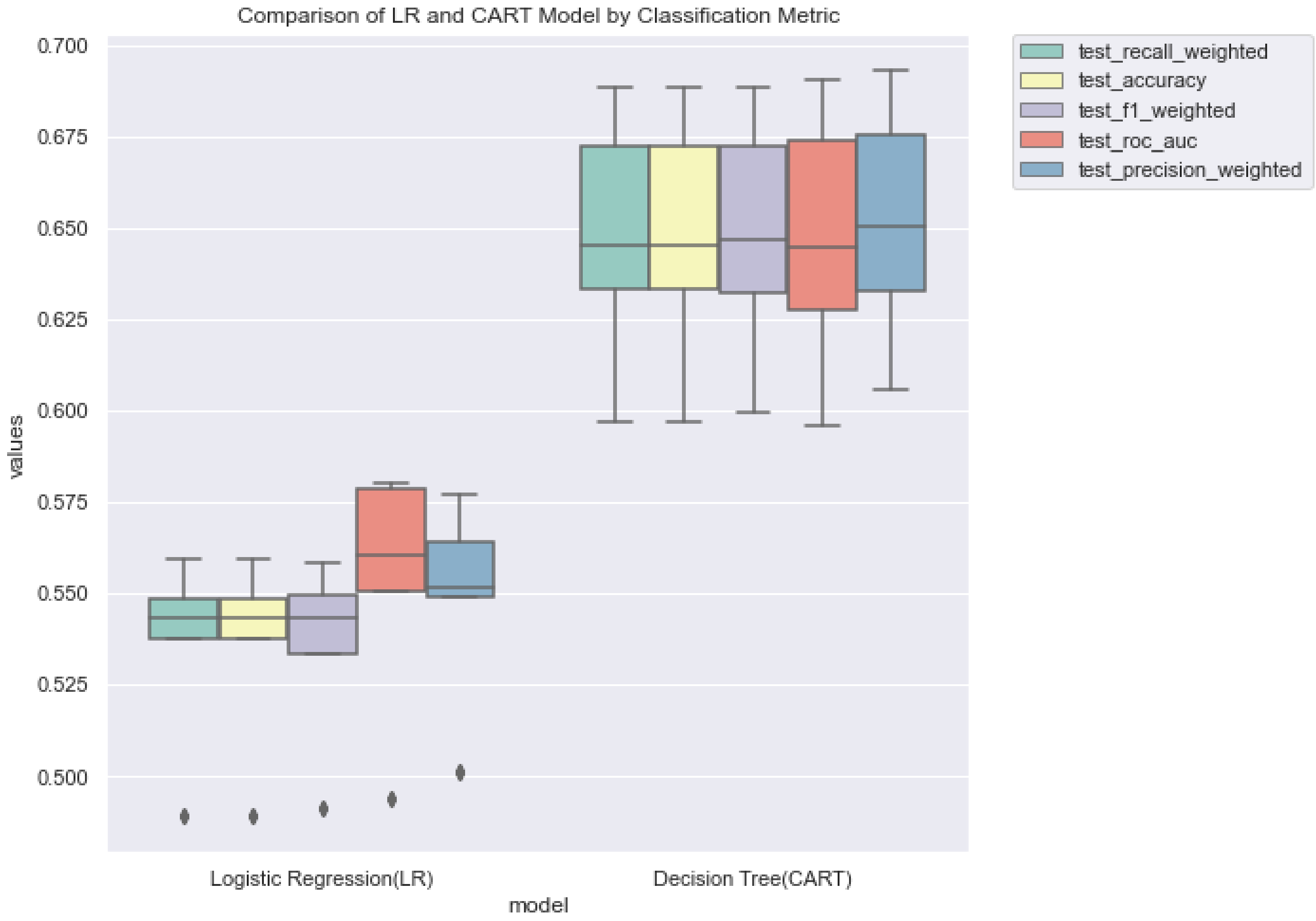
```
              precision    recall  f1-score   support

         Low       0.62      0.68      0.65       149
        High       0.45      0.38      0.41       101

    accuracy                           0.56       250
   macro avg       0.53      0.53      0.53       250
weighted avg       0.55      0.56      0.55       250
```

Receiver Operating Characteristic(ROC):




Receiver Operating Characteristic(ROC) - Decision Tree(CART)
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate

In [73]:
```
#Machine Learning models - Logistic regression and Decision tree to predict attrition and Comparison of Performance
perf_results_nofit, m_dataFrame = ml_ModelsComparison(result)
```



Comparison of Performance metrics

In [74]:

```
metricValues = list(set(perf_results_nofit.metrics.values))
#aggregate metric values with standard deviation and mean
m_dataFrame.groupby(['model'])[metricValues].agg([np.std, np.mean])
```

Out[74]:

	test_roc_auc		test_precision_weighted		test_recall_weighted		test_f1_weighted		test_accuracy	
	std	mean	std	mean	std	mean	std	mean	std	mean
model										
Decision Tree(CART)	0.030885	0.652509	0.028650	0.656883	0.028614	0.653047	0.028424	0.653472	0.028614	0.653047
Logistic Regression(LR)	0.028116	0.557448	0.022785	0.551660	0.021233	0.539247	0.020781	0.538785	0.021233	0.539247

In [95]:

```
dfFeature2 = df
dfFeature2 = transformToNumerical(dfFeature2)
featSelect2 = selected_features_chi2(dfFeature2) + selected_features_mutual_info(dfFeature2)
featSelect2 = list(set(featSelect2))
dfFeature2 = dfFeature2[featSelect2]
dfFeature2.head(2)
```

Out[95]:

	Tax	Selling Price	Cost Price	Gross Income	Unit Price	City
0	26.1415	548.9715	522.83	26.1415	74.69	0
1	3.8200	80.2200	76.40	3.8200	15.28	2

In [96]:

```
dfFeature2 = minMaxScaler(dfFeature2)
dfFeature2.head(2)
```

Out[96]:

	Tax	Selling Price	Cost Price	Gross Income	Unit Price	City
0	0.521616	0.521616	0.521616	0.521616	0.718847	0.0
1	0.067387	0.067387	0.067387	0.067387	0.057855	1.0

In [97]:

```
#Splitting the Dataset to Train and Test
X = dfFeature2.iloc[:, 0:dfFeature2.shape[1]]
Y = df.iloc[:, -1]

#Split the data into 75% training and 25% testing
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, random_state = 0)
```

In [98]:

```
#PCA Dimensionality Reduction
X_train, X_test = dimReductionPCA(X_train, X_test)
```

```
Variance attributed to each of the principal components:
[0.56511135 0.34336016 0.09152849]
```

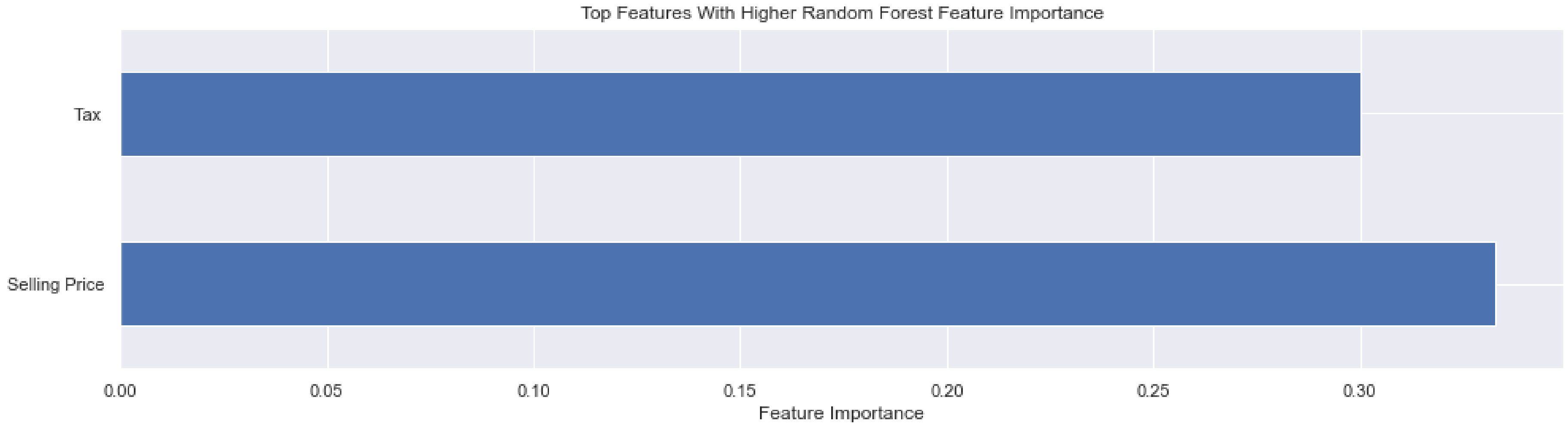
In [99]:

```
#Handling Imbalanced Dataset
X_train_smtom, y_train_smtom = handleClassImbalance(X_train, Y_train)
```

```
Before Sampling:
Counter({0: 510, 1: 240})
After Sampling:
Counter({1: 420, 0: 420})
```

In [100]:

```
#RandomForest Model for important features
randomforest = randomForestModel(X_train_smtom, y_train_smtom)
importantFeatures(randomforest, dfFeature2)
```



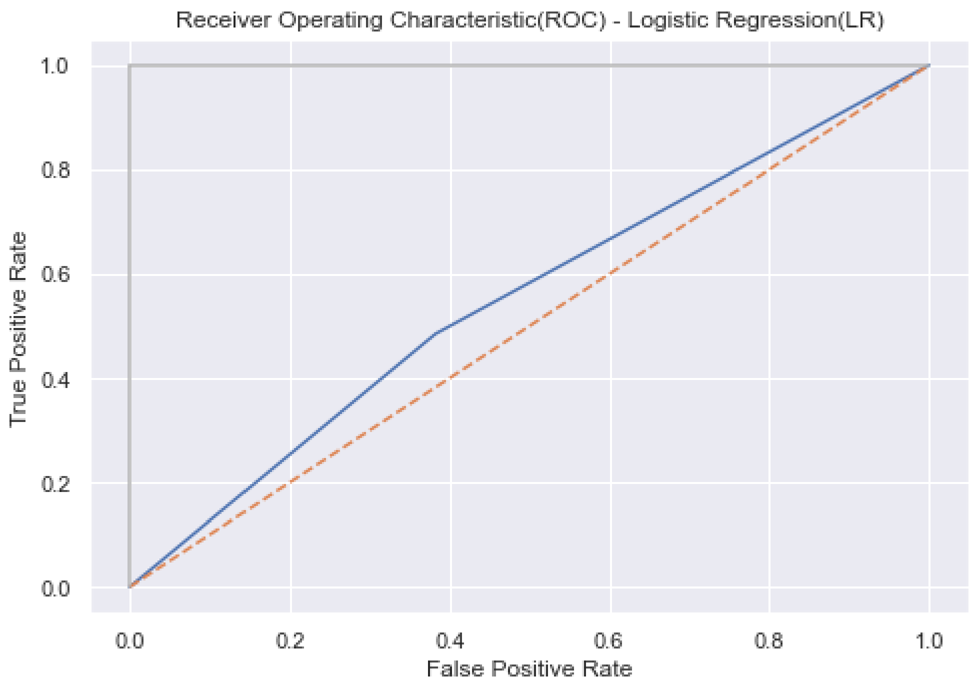
In [101]:
```
#Implement machine learning models to predict and gets the result of model and its performance metric values
result = mlPredict(X_train_smtom, y_train_smtom, Y_test)
```

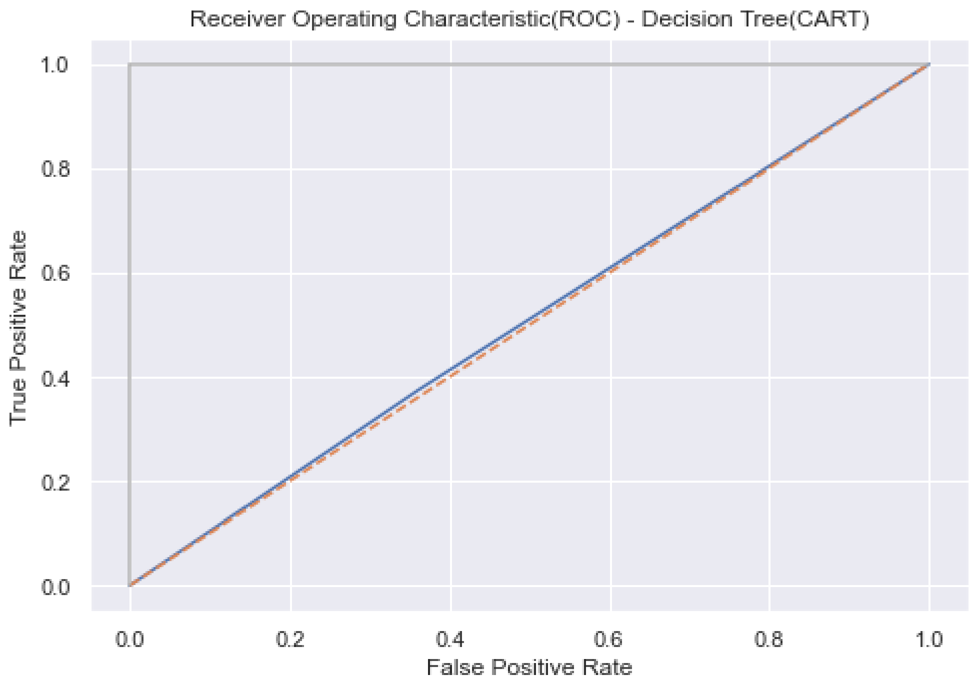
```
Logistic Regression(LR)

Confusion Matrix:
            Predicted Low  High
Actual Low             92    57
High                   52    49

Accuracy:
56.4 %

Cross Validation Accuracy:
53.1 %

Classification Report:
              precision    recall  f1-score   support

         Low       0.64      0.62      0.63       149
        High       0.46      0.49      0.47       101

    accuracy                           0.56       250
   macro avg       0.55      0.55      0.55       250
weighted avg       0.57      0.56      0.57       250


Receiver Operating Characteristic(ROC):
Decision Tree(CART)

Confusion Matrix:
            Predicted Low  High
Actual Low             95    54
High                   63    38

Accuracy:
53.2 %

Cross Validation Accuracy:
71.43 %
```

Classification Report:

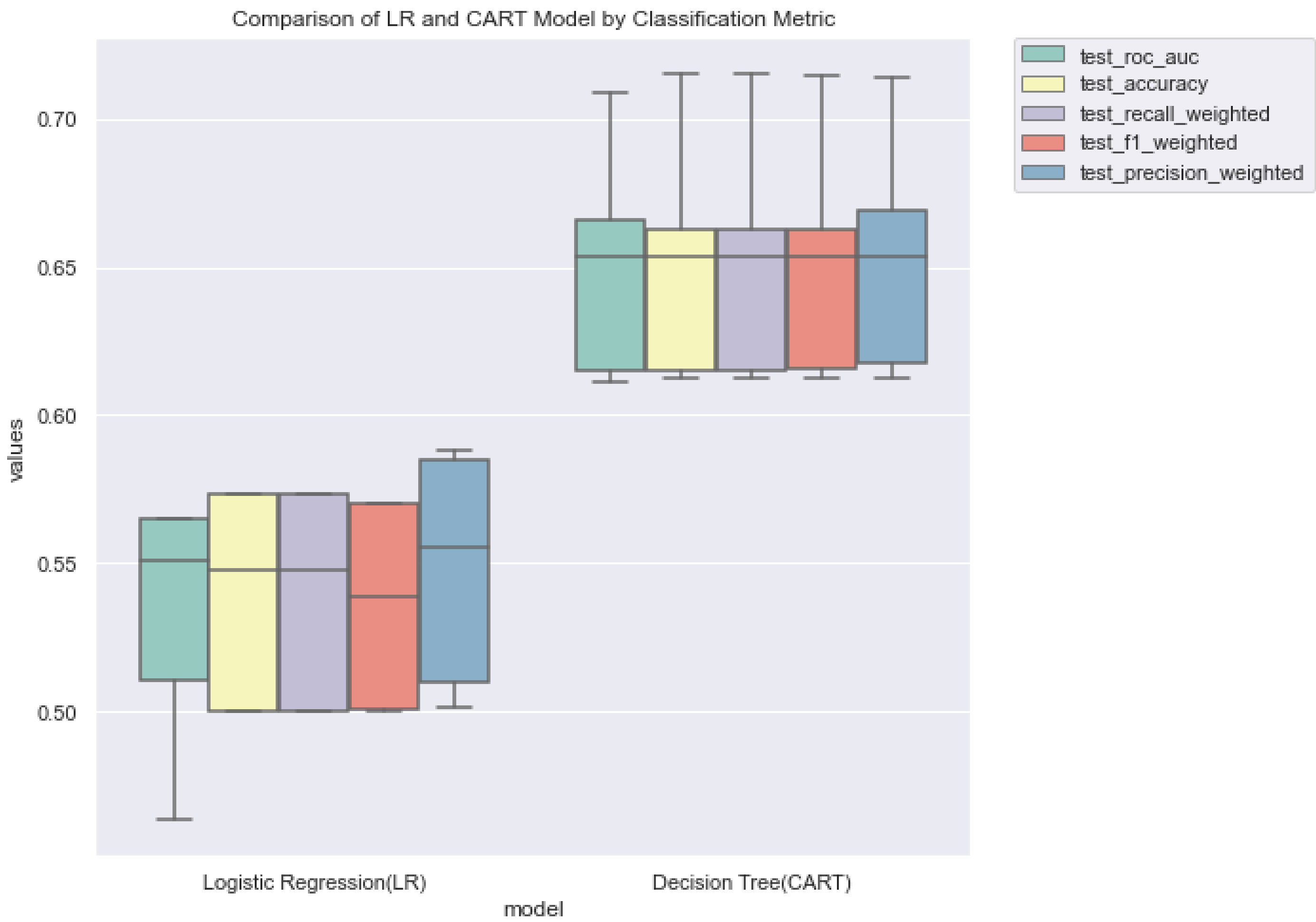
	precision	recall	f1-score	support
Low	0.60	0.64	0.62	149
High	0.41	0.38	0.39	101
accuracy			0.53	250
macro avg	0.51	0.51	0.51	250
weighted avg	0.53	0.53	0.53	250

Receiver Operating Characteristic(ROC):




Receiver Operating Characteristic(ROC) - Decision Tree(CART)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

In [93]:
```
#Machine Learning models - Logistic regression and Decision tree to predict attrition and Comparison of Performance
perf_results_nofit, m_dataFrame = ml_ModelsComparison(result)
```



In [102]:
```
#Comparison of Performance metrics
metricValues = list(set(perf_results_nofit.metrics.values))
#aggregate metric values with standard deviation and mean
m_dataFrame.groupby(['model'])[metricValues].agg([np.std, np.mean])
```

Out[102]:

	test_roc_auc		test_precision_weighted		test_recall_weighted		test_f1_weighted		test_accuracy	
	std	**mean**	**std**	**mean**	**std**	**mean**	**std**	**mean**	**std**	**mean**
model										
Decision Tree(CART)	0.036726	0.653031	0.037728	0.655696	0.038920	0.653889	0.038575	0.653844	0.038920	0.653889
Logistic Regression(LR)	0.039884	0.532562	0.036826	0.550070	0.031268	0.538111	0.030115	0.534811	0.031268	0.538111