In [1]:

```python
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import time

# Import functions/classes for data splitting and evaluation
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.utils import shuffle
from sklearn.metrics import confusion_matrix, accuracy_score, r2_score, mean_absolute_error,

# Import data preprocessing tools
from sklearn.preprocessing import MinMaxScaler

# Import feature selection techniques
from sklearn.feature_selection import RFE

# Import machine learning models
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier
```

Data reading

In [2]:

```python
# Load data from a CSV file into a pandas DataFrame
data = pd.read_csv('full_data_flightdelay_homogeneous.csv')

# Display the first few rows of the DataFrame
data.head()
```

Out[2]:

	MONTH	DAY_OF_WEEK	DEP_DEL15	DEP_TIME_BLK	DISTANCE_GROUP	SEGMENT_NUMBER	CO
0	1	7	0	0800-0859	2	1	
1	1	7	0	0700-0759	7	1	
2	1	7	0	0600-0659	7	1	
3	1	7	0	0600-0659	9	1	
4	1	7	0	0001-0559	7	1	

5 rows × 26 columns

In [3]:

```python
# Display information about the DataFrame
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1800000 entries, 0 to 1799999
Data columns (total 26 columns):
 #   Column                         Dtype  
---  ------                         -----  
 0   MONTH                          int64  
 1   DAY_OF_WEEK                    int64  
 2   DEP_DEL15                      int64  
 3   DEP_TIME_BLK                   object 
 4   DISTANCE_GROUP                 int64  
 5   SEGMENT_NUMBER                 int64  
 6   CONCURRENT_FLIGHTS             int64  
 7   NUMBER_OF_SEATS                int64  
 8   CARRIER_NAME                   object 
 9   AIRPORT_FLIGHTS_MONTH          int64  
 10  AIRLINE_FLIGHTS_MONTH          int64  
 11  AIRLINE_AIRPORT_FLIGHTS_MONTH  int64  
 12  AVG_MONTHLY_PASS_AIRPORT       int64  
 13  AVG_MONTHLY_PASS_AIRLINE       int64  
 14  FLT_ATTENDANTS_PER_PASS        float64
 15  GROUND_SERV_PER_PASS           float64
 16  PLANE_AGE                      int64  
 17  DEPARTING_AIRPORT              object 
 18  LATITUDE                       float64
 19  LONGITUDE                      float64
 20  PREVIOUS_AIRPORT               object 
 21  PRCP                           float64
 22  SNOW                           float64
 23  SNWD                           float64
 24  TMAX                           float64
 25  AWND                           float64
dtypes: float64(9), int64(13), object(4)
memory usage: 357.1+ MB
```

Missing value checking

In [4]:

```
# Calculate the number of missing values in each column
missing_values_count = data.isna().sum()

# Display the counts of missing values for each column
print(missing_values_count)
```

```
MONTH                            0
DAY_OF_WEEK                      0
DEP_DEL15                        0
DEP_TIME_BLK                     0
DISTANCE_GROUP                   0
SEGMENT_NUMBER                   0
CONCURRENT_FLIGHTS               0
NUMBER_OF_SEATS                  0
CARRIER_NAME                     0
AIRPORT_FLIGHTS_MONTH            0
AIRLINE_FLIGHTS_MONTH            0
AIRLINE_AIRPORT_FLIGHTS_MONTH    0
AVG_MONTHLY_PASS_AIRPORT         0
AVG_MONTHLY_PASS_AIRLINE         0
FLT_ATTENDANTS_PER_PASS          0
GROUND_SERV_PER_PASS             0
PLANE_AGE                        0
DEPARTING_AIRPORT                0
LATITUDE                         0
LONGITUDE                        0
PREVIOUS_AIRPORT                 0
PRCP                             0
SNOW                             0
SNWD                             0
TMAX                             0
AWND                             0
dtype: int64
```

In [5]:

```
# Calculate the total number of missing values in the entire DataFrame
total_missing_values = data.isna().sum().sum()

# Display the total count of missing values
print(total_missing_values)
```

```
0
```

Data overview

In [6]:

```
# Generate descriptive statistics for numerical columns and transpose the result
descriptive_stats = data.describe().T

# Display the transposed descriptive statistics
print(descriptive_stats)
```

	count	mean	std
MONTH	1800000.0	3.294008e+00	2.357582e+00
DAY_OF_WEEK	1800000.0	3.918581e+00	1.977897e+00
DEP_DEL15	1800000.0	5.000000e-01	5.000001e-01
DISTANCE_GROUP	1800000.0	3.865207e+00	2.387380e+00
SEGMENT_NUMBER	1800000.0	3.163912e+00	1.754791e+00
CONCURRENT_FLIGHTS	1800000.0	2.792447e+01	2.071932e+01
NUMBER_OF_SEATS	1800000.0	1.344216e+02	4.648333e+01
AIRPORT_FLIGHTS_MONTH	1800000.0	1.265846e+04	8.398980e+03
AIRLINE_FLIGHTS_MONTH	1800000.0	6.030820e+04	3.338628e+04
AIRLINE_AIRPORT_FLIGHTS_MONTH	1800000.0	3.460170e+03	4.130884e+03
AVG_MONTHLY_PASS_AIRPORT	1800000.0	1.654731e+06	1.112076e+06
AVG_MONTHLY_PASS_AIRLINE	1800000.0	7.860622e+06	5.033326e+06
FLT_ATTENDANTS_PER_PASS	1800000.0	9.738908e-05	8.572879e-05
GROUND_SERV_PER_PASS	1800000.0	1.357096e-04	4.683983e-05
PLANE_AGE	1800000.0	1.163163e+01	6.817443e+00
LATITUDE	1800000.0	3.660203e+01	5.322176e+00
LONGITUDE	1800000.0	-9.329169e+01	1.729925e+01
PRCP	1800000.0	1.272290e-01	3.585493e-01
SNOW	1800000.0	6.682433e-02	4.585613e-01
SNWD	1800000.0	2.088315e-01	1.122281e+00
TMAX	1800000.0	6.415482e+01	2.002129e+01
AWND	1800000.0	8.767776e+00	3.899940e+00

	min	25%	50%
MONTH	1.000000	1.000000e+00	2.000000e+00
DAY_OF_WEEK	1.000000	2.000000e+00	4.000000e+00
DEP_DEL15	0.000000	0.000000e+00	5.000000e-01
DISTANCE_GROUP	1.000000	2.000000e+00	3.000000e+00
SEGMENT_NUMBER	1.000000	2.000000e+00	3.000000e+00
CONCURRENT_FLIGHTS	1.000000	1.100000e+01	2.300000e+01
NUMBER_OF_SEATS	44.000000	9.000000e+01	1.430000e+02
AIRPORT_FLIGHTS_MONTH	1100.000000	5.629000e+03	1.150000e+04
AIRLINE_FLIGHTS_MONTH	5582.000000	2.420400e+04	6.727300e+04
AIRLINE_AIRPORT_FLIGHTS_MONTH	1.000000	6.870000e+02	2.374000e+03
AVG_MONTHLY_PASS_AIRPORT	70476.000000	7.325950e+05	1.486066e+06
AVG_MONTHLY_PASS_AIRLINE	473794.000000	2.688839e+06	8.501631e+06
FLT_ATTENDANTS_PER_PASS	0.000000	3.419267e-05	6.178236e-05
GROUND_SERV_PER_PASS	0.000007	9.889412e-05	1.246511e-04
PLANE_AGE	0.000000	5.000000e+00	1.200000e+01
LATITUDE	18.440000	3.343600e+01	3.736300e+01
LONGITUDE	-159.346000	-1.048800e+02	-8.790600e+01
PRCP	0.000000	0.000000e+00	0.000000e+00
SNOW	0.000000	0.000000e+00	0.000000e+00
SNWD	0.000000	0.000000e+00	0.000000e+00
TMAX	-10.000000	5.000000e+01	6.500000e+01
AWND	0.000000	5.820000e+00	8.050000e+00

	75%	max
MONTH	5.000000e+00	9.000000e+00
DAY_OF_WEEK	6.000000e+00	7.000000e+00
DEP_DEL15	1.000000e+00	1.000000e+00
DISTANCE_GROUP	5.000000e+00	1.100000e+01
SEGMENT_NUMBER	4.000000e+00	1.500000e+01
CONCURRENT_FLIGHTS	3.800000e+01	1.090000e+02
NUMBER_OF_SEATS	1.720000e+02	3.370000e+02
AIRPORT_FLIGHTS_MONTH	1.772500e+04	3.525600e+04
AIRLINE_FLIGHTS_MONTH	8.414200e+04	1.177280e+05
AIRLINE_AIRPORT_FLIGHTS_MONTH	4.621000e+03	2.183700e+04
AVG_MONTHLY_PASS_AIRPORT	2.006675e+06	4.365661e+06
AVG_MONTHLY_PASS_AIRLINE	1.246018e+07	1.338300e+07
FLT_ATTENDANTS_PER_PASS	1.441659e-04	3.484077e-04
GROUND_SERV_PER_PASS	1.772872e-04	2.289855e-04
PLANE_AGE	1.700000e+01	3.200000e+01

```
LATITUDE                        4.069600e+01  6.116900e+01
LONGITUDE                      -8.028600e+01 -6.600200e+01
PRCP                            6.000000e-02  1.163000e+01
SNOW                            0.000000e+00  1.720000e+01
SNWD                            0.000000e+00  2.520000e+01
TMAX                            8.000000e+01  1.150000e+02
AWND                            1.096000e+01  3.378000e+01
```

Checking for correlation to Delay

In [7]:

```python
# Calculate the correlation between 'DEP_DEL15' and other columns, then sort in descending or
correlation = data.corr()['DEP_DEL15'].sort_values(ascending=False)

# Convert the correlation Series to a dictionary
correlation = dict(correlation)

# Display the dictionary of correlations
print(correlation)
```

```
{'DEP_DEL15': 1.0, 'MONTH': 0.6818409946756656, 'TMAX': 0.46268815781141864, 'SEGM
ENT_NUMBER': 0.17619800585620826, 'PRCP': 0.10795646853423063, 'AIRLINE_FLIGHTS_MO
NTH': 0.08347182043065618, 'AIRPORT_FLIGHTS_MONTH': 0.06833123970612442, 'AIRLINE_
AIRPORT_FLIGHTS_MONTH': 0.034240164814195756, 'LONGITUDE': 0.02310964496049418, 'D
ISTANCE_GROUP': 0.01980112050587317, 'CONCURRENT_FLIGHTS': 0.018207650004022406,
'LATITUDE': 0.01755962802789539, 'DAY_OF_WEEK': 0.013517450497152927, 'NUMBER_OF_S
EATS': 0.013483655637696155, 'FLT_ATTENDANTS_PER_PASS': 0.01108868603363913, 'PLAN
E_AGE': 0.007047365389451535, 'AVG_MONTHLY_PASS_AIRPORT': 0.003078476307401366, 'A
VG_MONTHLY_PASS_AIRLINE': -0.0010069409932715074, 'AWND': -0.002199490270674606б,
'SNOW': -0.017772500269065017, 'GROUND_SERV_PER_PASS': -0.02397417927019624, 'SNW
D': -0.06810342489840361}
```

In [8]:

```python
# Create a copy of the correlation dictionary
corr_matrix = correlation.copy()

# Initialize a list to store column names to be dropped
cols_to_drop = []

# Iterate over the columns in the correlation dictionary
for key in corr_matrix:
    value = corr_matrix[key]

    # Check if the absolute value of the correlation is less than 0.05 or if value is None
    if (abs(value) < 0.05) or pd.isnull(value):
        cols_to_drop.append(key)

# Drop the columns from the DataFrame
data = data.drop(cols_to_drop, axis=1)

# Display the list of columns to be dropped
print(cols_to_drop)
```

```
['AIRLINE_AIRPORT_FLIGHTS_MONTH', 'LONGITUDE', 'DISTANCE_GROUP', 'CONCURRENT_FLIGH
TS', 'LATITUDE', 'DAY_OF_WEEK', 'NUMBER_OF_SEATS', 'FLT_ATTENDANTS_PER_PASS', 'PLA
NE_AGE', 'AVG_MONTHLY_PASS_AIRPORT', 'AVG_MONTHLY_PASS_AIRLINE', 'AWND', 'SNOW',
'GROUND_SERV_PER_PASS']
```

In [9]:

```
# Retrieve the dimensions (number of rows and columns) of the DataFrame
data_shape = data.shape

# Display the dimensions
print(data_shape)
```

```
(1800000, 12)
```

In [10]:

```
# Import the LabelEncoder from scikit-learn
from sklearn.preprocessing import LabelEncoder

# Create a LabelEncoder object
le = LabelEncoder()

# Define a function to clean and encode categorical labels
def clean_labels_encoder(list_of_labels, df):
    for label in list_of_labels:
        # Apply the LabelEncoder to each categorical column
        df[label] = le.fit_transform(df[label])
    return df

# List of categorical labels to be encoded
list_of_labels = ['CARRIER_NAME', 'DEPARTING_AIRPORT', 'PREVIOUS_AIRPORT', 'DEP_TIME_BLK']

# Call the clean_labels_encoder function to encode categorical labels in the DataFrame
data = clean_labels_encoder(list_of_labels, data)

# Display the first few rows of the updated DataFrame
data.head()
```

Out[10]:

	MONTH	DEP_DEL15	DEP_TIME_BLK	SEGMENT_NUMBER	CARRIER_NAME	AIRPORT_FLIGHTS_MO
0	1	0	3	1	14	1[illegible]
1	1	0	2	1	6	1[illegible]
2	1	0	1	1	6	1[illegible]
3	1	0	1	1	6	1[illegible]
4	1	0	0	1	15	1[illegible]

In [11]:

```
# Check the data types of the columns
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1800000 entries, 0 to 1799999
Data columns (total 12 columns):
 #   Column                Dtype  
---  ------                -----  
 0   MONTH                 int64  
 1   DEP_DEL15             int64  
 2   DEP_TIME_BLK          int32  
 3   SEGMENT_NUMBER        int64  
 4   CARRIER_NAME          int32  
 5   AIRPORT_FLIGHTS_MONTH int64  
 6   AIRLINE_FLIGHTS_MONTH int64  
 7   DEPARTING_AIRPORT     int32  
 8   PREVIOUS_AIRPORT      int32  
 9   PRCP                  float64
 10  SNWD                  float64
 11  TMAX                  float64
dtypes: float64(3), int32(4), int64(5)
memory usage: 137.3 MB
```

In [12]:

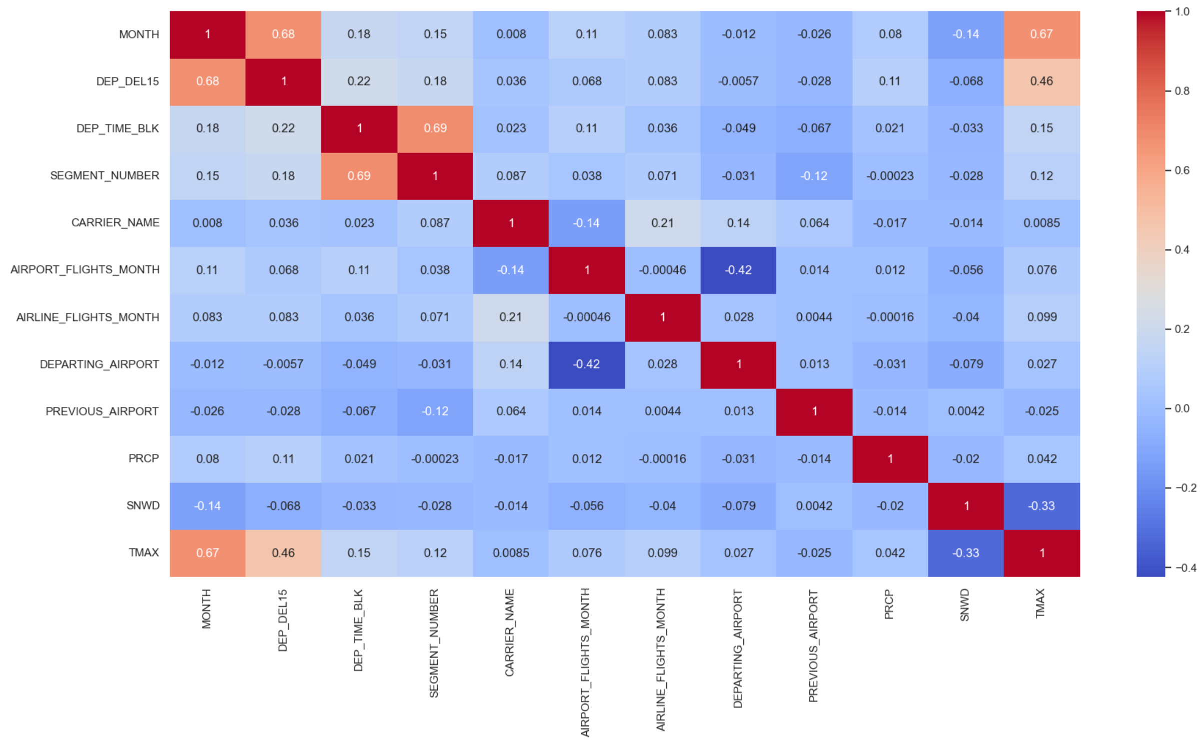
```
# Fill the missing values with mean
data.fillna(data.mean(), inplace=True)

# Show correlation
data.corr()
```

Out[12]:

	MONTH	DEP_DEL15	DEP_TIME_BLK	SEGMENT_NUMBER	CARRIER_NAI
MONTH	1.000000	0.681841	0.175822	0.149307	0.0080
DEP_DEL15	0.681841	1.000000	0.218007	0.176198	0.0361
DEP_TIME_BLK	0.175822	0.218007	1.000000	0.685484	0.0226
SEGMENT_NUMBER	0.149307	0.176198	0.685484	1.000000	0.0865
CARRIER_NAME	0.008007	0.036173	0.022698	0.086529	1.0000
AIRPORT_FLIGHTS_MONTH	0.112468	0.068331	0.108877	0.038220	-0.1446
AIRLINE_FLIGHTS_MONTH	0.082950	0.083472	0.035732	0.070835	0.2123
DEPARTING_AIRPORT	-0.012145	-0.005653	-0.048636	-0.031220	0.1365
PREVIOUS_AIRPORT	-0.025931	-0.028493	-0.066602	-0.115422	0.0637
PRCP	0.079968	0.107956	0.021305	-0.000232	-0.0171
SNWD	-0.135256	-0.068103	-0.032791	-0.027501	-0.0138
TMAX	0.674452	0.462688	0.150210	0.115568	0.0085

In [13]:

```python
# Import necessary libraries for visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Define a function to show the correlation heatmap
def show_correlation(df):
    # Set the size of the figure
    plt.figure(figsize=(20, 10))

    # Set style and context for the plot
    sns.set(style='whitegrid', context='notebook')

    # Generate the heatmap of the correlation matrix
    sns.heatmap(df.corr(), annot=True, square=False, cmap='coolwarm')

    # Display the plot
    plt.show()

# Call the show_correlation function to visualize the correlation heatmap
show_correlation(data)
```



Data normalization

In [14]:

```
# Shuffle the rows of the DataFrame
data = shuffle(data)

# Import the MinMaxScaler from scikit-learn
from sklearn.preprocessing import MinMaxScaler

# Create a MinMaxScaler object
scaler = MinMaxScaler()

# Fit the scaler on the data and transform it
scaled = scaler.fit_transform(data)
```

In [15]:

```
# Create a new DataFrame with scaled values
data_scaled = pd.DataFrame(scaled, index=data.index, columns=data.columns)
```

In [16]:

```
# Extract input features (X) and target variable (Y)
X = data_scaled.drop(['DEP_DEL15'], axis=1)
Y = data_scaled['DEP_DEL15']
```

In [17]:

```
# Import the train_test_split function from scikit-learn
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets
# X_train: training input features
# X_test: testing input features
# y_train: training target variable
# y_test: testing target variable
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, random_state=4)

# Display the shape of the training input features
print(X_train.shape)
```

```
(1206000, 11)
```

In [18]:

```
labels = ['False','True']
```

Train and Test

In [19]:

```
# Build a classification model using various supervised machine
# learning models and check which model gives you the best accuracy

# use the following models
# 1. Logistic Regression
# 2. Decision Tree
# 3. GaussianNB
# 4. MLPClassifier
# 5. RandomForestClassifier
```

In [20]:

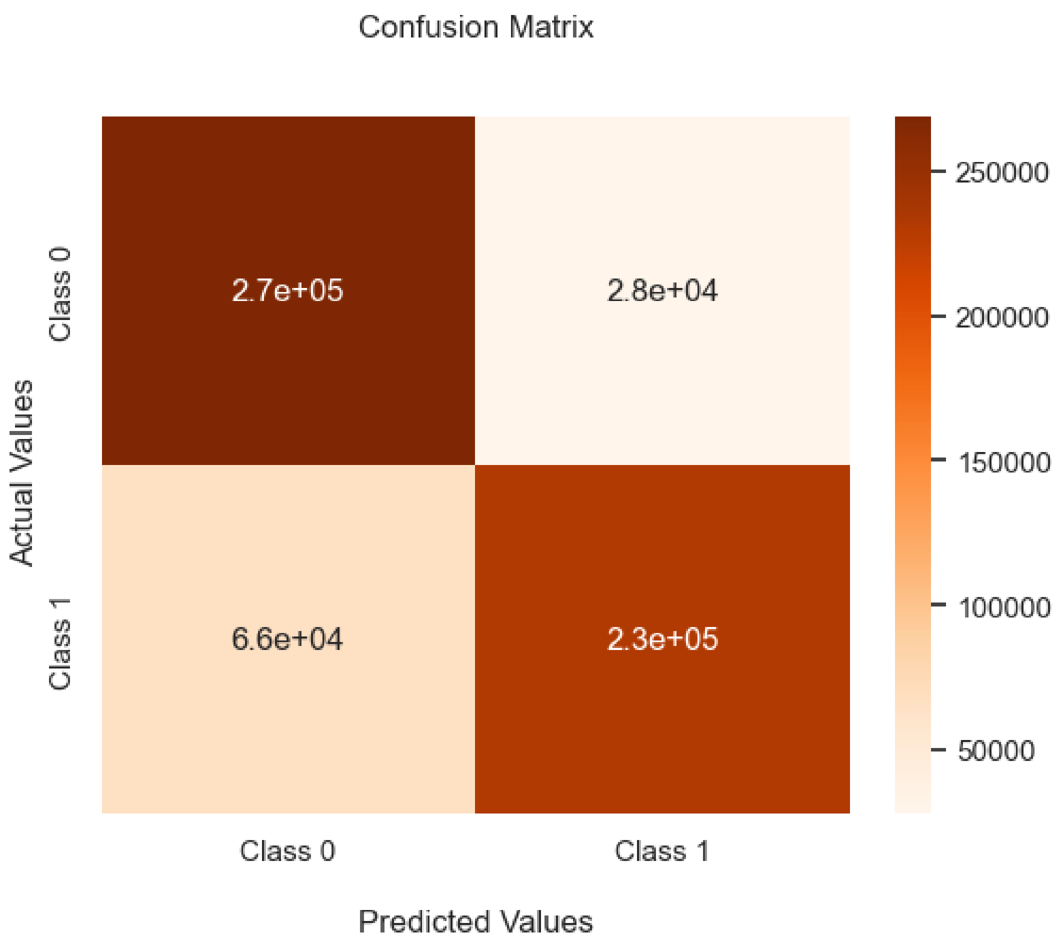
```
# Import necessary libraries for metrics and visualization
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns

# Define a function to print a separator line
def separator(count=50):
    print('-' * count)

# Define the function to train the model and print accuracy metrics
def train_model_and_print_accuracy(model, X_train, y_train, X_test, y_test):
    # Train the model
    model.fit(X_train, y_train)

    # Calculate and print train and test scores
    scoreTrain = model.score(X_train, y_train)
    scoreTest = model.score(X_test, y_test)

    # Predict the test data
    predict_test = model.predict(X_test)

    # Calculate confusion matrix and classification report
    cm_result = confusion_matrix(y_test, predict_test)
    cr_result = classification_report(y_test, predict_test)

    # Get the model name
    model_name = str(model).split('(')[0]

    # Print model name in bold
    print('\033[1m' + model_name + '\033[0m')

    # Print separator
    separator()
    print('Train Score for ' + model_name + ':', scoreTrain)
    separator()
    print('Test Score for ' + model_name + ':', scoreTest)
    separator()
    print('Confusion Matrix for ' + model_name + ' for test:\n', cm_result)
    separator()
    print('Classification Report for ' + model_name + ' for test:\n', str(cr_result))
    separator()

    # Plot confusion matrix
    model_confusion_matrix = confusion_matrix(y_test, predict_test)
    print('Confusion Matrix:\n', str(model_confusion_matrix))
    separator()
    ax = sns.heatmap(model_confusion_matrix, annot=True, cmap='Oranges')
    ax.set_title('Confusion Matrix\n\n')
    ax.set_xlabel('\nPredicted Values')
    ax.set_ylabel('Actual Values ')
    labels = ['Class 0', 'Class 1']  # Modify according to your class labels
    ax.xaxis.set_ticklabels(labels)
    ax.yaxis.set_ticklabels(labels)
    plt.show()

    separator()
```

In [21]:

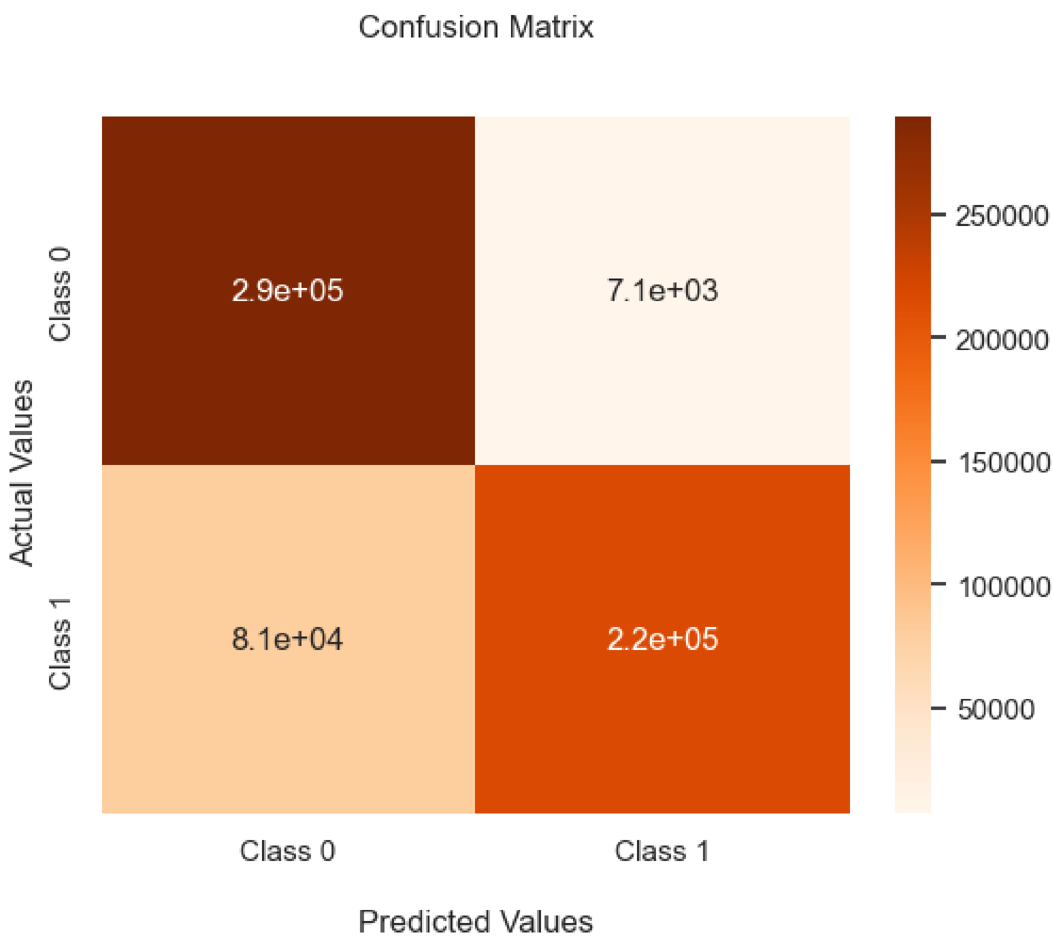
```python
# using logistic regression
# 1. Logistic Regression
# 2. Decision Tree
# 3. GaussianNB
# 4. MLPClassifier
# 5. RandomForestClassifier

# Import necessary classifier classes
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier

# Initialize the classifiers
log_reg = LogisticRegression()
dt = DecisionTreeClassifier(max_depth=3)
gnb = GaussianNB()
mlp = MLPClassifier(random_state=1, max_iter=300)
rfc = RandomForestClassifier(max_depth=3)

# List of models
models = [log_reg, dt, gnb, rfc, mlp]

# Train each model and print accuracy metrics
for model in models:
    train_model_and_print_accuracy(model, X_train, y_train, X_test, y_test)
```

LogisticRegression

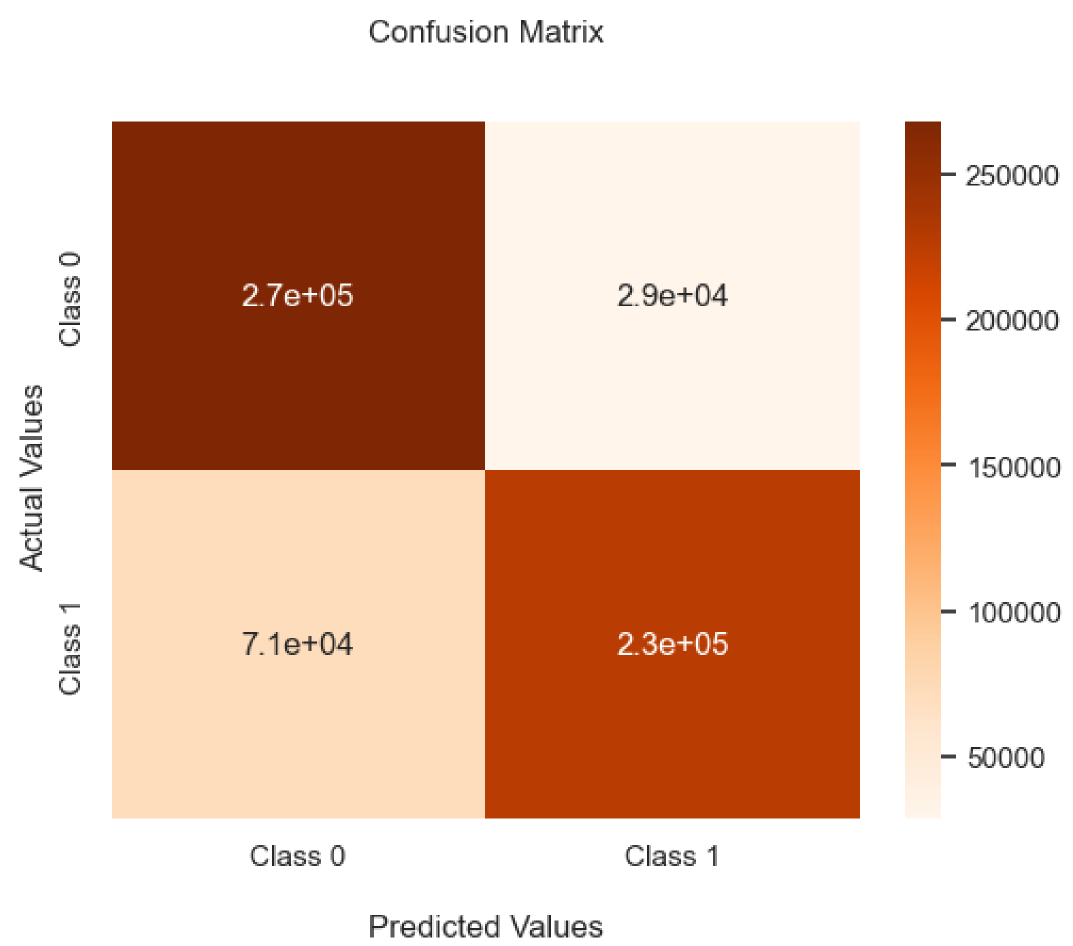
```
--------------------------------------------------
Train Score for LogisticRegression: 0.840879767827529
--------------------------------------------------
Test Score for LogisticRegression: 0.8413080808080808
--------------------------------------------------
Confusion Matrix for LogisticRegression for test:
 [[268501  27978]
 [ 66285 231236]]
--------------------------------------------------
Classification Report for LogisticRegression for test:
              precision    recall  f1-score   support

         0.0       0.80      0.91      0.85    296479
         1.0       0.89      0.78      0.83    297521

    accuracy                           0.84    594000
   macro avg       0.85      0.84      0.84    594000
weighted avg       0.85      0.84      0.84    594000

--------------------------------------------------
Confusion Matrix:
 [[268501  27978]
 [ 66285 231236]]
--------------------------------------------------
```



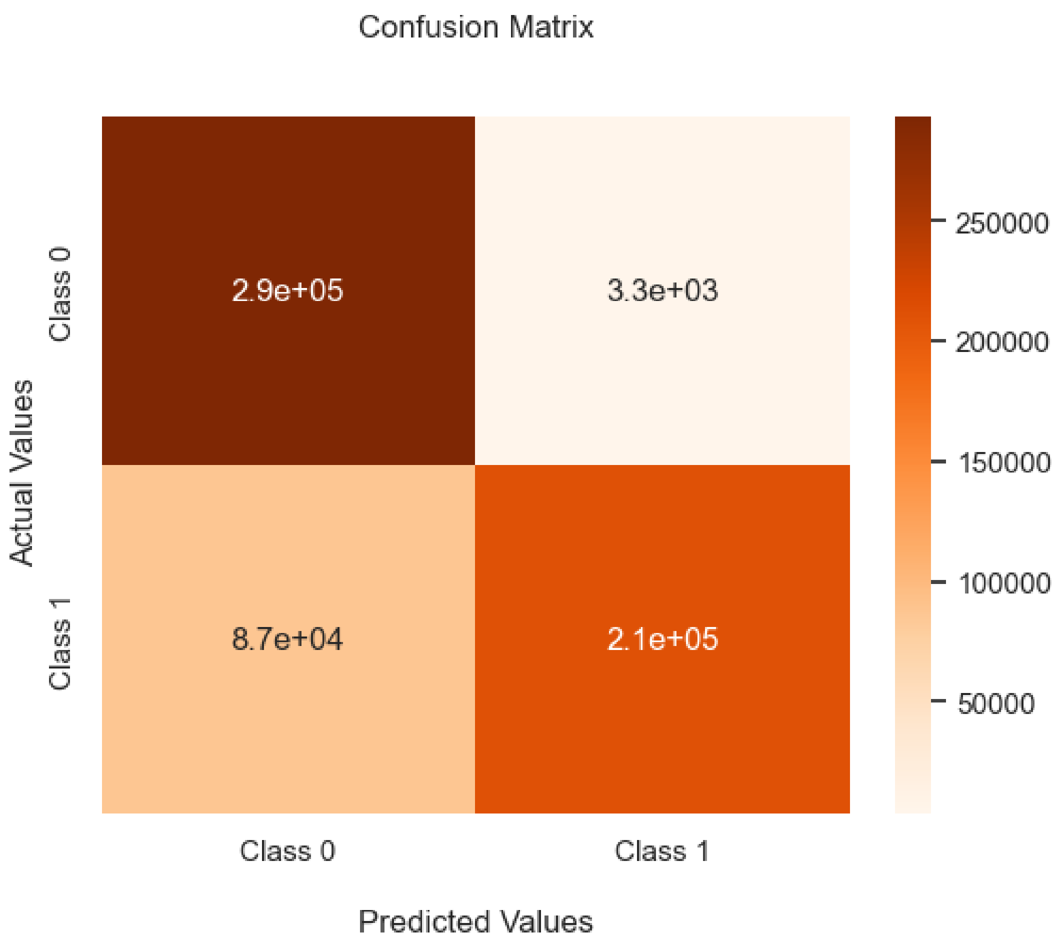

```
--------------------------------------------------
DecisionTreeClassifier
--------------------------------------------------
Train Score for DecisionTreeClassifier: 0.8509618573797678
--------------------------------------------------
Test Score for DecisionTreeClassifier: 0.8517508417508417
--------------------------------------------------
Confusion Matrix for DecisionTreeClassifier for test:
 [[289373   7106]
 [ 80954 216567]]
--------------------------------------------------
Classification Report for DecisionTreeClassifier for test:
              precision    recall  f1-score   support

         0.0       0.78      0.98      0.87    296479
         1.0       0.97      0.73      0.83    297521

    accuracy                           0.85    594000
   macro avg       0.87      0.85      0.85    594000
weighted avg       0.87      0.85      0.85    594000

--------------------------------------------------
Confusion Matrix:
 [[289373   7106]
 [ 80954 216567]]
--------------------------------------------------
```




```
--------------------------------------------------
GaussianNB
--------------------------------------------------
Train Score for GaussianNB: 0.8310082918739635
--------------------------------------------------
Test Score for GaussianNB: 0.831925925925926
--------------------------------------------------
Confusion Matrix for GaussianNB for test:
 [[267843  28636]
 [ 71200 226321]]
--------------------------------------------------
Classification Report for GaussianNB for test:
               precision    recall  f1-score   support

         0.0       0.79      0.90      0.84    296479
         1.0       0.89      0.76      0.82    297521

    accuracy                           0.83    594000
   macro avg       0.84      0.83      0.83    594000
weighted avg       0.84      0.83      0.83    594000

--------------------------------------------------
Confusion Matrix:
 [[267843  28636]
 [ 71200 226321]]
--------------------------------------------------
```



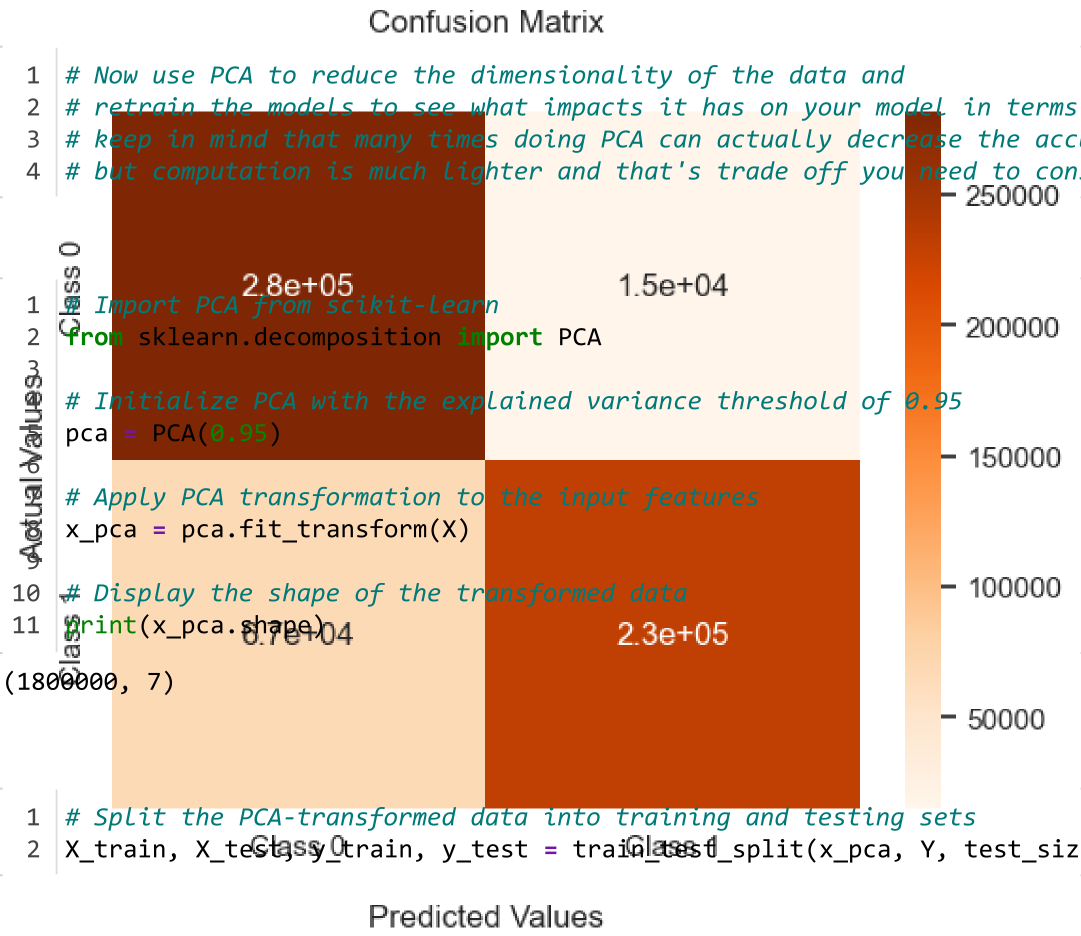

```
--------------------------------------------------
RandomForestClassifier
--------------------------------------------------
Train Score for RandomForestClassifier: 0.8475149253731343
--------------------------------------------------
Test Score for RandomForestClassifier: 0.8485235690235691
--------------------------------------------------
Confusion Matrix for RandomForestClassifier for test:
 [[293206   3273]
 [ 86704 210817]]
--------------------------------------------------
Classification Report for RandomForestClassifier for test:
               precision    recall  f1-score   support

         0.0       0.77      0.99      0.87    296479
         1.0       0.98      0.71      0.82    297521

    accuracy                           0.85    594000
   macro avg       0.88      0.85      0.85    594000
weighted avg       0.88      0.85      0.85    594000

--------------------------------------------------
Confusion Matrix:
 [[293206   3273]
 [ 86704 210817]]
--------------------------------------------------
```




```
--------------------------------------------------
MLPClassifier
--------------------------------------------------
Train Score for MLPClassifier: 0.8625331674958541
--------------------------------------------------
Test Score for MLPClassifier: 0.8625488215488215
--------------------------------------------------
Confusion Matrix for MLPClassifier for test:
 [[281357  15122]
 [ 66524 230997]]
--------------------------------------------------
Classification Report for MLPClassifier for test:
              precision    recall  f1-score   support

         0.0       0.81      0.95      0.87    296479
         1.0       0.94      0.78      0.85    297521

    accuracy                           0.86    594000
   macro avg       0.87      0.86      0.86    594000
weighted avg       0.87      0.86      0.86    594000

--------------------------------------------------
Confusion Matrix:
 [[281357  15122]
 [ 66524 230997]]
--------------------------------------------------
```

In [22]:

```
# conclusion before PCA - principal component analysis
# show that best modal is MLPClassifier with 0.86 accuracy (approx)
```




```python
# Now use PCA to reduce the dimensionality of the data and
# retrain the models to see what impacts it has on your model in terms of accuracy.
# keep in mind that many times doing PCA can actually decrease the accuracy of your model
# but computation is much lighter and that's trade off you need to consider while build model
```

```python
# Import PCA from scikit-learn
from sklearn.decomposition import PCA

# Initialize PCA with the explained variance threshold of 0.95
pca = PCA(0.95)

# Apply PCA transformation to the input features
x_pca = pca.fit_transform(X)

# Display the shape of the transformed data
print(x_pca.shape)
```

```
(1800000, 7)
```

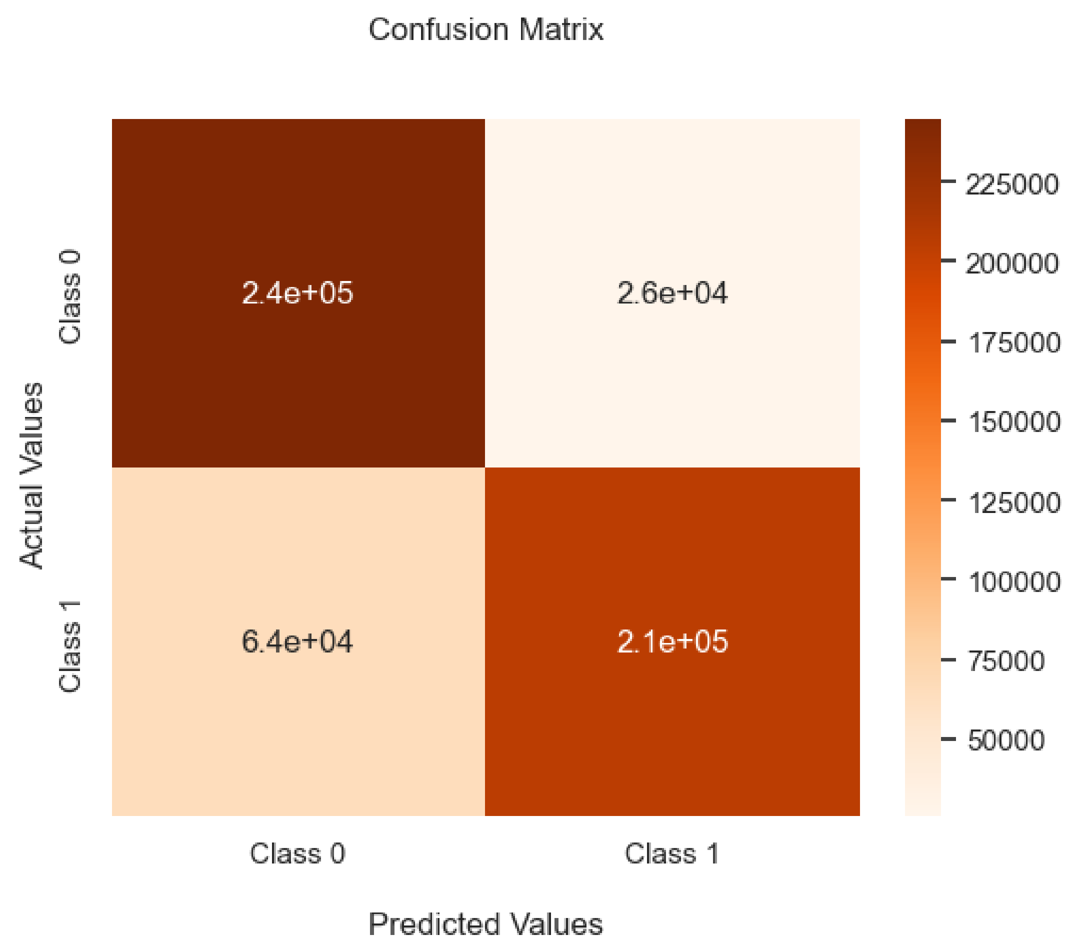
```python
# Split the PCA-transformed data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(x_pca, Y, test_size=0.3, random_state=42
```

```
--------------------------------------------------
```

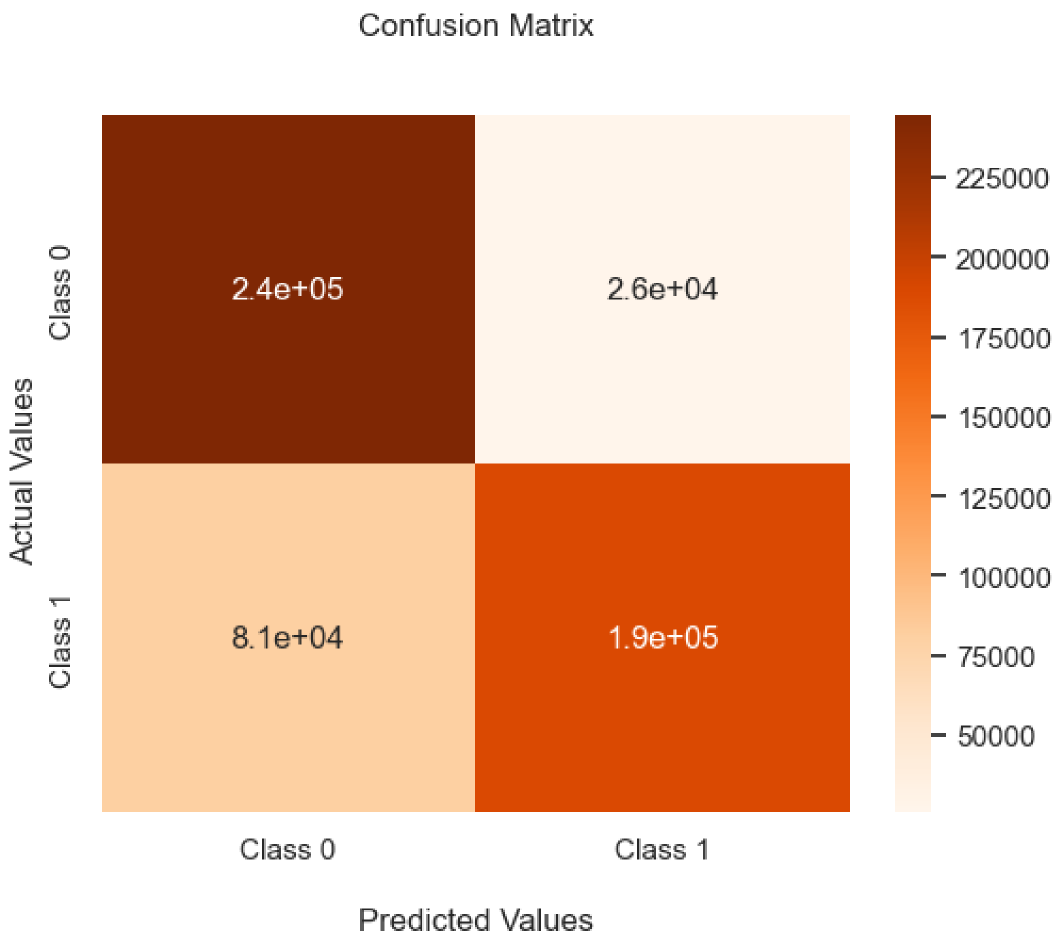
In [26]:

```
# now retrain the models
print('*'*25, 'PCA', '*'*25)
for model in models:
    train_model_and_print_accuracy(model, X_train, y_train, X_test, y_test)
```

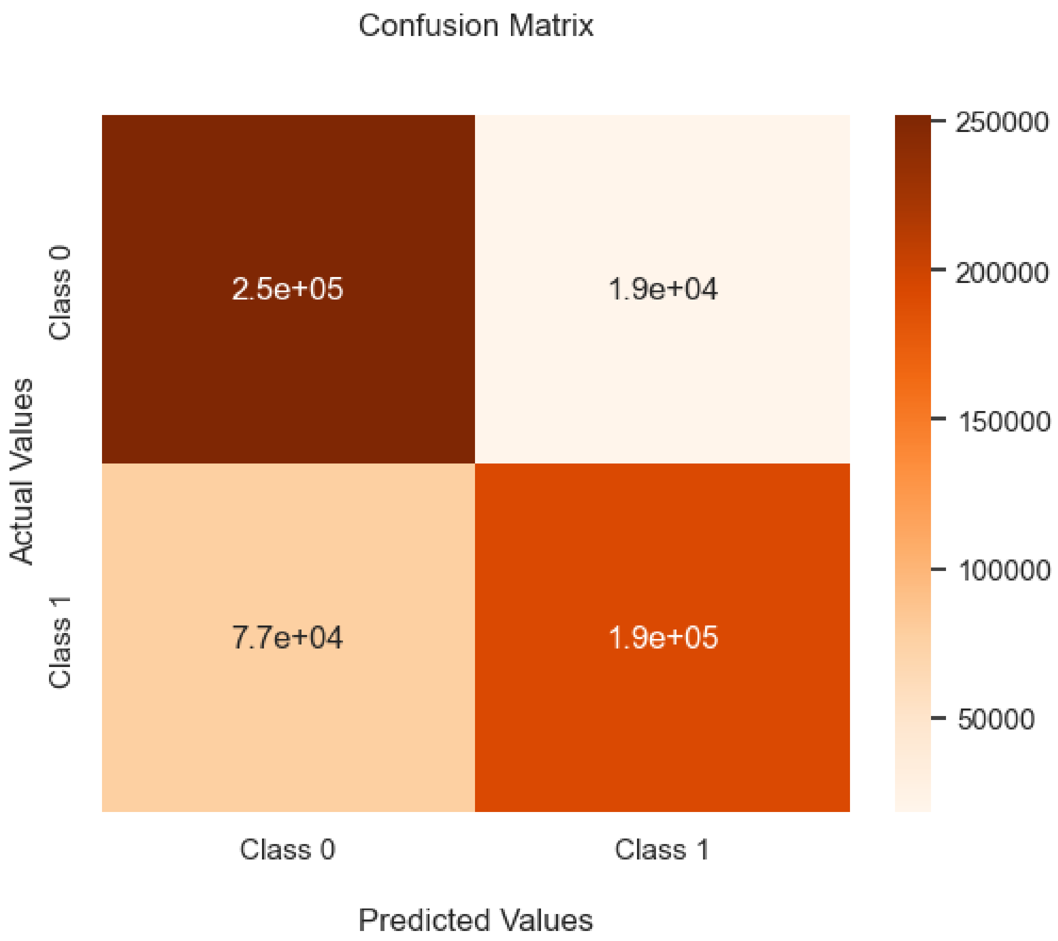
```
************************* PCA *************************
LogisticRegression
--------------------------------------------------
Train Score for LogisticRegression: 0.8334039682539682
--------------------------------------------------
Test Score for LogisticRegression: 0.8330814814814815
--------------------------------------------------
Confusion Matrix for LogisticRegression for test:
 [[244487  25753]
 [ 64383 205377]]
--------------------------------------------------
Classification Report for LogisticRegression for test:
               precision    recall  f1-score   support

         0.0       0.79      0.90      0.84    270240
         1.0       0.89      0.76      0.82    269760

    accuracy                           0.83    540000
   macro avg       0.84      0.83      0.83    540000
weighted avg       0.84      0.83      0.83    540000

--------------------------------------------------
Confusion Matrix:
 [[244487  25753]
 [ 64383 205377]]
--------------------------------------------------
```



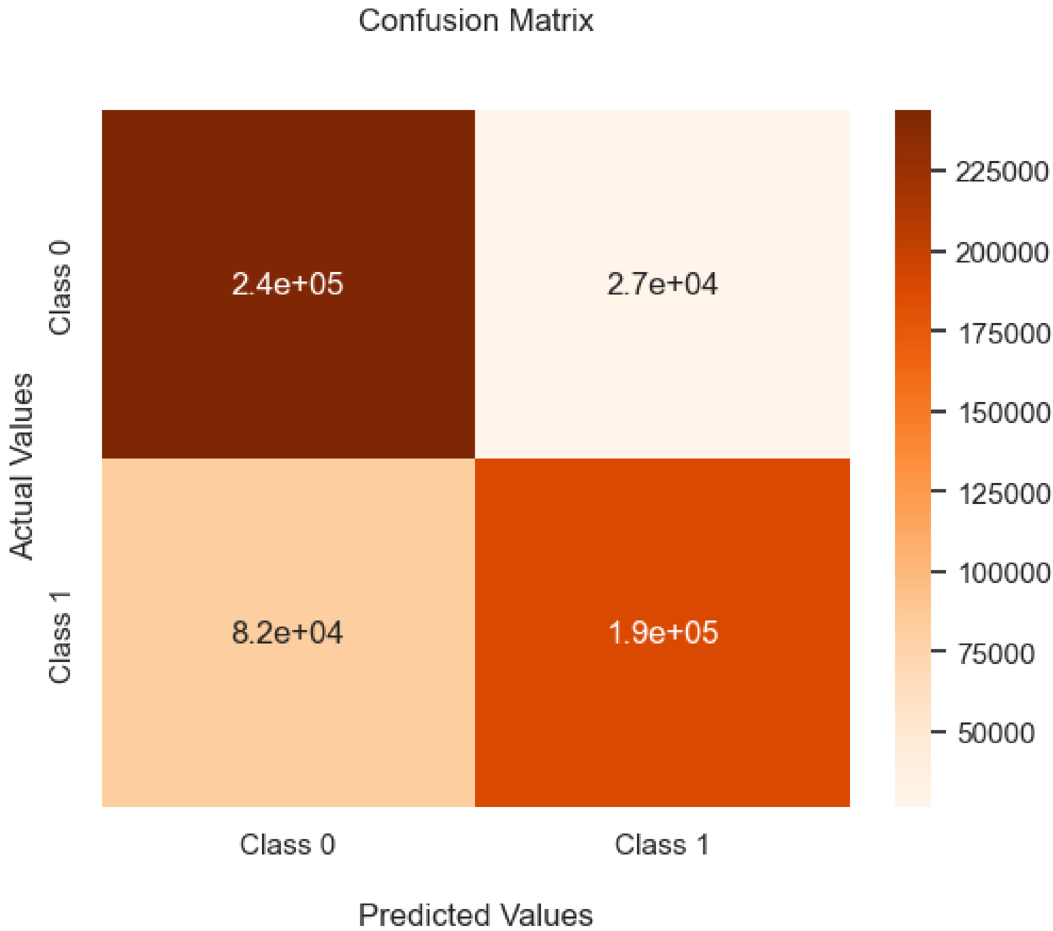
```
-------------------------------------------------
DecisionTreeClassifier
-------------------------------------------------
Train Score for DecisionTreeClassifier: 0.8025388888888889
-------------------------------------------------
Test Score for DecisionTreeClassifier: 0.801637037037037
-------------------------------------------------
Confusion Matrix for DecisionTreeClassifier for test:
 [[244370  25870]
 [ 81246 188514]]
-------------------------------------------------
Classification Report for DecisionTreeClassifier for test:
               precision    recall  f1-score   support

         0.0       0.75      0.90      0.82    270240
         1.0       0.88      0.70      0.78    269760

    accuracy                           0.80    540000
   macro avg       0.81      0.80      0.80    540000
weighted avg       0.81      0.80      0.80    540000

-------------------------------------------------
Confusion Matrix:
 [[244370  25870]
 [ 81246 188514]]
-------------------------------------------------
```



```
--------------------------------------------------
GaussianNB
--------------------------------------------------
Train Score for GaussianNB: 0.8232833333333334
--------------------------------------------------
Test Score for GaussianNB: 0.8225740740740741
--------------------------------------------------
Confusion Matrix for GaussianNB for test:
 [[251730  18510]
 [ 77300 192460]]
--------------------------------------------------
Classification Report for GaussianNB for test:
               precision    recall  f1-score   support

         0.0       0.77      0.93      0.84    270240
         1.0       0.91      0.71      0.80    269760

    accuracy                           0.82    540000
   macro avg       0.84      0.82      0.82    540000
weighted avg       0.84      0.82      0.82    540000

--------------------------------------------------
Confusion Matrix:
 [[251730  18510]
 [ 77300 192460]]
--------------------------------------------------
```



```
--------------------------------------------------
RandomForestClassifier
--------------------------------------------------
Train Score for RandomForestClassifier: 0.7998611111111111
--------------------------------------------------
Test Score for RandomForestClassifier: 0.799074074074074
--------------------------------------------------
Confusion Matrix for RandomForestClassifier for test:
 [[243621  26619]
 [ 81881 187879]]
--------------------------------------------------
Classification Report for RandomForestClassifier for test:
              precision    recall  f1-score   support

         0.0       0.75      0.90      0.82    270240
         1.0       0.88      0.70      0.78    269760

    accuracy                           0.80    540000
   macro avg       0.81      0.80      0.80    540000
weighted avg       0.81      0.80      0.80    540000

--------------------------------------------------
Confusion Matrix:
 [[243621  26619]
 [ 81881 187879]]
--------------------------------------------------
```



```
--------------------------------------------------
MLPClassifier
--------------------------------------------------
Train Score for MLPClassifier: 0.8563801587301587
--------------------------------------------------
Test Score for MLPClassifier: 0.8552351851851852
--------------------------------------------------
Confusion Matrix for MLPClassifier for test:
 [[260825   9415]
 [ 68758 201002]]
--------------------------------------------------
Classification Report for MLPClassifier for test:
               precision    recall  f1-score   support

         0.0       0.79      0.97      0.87    270240
         1.0       0.96      0.75      0.84    269760

    accuracy                           0.86    540000
   macro avg       0.87      0.86      0.85    540000
weighted avg       0.87      0.86      0.85    540000

--------------------------------------------------
Confusion Matrix:
 [[260825   9415]
 [ 68758 201002]]
--------------------------------------------------
```