advanced-data-analytics-project

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#

AirLine Passenger Satisfaction

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** #

Introduction

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`Dataset`

Context

This dataset contains an airline passenger satisfaction survey. What factors are highly correlated to a satisfied (or dissatisfied) passenger? Can you predict passenger satisfaction?

Content

Gender: Gender of the passengers (Female, Male)

Customer Type: The customer type (Loyal customer, disloyal customer)

Age: The actual age of the passengers

Type of Travel: Purpose of the flight of the passengers (Personal Travel, Business Travel)

Class: Travel class in the plane of the passengers (Business, Eco, Eco Plus)

Flight distance: The flight distance of this journey

Inflight wifi service: Satisfaction level of the inflight wifi service (0:Not Applicable;1-5)

Departure/Arrival time convenient: Satisfaction level of Departure/Arrival time convenient

Ease of Online booking: Satisfaction level of online booking

Gate location: Satisfaction level of Gate location

Food and drink: Satisfaction level of Food and drink

Online boarding: Satisfaction level of online boarding

Seat comfort: Satisfaction level of Seat comfort

Inflight entertainment: Satisfaction level of inflight entertainment

On-board service: Satisfaction level of On-board service

Leg room service: Satisfaction level of Leg room service

Baggage handling: Satisfaction level of baggage handling

Check-in service: Satisfaction level of Check-in service

Inflight service: Satisfaction level of inflight service

Cleanliness: Satisfaction level of Cleanliness

Departure Delay in Minutes: Minutes delayed when departure

Arrival Delay in Minutes: Minutes delayed when Arrival

Satisfaction: Airline satisfaction level(Satisfaction, neutral or dissatisfaction)

** #

Import Libraries

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[1]:
```
import pandas as pd
import numpy as np
from plotly.offline import init_notebook_mode
import plotly.graph_objs as go
import cufflinks as cf
import plotly.figure_factory as ff
from plotly.subplots import make_subplots
init_notebook_mode(connected=True)
cf.go_offline()
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay
from sklearn.metrics import classification_report
import warnings
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler,Normalizer
from sklearn.feature_selection import SelectFromModel
```

```
from sklearn.metrics import f1_score,accuracy_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import roc_curve,RocCurveDisplay
from sklearn.metrics import auc
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import PolynomialFeatures
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.decomposition import PCA
import keras
warnings.filterwarnings('ignore')
```

```
2024-05-09 01:18:47.285372: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
2024-05-09 01:18:47.285510: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2024-05-09 01:18:47.457095: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
```

** #

Read Data

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Read in the csv file as a dataframe called data

```
The tabulated data is meticulously arranged, featuring distinct columns housing a range of dive
```

[2]:
```
data=pd.read_csv('/kaggle/input/airline-passenger-satisfaction/train.csv')
data.drop('Unnamed: 0',axis=1,inplace=True)
```

Check the head of data

[3]:
```
data.head()
```

[3]:
```
       id  Gender      Customer Type  Age   Type of Travel     Class  \
0   70172    Male     Loyal Customer   13  Personal Travel  Eco Plus
1    5047    Male  disloyal Customer   25  Business travel  Business
2  110028  Female     Loyal Customer   26  Business travel  Business
3   24026  Female     Loyal Customer   25  Business travel  Business
4  119299    Male     Loyal Customer   61  Business travel  Business

   Flight Distance  Inflight wifi service  Departure/Arrival time convenient  \
0              460                      3                                  4
1              235                      3                                  2
2             1142                      2                                  2
3              562                      2                                  5
4              214                      3                                  3

   Ease of Online booking  …  Inflight entertainment  On-board service  \
0                       3  …                       5                 4
1                       3  …                       1                 1
2                       2  …                       5                 4
3                       5  …                       2                 2
4                       3  …                       3                 3

   Leg room service  Baggage handling  Checkin service  Inflight service  \
0                 3                 4                4                 5
1                 5                 3                1                 4
2                 3                 4                4                 4
3                 5                 3                1                 4
4                 4                 4                3                 3

   Cleanliness  Departure Delay in Minutes  Arrival Delay in Minutes  \
0            5                          25                      18.0
1            1                           1                       6.0
2            5                           0                       0.0
3            2                          11                       9.0
4            3                           0                       0.0

              satisfaction
0  neutral or dissatisfied
1  neutral or dissatisfied
2                satisfied
3  neutral or dissatisfied
4                satisfied

[5 rows x 24 columns]
```

Check the shape of data

[4]:
```
data.shape
```

[4]: (103904, 24)

```
The dataset comprises 103,904 rows and 24 columns
```

Check the info of data

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103904 entries, 0 to 103903
Data columns (total 24 columns):
 #   Column                             Non-Null Count   Dtype
---  ------                             --------------   -----
 0   id                                 103904 non-null  int64
 1   Gender                             103904 non-null  object
 2   Customer Type                      103904 non-null  object
 3   Age                                103904 non-null  int64
 4   Type of Travel                     103904 non-null  object
 5   Class                              103904 non-null  object
 6   Flight Distance                    103904 non-null  int64
 7   Inflight wifi service              103904 non-null  int64
 8   Departure/Arrival time convenient  103904 non-null  int64
 9   Ease of Online booking             103904 non-null  int64
 10  Gate location                      103904 non-null  int64
 11  Food and drink                     103904 non-null  int64
 12  Online boarding                    103904 non-null  int64
 13  Seat comfort                       103904 non-null  int64
 14  Inflight entertainment             103904 non-null  int64
 15  On-board service                   103904 non-null  int64
 16  Leg room service                   103904 non-null  int64
 17  Baggage handling                   103904 non-null  int64
 18  Checkin service                    103904 non-null  int64
 19  Inflight service                   103904 non-null  int64
 20  Cleanliness                        103904 non-null  int64
 21  Departure Delay in Minutes         103904 non-null  int64
 22  Arrival Delay in Minutes           103594 non-null  float64
 23  satisfaction                       103904 non-null  object
dtypes: float64(1), int64(18), object(5)
memory usage: 19.0+ MB
```

```
The dataset includes 1 columns of floating-point values, 18 columns of integers, and 5 columns
```

Description of data

```
If the DataFrame contains numerical data, the description contains these information for each c

count - The number of not-empty values.
mean - The average (mean) value.
std - The standard deviation.
min - the minimum value.
```

25% - The 25% percentile*.
50% - The 50% percentile*.
75% - The 75% percentile*.
max - the maximum value.

[6]:
```
data.describe().transpose()
```

[6]:

```
                                      count          mean           std   min  \
id                                 103904.0  64924.210502  37463.812252   1.0
Age                                103904.0     39.379706     15.114964   7.0
Flight Distance                    103904.0   1189.448375    997.147281  31.0
Inflight wifi service              103904.0      2.729683      1.327829   0.0
Departure/Arrival time convenient  103904.0      3.060296      1.525075   0.0
Ease of Online booking             103904.0      2.756901      1.398929   0.0
Gate location                      103904.0      2.976883      1.277621   0.0
Food and drink                     103904.0      3.202129      1.329533   0.0
Online boarding                    103904.0      3.250375      1.349509   0.0
Seat comfort                       103904.0      3.439396      1.319088   0.0
Inflight entertainment             103904.0      3.358158      1.332991   0.0
On-board service                   103904.0      3.382363      1.288354   0.0
Leg room service                   103904.0      3.351055      1.315605   0.0
Baggage handling                   103904.0      3.631833      1.180903   1.0
Checkin service                    103904.0      3.304290      1.265396   0.0
Inflight service                   103904.0      3.640428      1.175663   0.0
Cleanliness                        103904.0      3.286351      1.312273   0.0
Departure Delay in Minutes         103904.0     14.815618     38.230901   0.0
Arrival Delay in Minutes           103594.0     15.178678     38.698682   0.0

                                        25%      50%       75%       max
id                                 32533.75  64856.5  97368.25  129880.0
Age                                   27.00     40.0     51.00      85.0
Flight Distance                      414.00    843.0   1743.00    4983.0
Inflight wifi service                  2.00      3.0      4.00       5.0
Departure/Arrival time convenient      2.00      3.0      4.00       5.0
Ease of Online booking                 2.00      3.0      4.00       5.0
Gate location                          2.00      3.0      4.00       5.0
Food and drink                         2.00      3.0      4.00       5.0
Online boarding                        2.00      3.0      4.00       5.0
Seat comfort                           2.00      4.0      5.00       5.0
Inflight entertainment                 2.00      4.0      4.00       5.0
On-board service                       2.00      4.0      4.00       5.0
Leg room service                       2.00      4.0      4.00       5.0
Baggage handling                       3.00      4.0      5.00       5.0
Checkin service                        3.00      3.0      4.00       5.0
Inflight service                       3.00      4.0      5.00       5.0
Cleanliness                            2.00      3.0      4.00       5.0
Departure Delay in Minutes             0.00      0.0     12.00    1592.0
```

```
Arrival Delay in Minutes                0.00       0.0      13.00     1584.0

For object data types, the describe method typically includes:

Count: The number of non-empty values.
Unique: The number of unique values.
Top: The most frequently occurring value.
Freq: The frequency of the top value.
```

[7]:
```python
data.describe(include='O').transpose()
```

[7]:

	count	unique	top	freq
Gender	103904	2	Female	52727
Customer Type	103904	2	Loyal Customer	84923
Type of Travel	103904	2	Business travel	71655
Class	103904	3	Business	49665
satisfaction	103904	2	neutral or dissatisfied	58879

check for null values in the data

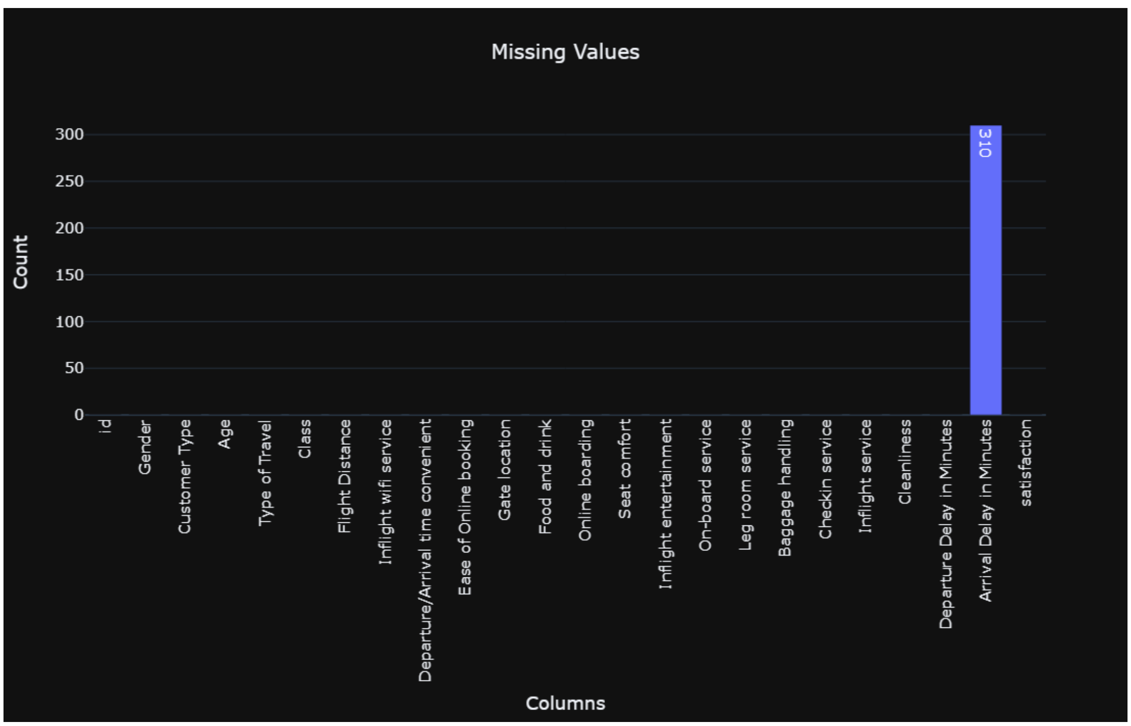
[8]:
```python
is_null,precentage = data.isnull().sum(),(data.isnull().sum()/data.shape[0])*100
df = pd.DataFrame()
df['Count'],df['Precentage%']=is_null,precentage
df
```

[8]:

	Count	Precentage%
id	0	0.000000
Gender	0	0.000000
Customer Type	0	0.000000
Age	0	0.000000
Type of Travel	0	0.000000
Class	0	0.000000
Flight Distance	0	0.000000
Inflight wifi service	0	0.000000
Departure/Arrival time convenient	0	0.000000
Ease of Online booking	0	0.000000
Gate location	0	0.000000
Food and drink	0	0.000000
Online boarding	0	0.000000
Seat comfort	0	0.000000
Inflight entertainment	0	0.000000
On-board service	0	0.000000
Leg room service	0	0.000000
Baggage handling	0	0.000000
Checkin service	0	0.000000
Inflight service	0	0.000000
Cleanliness	0	0.000000
Departure Delay in Minutes	0	0.000000

```
Arrival Delay in Minutes                 310      0.298352
satisfaction                               0      0.000000
```

[9]:
```
fig = go.Figure()
distribution = df['Count']
bar_trace = go.Bar(x=distribution.index, y=distribution.values, name="Missing␣
 ↪Values",text=distribution.values, textposition='inside')
fig.add_trace(bar_trace)
fig.update_layout(
    title_text='Missing Values',
    title_x=0.5,
    title_font=dict(size=20),
    xaxis_title="Columns",
    yaxis_title='Count',
    font=dict(size=15),
    width=1000,
    height=700,
    xaxis=dict(tickangle=-90),
    template='plotly_dark'
)
fig.update_annotations(font=dict(size=20))
fig.show()
```



Based on the provided data frame:

```
The "Arrival Delay in Minutes" attribute has 310 missing values, which constitute approximately
```

Handle null values

```
To handle null values in your dataset, you can use various methods depending on the type of da

For Numerical Data:
1. Mean/Median Imputation: Replace missing values with the mean or median of the column.
2. Random Imputation: Replace missing values with randomly sampled values from the distributio
3. Predictive Imputation: Use a predictive model to predict missing values based on other vari

For Categorical Data:
1. Most Frequent Imputation: Replace missing values with the most frequent value in the column
2. Constant Imputation: Replace missing values with a specific constant value.
3. Predictive Imputation: You can also use a predictive model tailored for categorical data to

Best Practices:
In this case i willo drop null values
```

[10]:
```python
data.dropna(inplace=True)
```

[11]:
```python
is_null,precentage = data.isnull().sum(),(data.isnull().sum()/data.shape[0])*100
df = pd.DataFrame()
df['Count'],df['Precentage%']=is_null,precentage
df
```

[11]:

	Count	Precentage%
id	0	0.0
Gender	0	0.0
Customer Type	0	0.0
Age	0	0.0
Type of Travel	0	0.0
Class	0	0.0
Flight Distance	0	0.0
Inflight wifi service	0	0.0
Departure/Arrival time convenient	0	0.0
Ease of Online booking	0	0.0
Gate location	0	0.0
Food and drink	0	0.0
Online boarding	0	0.0
Seat comfort	0	0.0
Inflight entertainment	0	0.0
On-board service	0	0.0
Leg room service	0	0.0
Baggage handling	0	0.0
Checkin service	0	0.0
Inflight service	0	0.0
Cleanliness	0	0.0

```
Departure Delay in Minutes               0          0.0
Arrival Delay in Minutes                 0          0.0
satisfaction                             0          0.0
```

check duplicate data

data[data.duplicated(keep=False)]
returns all rows in the DataFrame that are duplicates, including both the original rows and the

[12]:
```python
data[data.duplicated(keep=False)]
```

[12]:
```
Empty DataFrame
Columns: [id, Gender, Customer Type, Age, Type of Travel, Class, Flight
Distance, Inflight wifi service, Departure/Arrival time convenient, Ease of
Online booking, Gate location, Food and drink, Online boarding, Seat comfort,
Inflight entertainment, On-board service, Leg room service, Baggage handling,
Checkin service, Inflight service, Cleanliness, Departure Delay in Minutes,
Arrival Delay in Minutes, satisfaction]
Index: []

[0 rows x 24 columns]
```

keep='first': When you use data.duplicated(keep='first')
it identifies and marks duplicates in the DataFrame, keeping only the first occurrence of each

[13]:
```python
data[data.duplicated(keep='first')]
```

[13]:
```
Empty DataFrame
Columns: [id, Gender, Customer Type, Age, Type of Travel, Class, Flight
Distance, Inflight wifi service, Departure/Arrival time convenient, Ease of
Online booking, Gate location, Food and drink, Online boarding, Seat comfort,
Inflight entertainment, On-board service, Leg room service, Baggage handling,
Checkin service, Inflight service, Cleanliness, Departure Delay in Minutes,
Arrival Delay in Minutes, satisfaction]
Index: []

[0 rows x 24 columns]
```

keep='last': Conversely, when you use data.duplicated(keep='last')
it also identifies and marks duplicates in the DataFrame. However, it keeps only the last occu

[14]:
```python
data[data.duplicated(keep='last')]
```

[14]:
```
Empty DataFrame
Columns: [id, Gender, Customer Type, Age, Type of Travel, Class, Flight
Distance, Inflight wifi service, Departure/Arrival time convenient, Ease of
Online booking, Gate location, Food and drink, Online boarding, Seat comfort,
Inflight entertainment, On-board service, Leg room service, Baggage handling,
Checkin service, Inflight service, Cleanliness, Departure Delay in Minutes,
```

```
Arrival Delay in Minutes, satisfaction]
Index: []

[0 rows x 24 columns]
```

** #

EDA

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Exploratory Data Analysis (EDA) is a crucial step in data analysis where you explore and summa

Helper Functions

[15]:
```python
def hist_hue(feature,hue,title_f,title_h,title):
    num_bins=20
    total_hist, _ = np.histogram(data[feature], bins=num_bins)
    fig = make_subplots(rows=1, cols=2, subplot_titles=(title_f, f"{title_f} VS␣
 ↪{title_h}"))
    histogram_trace_total = go.Bar(x=np.arange(num_bins), y=total_hist,␣
 ↪name=title_f, text=total_hist, textposition='inside')
    fig.add_trace(histogram_trace_total, row=1, col=1)
    for category in data[hue].unique():
        category_data = data[data[hue] == category][feature]
        category_hist, _ = np.histogram(category_data, bins=num_bins)
        histogram_trace_by_hue = go.Bar(x=np.arange(num_bins), y=category_hist,␣
 ↪name=f'{title_f} VS {title_h} ({category})', text=category_hist,␣
 ↪textposition='inside')
        fig.add_trace(histogram_trace_by_hue, row=1, col=2)
    fig.update_layout(
       title_text=title,
       title_x=0.5,
       title_font=dict(size=20),
       font=dict(size=15),
       width=1000,
       height=700,
       barmode='stack',
       template='plotly_dark',
        xaxis_title=title_f,
        yaxis_title='Count',
        xaxis2_title=title_f,
    )
    fig.update_annotations(font=dict(size=20))
    fig.show()
```

[16]:
```python
def Bar_hue(feature,hue,title_f,title_h,title):
    fig = make_subplots(rows=1, cols=2, subplot_titles=(title_f, f"{title_f} VS␣
 ↪{title_h}"))
```

```
    distribution = data[feature].value_counts()
    bar_trace = go.Bar(x=distribution.index, y=distribution.values,␣
↪name=title_f,text=distribution.values, textposition='inside')
    fig.add_trace(bar_trace, row=1, col=1)
    for category in data[hue].unique():
        category_data = data[data[hue] == category][feature].value_counts()
        bar_trace_by_hue = go.Bar(x=category_data.index, y=category_data.
↪values, name=f'{title_f} VS {title_h} ({category})', text=category_data.
↪values, textposition='inside')
        fig.add_trace(bar_trace_by_hue, row=1, col=2)
    fig.update_layout(
        title_text=title,
        title_x=0.5,
        title_font=dict(size=20),
        xaxis_title=title_f,
        yaxis_title='Count',
        xaxis2_title=title_f,
        font=dict(size=15),
        barmode='stack',
        width=1100,
        height=700,
        xaxis=dict(tickangle=-90),
        xaxis2=dict(tickangle=-90),
        template='plotly_dark'
    )
    fig.update_annotations(font=dict(size=20))
    fig.show()
```

[17]:
```
def␣
↪Bar_2hue(feature,hue1,title_f,title_h1,title='',make_subplot=True,hue2='',title_h2=''):
↪
    if make_subplot:
        fig = make_subplots(rows=1, cols=2, subplot_titles=(f"{title_f} VS␣
↪{title_h1}",f"{title_f} VS {title_h2}"))
        for category in data[hue1].unique():
            category_data = data[data[hue1] == category][feature].value_counts()
            bar_trace_by_hue = go.Bar(x=category_data.index, y=category_data.
↪values, name=f'{title_f} VS {title_h1} ({category})',text=category_data.
↪values, textposition='inside')
            fig.add_trace(bar_trace_by_hue, row=1, col=1)
        for category in data[hue2].unique():
            category_data = data[data[hue2] == category][feature].value_counts()
            bar_trace_by_hue = go.Bar(x=category_data.index, y=category_data.
↪values, name=f'{title_f} VS {title_h2} ({category})',text=category_data.
↪values, textposition='inside')
            fig.add_trace(bar_trace_by_hue, row=1, col=2)
        fig.update_layout(
```

```
            title_text=title,
            title_x=0.5,
            title_font=dict(size=20),
            xaxis_title=title_f,
            yaxis_title='Count',
            xaxis2_title=title_f,
            font=dict(
                size=15,
            ),
            barmode='stack',
            width=1100,
            height=700,
            xaxis=dict(tickangle=-90),
            xaxis1=dict(tickangle=-90),
            xaxis2=dict(tickangle=-90),
            template='plotly_dark'
        )
        fig.update_annotations(font=dict(size=20))
        fig.show()
    else:
        fig = go.Figure()
        for category in data[hue1].unique():
            category_data = data[data[hue1] == category][feature].value_counts()
            bar_trace_by_hue = go.Bar(x=category_data.index, y=category_data.
↪values, name=f'{title_f} VS {title_h1} ({category})',text=category_data.
↪values, textposition='inside')
            fig.add_trace(bar_trace_by_hue)
        fig.update_layout(
            title_text=f'{title_f} VS {title_h1}',
            title_x=0.5,
            title_font=dict(size=20),
            xaxis_title=title_f,
            yaxis_title='Count',
            font=dict(
                size=15,
            ),
            barmode="stack",
            width=800,
            height=700,
            xaxis=dict(tickangle=-90),
            template='plotly_dark'
        )
        fig.update_annotations(font=dict(size=20))
        fig.show()
```

[18]:
```
def Boxplot_outlier(feature,title):
```

```
    fig = make_subplots(rows=1, cols=2, subplot_titles=("Box Plot", "Violin␣
↪Plot"))
    fig.add_trace(
        go.Box(y=data[feature], name='BoxPlot'),
        row=1, col=1
    )
    fig.add_trace(
        go.Violin(y=data[feature], name='ViolinPlot'),
        row=1, col=2
    )
    fig.update_layout(
        title_text=title,
        title_x=0.5,
        title_font=dict(size=20),
        font=dict(size=15),
        width=1000,
        height=500,
        template='plotly_dark'
    )
    fig.update_annotations(font=dict(size=20))
    fig.show()
```

[19]:
```
def Pie(feature,title_f,title):
    distribution = data[feature].value_counts()
    pie_trace = go.Pie(labels=distribution.index, values=distribution.values,␣
↪name=title_f)
    pie_layout = go.Layout(
        title=title,
        title_font=dict(size=20),
        width=600,
        height=500,
        title_x=0.5,
        template='plotly_dark'
    )
    fig_pie = go.Figure(data=[pie_trace], layout=pie_layout)
    fig_pie.show()
```

[20]:
```
def Heatmap(pivot1, title, feature, feature_h1, make_subplot=True,␣
↪feature_h2='', pivot2='', color='inferno'):
    fig_heatmap = None
    if make_subplot:
        fig = make_subplots(rows=1, cols=2, subplot_titles=(f"{feature} VS␣
↪{feature_h1}", f"{feature} VS {feature_h2}"))
        heat1 = go.Heatmap(
            z=pivot1.values,
            x=pivot1.columns,
            y=pivot1.index,
```

```
            colorscale=color,
            colorbar=dict(title='Count'),
            colorbar_x=0.45,
            colorbar_len=0.8
        )
        fig.add_trace(heat1, row=1, col=1)
        heat2 = go.Heatmap(
            z=pivot2.values,
            x=pivot2.columns,
            y=pivot2.index,
            colorscale=color,
            colorbar=dict(title='Count'),
            colorbar_x=1,
            colorbar_len=0.8
        )
        fig.add_trace(heat2, row=1, col=2)
        fig.update_layout(
            title=title,
            title_x=0.5,
            title_font=dict(size=20),
            width=1100,
            height=500,
            xaxis=dict(title=feature_h1, tickangle=-90),
            xaxis2=dict(title=feature_h2, tickangle=-90),
            yaxis=dict(title=feature, tickangle=-90),
            yaxis2=dict(tickangle=-90),
            font=dict(size=15),
            template='plotly_dark'
        )
        fig_heatmap = fig
    else:
        fig_heatmap = go.Figure(data=go.Heatmap(
            z=pivot1.values,
            x=pivot1.columns,
            y=pivot1.index,
            colorscale=color,
            colorbar=dict(title='Count')
        ))
        fig_heatmap.update_layout(
            title=title,
            title_x=0.5,
            title_font=dict(size=20),
            xaxis=dict(title=feature_h1),
            yaxis=dict(title=feature),
            font=dict(size=15),
            width=800,
            height=500,
```

```
            template='plotly_dark'
        )
    fig_heatmap.update_annotations(font=dict(size=20))
    fig_heatmap.show()
```

[21]:
```
def mean(pivot_table,pivot_table1,feature,hue1,hue2,title,title_f):
    fig = make_subplots(rows=1, cols=2, subplot_titles=(f"Average {title_f} VS␣
↪{hue1}", f"Average {title_f} VS {hue2}"))
    for i in data[hue1].unique():
        cate = pivot_table[pivot_table.index==i]
        bar_trace = go.Bar(x=cate.index, y=cate[feature],␣
↪text=round(cate[feature],2), textposition='inside', name=i)
        fig.add_trace(bar_trace, row=1, col=1)
    for i in data[hue2].unique():
        cate = pivot_table1[pivot_table1.index==i]
        bar_trace = go.Bar(x=cate.index, y=cate[feature],␣
↪text=round(cate[feature],2), textposition='inside', name=i)
        fig.add_trace(bar_trace, row=1, col=2)
    fig.update_layout(
        title_text=title,
        title_x=0.5,
        title_font=dict(size=20),
        xaxis_title=hue1,
        yaxis_title='Average',
        xaxis2_title=hue2,
        font=dict(size=15),
        barmode='stack',
        width=1100,
        height=700,
        xaxis=dict(tickangle=-90),
        xaxis1=dict(tickangle=-90),
        template='plotly_dark'
    )

    fig.update_annotations(font=dict(size=20))
    fig.show()
```

[22]:
```
def pivot(values_f,index_f,mean=True):
    if mean:
        return pd.pivot_table(data, values=values_f, index=index_f,␣
↪aggfunc='mean')
    else:
        return pd.pivot_table(data, index=values_f, columns=index_f,␣
↪aggfunc='size', fill_value=0)
def cross_t(index,columns):
    return pd.crosstab(index=data[index], columns=data[columns])
```

What is age distribution?

Find the minimum age

[23]:
```
data.Age.min()
```

[23]: 7

Find the maximum age

[24]:
```
data.Age.max()
```

[24]: 85

Find the top 5 most frequent ages

[25]:
```
data['Age'].value_counts().head(5)
```

[25]:
```
Age
39    2961
25    2790
40    2569
44    2479
42    2453
Name: count, dtype: int64
```

Based on the output, it seems that the age group 31 to 36 has the highest counts of observatio

Age 25: 2790 observations
Age 39: 2961 observations
Age 40: 2569 observations
Age 42: 2453 observations
Age 44: 2479 observations

calculate the mean age for each category in the "satisfaction" column

[26]:
```
pivot_table = pivot('Age','satisfaction')
pivot_table
```

[26]:

	Age
satisfaction	
neutral or dissatisfied	37.569126
satisfied	41.748558

Visualization

[27]:
```
hist_hue('Age','satisfaction','Age','Satisfaction','Age Distribution')
```

[28]:
```
Boxplot_outlier('Age','Age Distribution')
```

Observation: Based on the figure, it appears that the "age" column don't contains outliers.

What is Gender distribution?

calculate the value counts for the "Gender" column

```
[29]: data.Gender.value_counts().to_frame()
```

```
[29]:         count
Gender
Female   52576
Male     51018
```

count the occurrences of each combination of Gender and satisfaction

```
[30]: pivot_table = pivot('Gender','satisfaction',False)
pivot_table
```

```
[30]: satisfaction  neutral or dissatisfied  satisfied
Gender
Female                            30107      22469
Male                              28590      22428
```

Visualization

```
[31]: Pie('Gender','Gender','Gender Distribution')
```

```
[32]: Bar_hue('Gender','satisfaction','Gender','Satisfaction','Gender Distribution')
```

```
[33]: Heatmap(pivot_table,'Gender VS Satisfaction␣
↪Categories','Gender','Satisfaction',make_subplot=False)
```

observation based on figure: show frequency between Gender and Satisfaction

What is Customer Type distribution?

calculate the value counts for the "Customer Type" column

```
[34]: data['Customer Type'].value_counts().to_frame()
```

```
[34]:                     count
Customer Type
Loyal Customer      84662
disloyal Customer   18932
```

count the occurrences of each combination of Customer Type and satisfaction

```
[35]: pivot_table = pivot('Customer Type','satisfaction',False)
pivot_table
```

```
[35]: satisfaction       neutral or dissatisfied  satisfied
Customer Type
Loyal Customer                       44249      40413
disloyal Customer                    14448       4484
```

count the occurrences of each combination of Customer Type and Gender

[36]:
```
pivot_table1 = pivot('Customer Type','Gender',False)
pivot_table1
```

[36]:
```
Gender             Female   Male
Customer Type
Loyal Customer      42336  42326
disloyal Customer   10240   8692
```

count the occurrences of each combination of Customer Type , Gender and y

[37]:
```
data.groupby(['satisfaction','Gender','Customer Type'])['Customer Type'].
↪count().to_frame()
```

[37]:
```
                                                      Customer Type
satisfaction            Gender Customer Type
neutral or dissatisfied Female Loyal Customer                 22182
                               disloyal Customer               7925
                        Male   Loyal Customer                 22067
                               disloyal Customer               6523
satisfied               Female Loyal Customer                 20154
                               disloyal Customer               2315
                        Male   Loyal Customer                 20259
                               disloyal Customer               2169
```

Visalization

[38]:
```
Pie('Customer Type','Customer Type','Customer Type Distribution')
```

[39]:
```
Bar_hue('Customer Type','satisfaction','Customer Type','Satisfaction','Customer␣
↪Type Distribution')
```

[40]:
```
Bar_2hue('Customer Type','Gender','Customer Type','Gender',make_subplot=False)
```

[41]:
```
Heatmap(pivot_table,'Customer Type VS Satisfaction Categories','Customer␣
↪Type','Satisfaction',make_subplot=False)
```

[42]:
```
Heatmap(pivot_table1,'Customer Type VS Gender Categories','Customer␣
↪Type','Gender',make_subplot=False)
```

What is Type of Type of Travel distribution?

calculate the value counts for the "Type of Travel" column

[43]:
```
data['Type of Travel'].value_counts().to_frame()
```

[43]:
```
                 count
Type of Travel
Business travel  71465
```

```
Personal Travel  32129
```

count the occurrences of each combination of Type of Travel and satisfaction

[44]:
```
pivot_table = pivot('Type of Travel','satisfaction',False)
pivot_table
```

[44]:
```
satisfaction     neutral or dissatisfied  satisfied
Type of Travel
Business travel                    29831      41634
Personal Travel                    28866       3263
```

count the occurrences of each combination of Type of Travel and Gender

[45]:
```
pivot_table1 = pivot('Type of Travel','Gender',False)
pivot_table1
```

[45]:
```
Gender           Female   Male
Type of Travel
Business travel   36433  35032
Personal Travel   16143  15986
```

count the occurrences of each combination of Type of Travel and Customer Type

[46]:
```
pivot_table2 = pivot('Type of Travel','Customer Type',False)
pivot_table2
```

[46]:
```
Customer Type    Loyal Customer  disloyal Customer
Type of Travel
Business travel           52696              18769
Personal Travel           31966                163
```

count the occurrences of each combination of Type of Travel , Gender , Customer Type and sati

[47]:
```
data.groupby(['satisfaction','Gender','Customer Type','Type of Travel'])['Type␣
↪of Travel'].count().to_frame()
```

[47]:
```
                                                                 Type of Travel
satisfaction            Gender Customer Type     Type of Travel
neutral or dissatisfied Female Loyal Customer    Business travel           7761
                                                 Personal Travel          14421
                               disloyal Customer Business travel           7853
                                                 Personal Travel             72
                        Male   Loyal Customer    Business travel           7760
                                                 Personal Travel          14307
                               disloyal Customer Business travel           6457
                                                 Personal Travel             66
satisfied               Female Loyal Customer    Business travel          18516
                                                 Personal Travel           1638
                               disloyal Customer Business travel           2303
```

```
                                          Personal Travel           12
                    Male   Loyal Customer    Business travel        18659
                                          Personal Travel         1600
                           disloyal Customer Business travel        2156
                                          Personal Travel           13
```

Visualization

[48]:
```python
Pie('Type of Travel','Type of Travel','Type of Travel Distribution')
```

[49]:
```python
Bar_hue('Type of Travel','satisfaction','Type of Travel','Satisfaction','Type␣
 ↪of Travel Distribution')
```

[50]:
```python
Bar_2hue('Type of Travel','Gender','Travel','Gender',title='Type of Travel␣
 ↪Distribution',hue2='Customer Type',title_h2='Customer Type')
```

[51]:
```python
Heatmap(pivot_table,'Type of Travel VS Satisfaction Categories','Type of␣
 ↪Travel','Satisfaction',make_subplot=False)
```

[52]:
```python
Heatmap(pivot_table1,'Type of Travel VS Gender Categories','Type of␣
 ↪Travel','Gender',make_subplot=False)
```

[53]:
```python
Heatmap(pivot_table2,'Type of Travel VS Customer Type Categories','Type of␣
 ↪Travel','Customer Type',make_subplot=False)
```

What is Type of Class distribution?

calculate the value counts for the "Class" column

[54]:
```python
data.Class.value_counts().to_frame()
```

[54]:
```
          count
Class
Business  49533
Eco       46593
Eco Plus   7468
```

count the occurrences of each combination of Class and satisfaction

[55]:
```python
pivot_table = pivot('Class','satisfaction',False)
pivot_table
```

[55]:
```
satisfaction  neutral or dissatisfied  satisfied
Class
Business                        15143      34390
Eco                             37922       8671
Eco Plus                         5632       1836
```

count the occurrences of each combination of Class and Gender

```
[56]: pivot_table1 = pivot('Class','Gender',False)
pivot_table1
```

```
[56]: Gender     Female   Male
      Class
      Business    24868  24665
      Eco         23776  22817
      Eco Plus     3932   3536
```

count the occurrences of each combination of Class and Customer Type

```
[57]: pivot_table2 = pivot('Class','Customer Type',False)
pivot_table2
```

```
[57]: Customer Type  Loyal Customer  disloyal Customer
      Class
      Business                42191               7342
      Eco                     35716              10877
      Eco Plus                 6755                713
```

count the occurrences of each combination of Class and Type of Travel

```
[58]: pivot_table3 = pivot('Class','Type of Travel',False)
pivot_table3
```

```
[58]: Type of Travel  Business travel  Personal Travel
      Class
      Business                  47384             2149
      Eco                       20202            26391
      Eco Plus                   3879             3589
```

count the occurrences of each combination of Class , Type of Travel , Gender , Customer Type a

```
[59]: data.groupby(['satisfaction','Gender','Customer Type','Type of␣
 ↪Travel','Class'])['Class'].count().to_frame()
```

```
[59]:                                                                                  Class
      satisfaction            Gender Customer Type     Type of Travel  Class
      neutral or dissatisfied Female Loyal Customer    Business travel Business   4439
                                                                       Eco        2493
                                                                       Eco Plus    829
                                                       Personal Travel Business    935
                                                                       Eco       11826
                                                                       Eco Plus   1660
                                     disloyal Customer Business travel Business   2313
                                                                       Eco        5025
                                                                       Eco Plus    515
                                                       Personal Travel Business      7
                                                                       Eco          65
```

```
                        Male   Loyal Customer    Business travel Business    4392
                                                                 Eco         2496
                                                                 Eco Plus     872
                                                 Personal Travel Business     939
                                                                 Eco        11754
                                                                 Eco Plus    1614
                               disloyal Customer Business travel Business    2114
                                                                 Eco         4205
                                                                 Eco Plus     138
                                                 Personal Travel Business       4
                                                                 Eco           58
                                                                 Eco Plus       4
satisfied               Female Loyal Customer    Business travel Business   15559
                                                                 Eco         2231
                                                                 Eco Plus     726
                                                 Personal Travel Business     130
                                                                 Eco         1351
                                                                 Eco Plus     157
                               disloyal Customer Business travel Business    1485
                                                                 Eco          773
                                                                 Eco Plus      45
                                                 Personal Travel Eco           12
                        Male   Loyal Customer    Business travel Business   15663
                                                                 Eco         2253
                                                                 Eco Plus     743
                                                 Personal Travel Business     134
                                                                 Eco         1312
                                                                 Eco Plus     154
                               disloyal Customer Business travel Business    1419
                                                                 Eco          726
                                                                 Eco Plus      11
                                                 Personal Travel Eco           13
```

Visualization

[60]:
```
Pie('Class','Class','Class Distribution')
```

[61]:
```
Bar_hue('Class','satisfaction','Class','Satisfaction','Class Distribution')
```

[62]:
```
Bar_2hue('Class','Gender','Class','Gender',title='Class␣
↪Distribution',hue2='Customer Type',title_h2='Customer Type')
```

[63]:
```
Bar_2hue('Class','Type of Travel','Class','Type of Travel',make_subplot=False)
```

[64]:
```
Heatmap(pivot_table,'Class␣
↪Distribution','Class','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=pivot_tab
```

```
[65]: Heatmap(pivot_table2,'Class Distribution','Class','Customer␣
        ↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=pivot_table3)
```

What is Flight Distance distribution?

Find the minimum Flight Distance

```
[66]: data['Flight Distance'].min()
```

```
[66]: 31
```

Find the maximum Flight Distance

```
[67]: data['Flight Distance'].max()
```

```
[67]: 4983
```

average the occurrences of each combination of Flight Distance and Type of Travel

```
[68]: pivot_table = pivot('Flight Distance','Type of Travel')
      pivot_table
```

```
[68]:                  Flight Distance
      Type of Travel
      Business travel      1368.294872
      Personal Travel       791.240375
```

average the occurrences of each combination of Flight Distance and Class

```
[69]: pivot_table1 = pivot('Flight Distance','Class')
      pivot_table1
```

```
[69]:           Flight Distance
      Class
      Business      1676.078493
      Eco            742.843281
      Eco Plus       746.446438
```

Visualization

```
[70]: Boxplot_outlier('Flight Distance','Flight Distance Distribution')
```

Observation: Based on the figure, it appears that the "Flight Distance" column contains outlie

```
[71]: mean(pivot_table,pivot_table1,'Flight Distance','Type of␣
        ↪Travel','Class','Average Flight Distance',title_f='Flight Distance')
```

What is Type of Inflight wifi service distribution?

calculate the value counts for the "Inflight wifi service" column

```
[72]: data['Inflight wifi service'].value_counts().to_frame()
```

[72]:
```
                        count
Inflight wifi service
3                       25789
2                       25755
4                       19737
1                       17781
5                       11436
0                        3096
```

count the occurrences of each combination of Inflight wifi service and satisfaction

[73]:
```
cross = cross_t('Inflight wifi service','satisfaction')
cross
```

[73]:
```
satisfaction           neutral or dissatisfied  satisfied
Inflight wifi service
0                                            8       3088
1                                        11995       5786
2                                        19346       6409
3                                        19327       6462
4                                         7915      11822
5                                          106      11330
```

count the occurrences of each combination of Inflight wifi service and Gender

[74]:
```
cross1 = cross_t('Inflight wifi service','Gender')
cross1
```

[74]:
```
Gender                 Female   Male
Inflight wifi service
0                        1590   1506
1                        9056   8725
2                       13212  12543
3                       13141  12648
4                        9885   9852
5                        5692   5744
```

count the occurrences of each combination of Inflight wifi service and Customer Type

[75]:
```
cross2 = cross_t('Inflight wifi service','Customer Type')
cross2
```

[75]:
```
Customer Type          Loyal Customer  disloyal Customer
Inflight wifi service
0                                2403                693
1                               14795               2986
2                               20941               4814
3                               20925               4864
4                               15926               3811
```

```
5                                    9672             1764
```

count the occurrences of each combination of Inflight wifi service and Type of Travel

[76]:
```python
cross3 = cross_t('Inflight wifi service','Type of Travel')
cross3
```

[76]:
```
Type of Travel          Business travel  Personal Travel
Inflight wifi service
0                                  2449              647
1                                 12001             5780
2                                 16213             9542
3                                 16021             9768
4                                 14640             5097
5                                 10141             1295
```

count the occurrences of each combination of Inflight wifi service and Class

[77]:
```python
cross4 = cross_t('Inflight wifi service','Class')
cross4
```

[77]:
```
Class                  Business    Eco  Eco Plus
Inflight wifi service
0                          1977    924       195
1                          9014   7638      1129
2                         11060  12761      1934
3                         10834  13022      1933
4                          9411   8815      1511
5                          7237   3433       766
```

Visualization

[78]:
```python
Pie('Inflight wifi service','Wifi service','Wifi service Distribution')
```

[79]:
```python
Bar_hue('Inflight wifi service','satisfaction','Wifi␣
↪service','Satisfaction','Wifi service Distribution')
```

[80]:
```python
Bar_2hue('Inflight wifi service','Gender','Wifi service','Gender',title='Wifi␣
↪service Distribution',hue2='Customer Type',title_h2='Customer')
```

[81]:
```python
Bar_2hue('Inflight wifi service','Type of Travel','Wifi service','Type of␣
↪Travel',title='Wifi service Distribution',hue2='Class',title_h2='Class')
```

[82]:
```python
Heatmap(cross,'Wifi service Distribution','Wifi␣
↪service','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[83]:
```python
Heatmap(cross2,'Wifi service Distribution','Wifi service','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[84]:
```
Heatmap(cross4,'Wifi service Vs Class Categories','Wifi␣
 ↪service','Class',make_subplot=False)
```

What is Type of Departure/Arrival time convenient distribution?

calculate the value counts for the "Departure/Arrival time convenient" column

[85]:
```
data['Departure/Arrival time convenient'].value_counts().to_frame()
```

[85]:

Departure/Arrival time convenient	count
4	25474
5	22333
3	17903
2	17142
1	15452
0	5290

count the occurrences of each combination of Inflight wifi service and satisfaction

[86]:
```
cross = cross_t('Departure/Arrival time convenient','satisfaction')
cross
```

[86]:

satisfaction / Departure/Arrival time convenient	neutral or dissatisfied	satisfied
0	2774	2516
1	7933	7519
2	9503	7639
3	10056	7847
4	15595	9879
5	12836	9497

count the occurrences of each combination of Inflight wifi service and Gender

[87]:
```
cross1 = cross_t('Departure/Arrival time convenient','Gender')
cross1
```

[87]:

Gender / Departure/Arrival time convenient	Female	Male
0	2765	2525
1	7839	7613
2	8801	8341
3	9126	8777
4	12856	12618
5	11189	11144

count the occurrences of each combination of Inflight wifi service and Customer Type

[88]:
```
cross2 = cross_t('Departure/Arrival time convenient','Customer Type')
cross2
```

[88]:

Customer Type	Loyal Customer	disloyal Customer
Departure/Arrival time convenient		
0	2028	3262
1	12908	2544
2	13284	3858
3	14020	3883
4	21933	3541
5	20489	1844

count the occurrences of each combination of Inflight wifi service and Type of Travel

[89]:
```
cross3 = cross_t('Departure/Arrival time convenient','Type of Travel')
cross3
```

[89]:

Type of Travel	Business travel	Personal Travel
Departure/Arrival time convenient		
0	4422	868
1	12737	2715
2	14097	3045
3	14119	3784
4	14039	11435
5	12051	10282

count the occurrences of each combination of Inflight wifi service and Class

[90]:
```
cross4 = cross_t('Departure/Arrival time convenient','Class')
cross4
```

[90]:

Class	Business	Eco	Eco Plus
Departure/Arrival time convenient			
0	2269	2785	236
1	8752	5634	1066
2	9407	6596	1139
3	9460	7210	1233
4	10237	13243	1994
5	9408	11125	1800

Visualization

[91]:
```
Pie('Departure/Arrival time convenient','Arrival time','Arrival timee␣
↪Distribution')
```

[92]:
```
Bar_hue('Departure/Arrival time convenient','satisfaction','Arrival␣
↪time','Satisfaction','Arrival time Distribution')
```

[93]:
```
Bar_2hue('Departure/Arrival time convenient','Gender','Arrival␣
↪time','Gender',title='Arrival time Distribution',hue2='Customer␣
↪Type',title_h2='Customer')
```

[94]:
```
Bar_2hue('Departure/Arrival time convenient','Type of Travel','Arrival␣
↪time','Type of Travel',title='Arrival time␣
↪Distribution',hue2='Class',title_h2='Class')
```

[95]:
```
Heatmap(cross,'Arrival time Distribution','Arrival␣
↪time','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[96]:
```
Heatmap(cross2,'Arrival time Distribution','Arrival time','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[97]:
```
Heatmap(cross4,'Arrival time Vs Class Categories','Arrival␣
↪time','Class',make_subplot=False)
```

What is Type of Ease of Online booking distribution?

calculate the value counts for the "Ease of Online booking" column

[98]:
```
data['Ease of Online booking'].value_counts().to_frame()
```

[98]:

Ease of Online booking	count
3	24370
2	23962
4	19508
1	17466
5	13815
0	4473

count the occurrences of each combination of Ease of Online booking and satisfaction

[99]:
```
cross = cross_t('Ease of Online booking','satisfaction')
cross
```

[99]:

satisfaction Ease of Online booking	neutral or dissatisfied	satisfied
0	1500	2973
1	10897	6569
2	16673	7289
3	16858	7512
4	9152	10356
5	3617	10198

count the occurrences of each combination of Ease of Online booking and Gender

[100]:
```
cross1 = cross_t('Ease of Online booking','Gender')
cross1
```

[100]:

Gender Ease of Online booking	Female	Male
0	2293	2180

```
1                          8895   8571
2                         12318  11644
3                         12338  12032
4                          9773   9735
5                          6959   6856
```

count the occurrences of each combination of Ease of Online booking and Customer Type

[101]:
```
cross2 = cross_t('Ease of Online booking','Customer Type')
cross2
```

[101]:
```
Customer Type           Loyal Customer  disloyal Customer
Ease of Online booking
0                                 3616                857
1                                14510               2956
2                                19281               4681
3                                19539               4831
4                                15758               3750
5                                11958               1857
```

count the occurrences of each combination of Ease of Online booking and Type of Travel

[102]:
```
cross3 = cross_t('Ease of Online booking','Type of Travel')
cross3
```

[102]:
```
Type of Travel          Business travel  Personal Travel
Ease of Online booking
0                                  2677             1796
1                                 12076             5390
2                                 14968             8994
3                                 15148             9222
4                                 14466             5042
5                                 12130             1685
```

count the occurrences of each combination of Ease of Online booking and Class

[103]:
```
cross4 = cross_t('Ease of Online booking','Class')
cross4
```

[103]:
```
Class                   Business    Eco  Eco Plus
Ease of Online booking
0                           2089   2045       339
1                           8193   7948      1325
2                           9917  12208      1837
3                          10096  12440      1834
4                          10162   8065      1281
5                           9076   3887       852
```

Visualization

[104]:
```
Pie('Ease of Online booking','Online booking','Online booking Distribution')
```

[105]:
```
Bar_hue('Ease of Online booking','satisfaction','Online␣
↪booking','Satisfaction','Online booking Distribution')
```

[106]:
```
Bar_2hue('Ease of Online booking','Gender','Online␣
↪booking','Gender',title='Online booking Distribution',hue2='Customer␣
↪Type',title_h2='Customer')
```

[107]:
```
Bar_2hue('Ease of Online booking','Type of Travel','Online booking','Type of␣
↪Travel',title='Online booking Distribution',hue2='Class',title_h2='Class')
```

[108]:
```
Heatmap(cross,'Online booking Distribution','Online␣
↪booking','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[109]:
```
Heatmap(cross2,'Online booking Distribution','Online booking','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[110]:
```
Heatmap(cross4,'Online booking Vs Class Categories','Online␣
↪booking','Class',make_subplot=False)
```

What is Type of Gate location distribution?

calculate the value counts for the "Gate location" column

[111]:
```
data['Gate location'].value_counts().to_frame()
```

[111]:

Gate location	count
3	28489
4	24353
2	19396
1	17511
5	13844
0	1

count the occurrences of each combination of Gate location and satisfaction

[112]:
```
cross = cross_t('Gate location','satisfaction')
cross
```

[112]:

Gate location \ satisfaction	neutral or dissatisfied	satisfied
0	0	1
1	8834	8677
2	10447	8949
3	18600	9889
4	14895	9458
5	5921	7923

count the occurrences of each combination of Ease of Online booking and Gender

[113]:
```
cross1 = cross_t('Gate location','Gender')
cross1
```

[113]:

Gender Gate location	Female	Male
0	1	0
1	8821	8690
2	9821	9575
3	14586	13903
4	12450	11903
5	6897	6947

count the occurrences of each combination of Ease of Online booking and Customer Type

[114]:
```
cross2 = cross_t('Gate location','Customer Type')
cross2
```

[114]:

Customer Type Gate location	Loyal Customer	disloyal Customer
0	1	0
1	14933	2578
2	16376	3020
3	21878	6611
4	18970	5383
5	12504	1340

count the occurrences of each combination of Ease of Online booking and Type of Travel

[115]:
```
cross3 = cross_t('Gate location','Type of Travel')
cross3
```

[115]:

Type of Travel Gate location	Business travel	Personal Travel
0	1	0
1	12768	4743
2	13591	5805
3	17299	11190
4	16238	8115
5	11568	2276

count the occurrences of each combination of Ease of Online booking and Class

[116]:
```
cross4 = cross_t('Gate location','Class')
cross4
```

[116]:

Class Gate location	Business	Eco	Eco Plus

```
0                       1      0          0
1                    9398   6885       1228
2                    9782   8230       1384
3                   11228  15093       2168
4                   10507  12064       1782
5                    8617   4321        906
```

Visualization

[117]:
```
Pie('Gate location','Gate location','Gate location Distribution')
```

[118]:
```
Bar_hue('Gate location','satisfaction','Gate location','Satisfaction','Gate␣
 ↪location Distribution')
```

[119]:
```
Bar_2hue('Gate location','Gender','Gate location','Gender',title='Gate location␣
 ↪Distribution',hue2='Customer Type',title_h2='Customer')
```

[120]:
```
Bar_2hue('Gate location','Type of Travel','Gate location','Type of␣
 ↪Travel',title='Gate location Distribution',hue2='Class',title_h2='Class')
```

[121]:
```
Heatmap(cross,'Gate location Distribution','Gate␣
 ↪location','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[122]:
```
Heatmap(cross2,'Gate location Distribution','Gate location','Customer␣
 ↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[123]:
```
Heatmap(cross4,'Gate location Vs Class Categories','Gate␣
 ↪location','Class',make_subplot=False)
```

What is Type of Food and drink distribution?

caculate the value counts for the "Food and drink" column

[124]:
```
data['Food and drink'].value_counts().to_frame()
```

[124]:

	count
Food and drink	
4	24294
5	22239
3	22238
2	21918
1	12800
0	105

count the occurrences of each combination of Food and drink and satisfaction

[125]:
```
cross = cross_t('Food and drink','satisfaction')
cross
```

[125]:
```
satisfaction    neutral or dissatisfied  satisfied
Food and drink
0                                    56         49
1                                 10237       2563
2                                 13407       8511
3                                 13427       8811
4                                 11535      12759
5                                 10035      12204
```

count the occurrences of each combination of Food and drink and Gender

[126]:
```
cross1 = cross_t('Food and drink','Gender')
cross1
```

[126]:
```
Gender          Female   Male
Food and drink
0                   55     50
1                 6510   6290
2                11223  10695
3                11426  10812
4                12082  12212
5                11280  10959
```

count the occurrences of each combination of Food and drink and Customer Type

[127]:
```
cross2 = cross_t('Food and drink','Customer Type')
cross2
```

[127]:
```
Customer Type   Loyal Customer  disloyal Customer
Food and drink
0                           81                 24
1                         9436               3364
2                        17996               3922
3                        18276               3962
4                        20353               3941
5                        18520               3719
```

count the occurrences of each combination of Food and drink and Type of Travel

[128]:
```
cross3 = cross_t('Food and drink','Type of Travel')
cross3
```

[128]:
```
Type of Travel  Business travel  Personal Travel
Food and drink
0                            54               51
1                          7796             5004
2                         14965             6953
3                         15252             6986
4                         17611             6683
```

```
5                        15787             6452
```

count the occurrences of each combination of Food and drink and Class

[129]:
```
cross4 = cross_t('Food and drink','Class')
cross4
```

[129]:

Class Food and drink	Business	Eco	Eco Plus
0	31	56	18
1	4358	7341	1101
2	10569	9798	1551
3	10701	9947	1590
4	12379	10226	1689
5	11495	9225	1519

Visualization

[130]:
```
Pie('Food and drink','Food and drink','Food and drink Distribution')
```

[131]:
```
Bar_hue('Food and drink','satisfaction','Food and drink','Satisfaction','Food␣
↪and drink Distribution')
```

[132]:
```
Bar_2hue('Food and drink','Gender','Food and drink','Gender',title='Food and␣
↪drink Distribution',hue2='Customer Type',title_h2='Customer')
```

[133]:
```
Bar_2hue('Food and drink','Type of Travel','Food and drink','Type of␣
↪Travel',title='Food and drink Distribution',hue2='Class',title_h2='Class')
```

[134]:
```
Heatmap(cross,'Food and drink Distribution','Food and␣
↪drink','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[135]:
```
Heatmap(cross2,'Food and drink Distribution','Food and drink','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[136]:
```
Heatmap(cross4,'Food and drink Vs Class Categories','Food and␣
↪drink','Class',make_subplot=False)
```

What is Type of Online boarding distribution?

calculate the value counts for the "Online boarding" column

[137]:
```
data['Online boarding'].value_counts().to_frame()
```

[137]:

Online boarding	count
4	30671
3	21744
5	20652
2	17449

```
1                10658
0                 2420
```

count the occurrences of each combination of Online boarding and satisfaction

[138]:
```python
cross = cross_t('Online boarding','satisfaction')
cross
```

[138]:
```
satisfaction     neutral or dissatisfied  satisfied
Online boarding
0                                   1073       1347
1                                   9187       1471
2                                  15437       2012
3                                  18790       2954
4                                  11562      19109
5                                   2648      18004
```

count the occurrences of each combination of Online boarding and Gender

[139]:
```python
cross1 = cross_t('Online boarding','Gender')
cross1
```

[139]:
```
Gender           Female   Male
Online boarding
0                  1097   1323
1                  5084   5574
2                  8337   9112
3                 11040  10704
4                 16124  14547
5                 10894   9758
```

count the occurrences of each combination of Online boarding and Customer Type

[140]:
```python
cross2 = cross_t('Online boarding','Customer Type')
cross2
```

[140]:
```
Customer Type    Loyal Customer  disloyal Customer
Online boarding
0                          1601                819
1                          7661               2997
2                         12828               4621
3                         16927               4817
4                         26893               3778
5                         18752               1900
```

count the occurrences of each combination of Online boarding and Type of Travel

[141]:
```python
cross3 = cross_t('Online boarding','Type of Travel')
cross3
```

[141]:
```
Type of Travel   Business travel  Personal Travel
Online boarding
0                           1092             1328
1                           6109             4549
2                          10075             7374
3                          13317             8427
4                          23749             6922
5                          17123             3529
```

count the occurrences of each combination of Online boarding and Class

[142]:
```
cross4 = cross_t('Online boarding','Class')
cross4
```

[142]:
```
Class            Business    Eco  Eco Plus
Online boarding
0                     540   1614       266
1                    2945   6706      1007
2                    5019  10785      1645
3                    7679  12202      1863
4                   18685  10249      1737
5                   14665   5037       950
```

Visualization

[143]:
```
Pie('Online boarding','Online boarding','Online boarding Distribution')
```

[144]:
```
Bar_hue('Online boarding','satisfaction','Online␣
↪boarding','Satisfaction','Online boarding Distribution')
```

[145]:
```
Bar_2hue('Online boarding','Gender','Online boarding','Gender',title='Online␣
↪boarding Distribution',hue2='Customer Type',title_h2='Customer')
```

[146]:
```
Bar_2hue('Online boarding','Type of Travel','Online boarding','Type of␣
↪Travel',title='Online boarding Distribution',hue2='Class',title_h2='Class')
```

[147]:
```
Heatmap(cross,'Food and drink Distribution','Online␣
↪boarding','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[148]:
```
Heatmap(cross2,'Online boarding Distribution','Online boarding','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[149]:
```
Heatmap(cross4,'Online boarding Vs Class Categories','Online␣
↪boarding','Class',make_subplot=False)
```

What is Seat comfort distribution?

calculate the value counts for the "Seat comfort" column

[150]:
```
data['Seat comfort'].value_counts().to_frame()
```

[150]:

Seat comfort	count
4	31682
5	26393
3	18641
2	14846
1	12031
0	1

count the occurrences of each combination of Seat comfort and satisfaction

[151]:
```
cross = cross_t('Seat comfort','satisfaction')
cross
```

[151]:

Seat comfort	neutral or dissatisfied	satisfied
0	1	0
1	9341	2690
2	11516	3330
3	14697	3944
4	13907	17775
5	9235	17158

count the occurrences of each combination of Seat comfort and Gender

[152]:
```
cross1 = cross_t('Seat comfort','Gender')
cross1
```

[152]:

Seat comfort	Female	Male
0	1	0
1	5714	6317
2	7152	7694
3	9663	8978
4	16568	15114
5	13478	12915

count the occurrences of each combination of Seat comfort and Customer Type

[153]:
```
cross2 = cross_t('Seat comfort','Customer Type')
cross2
```

[153]:

Seat comfort	Loyal Customer	disloyal Customer
0	1	0
1	8305	3726
2	10954	3892
3	14842	3799
4	27888	3794

```
5                        22672             3721
```

count the occurrences of each combination of Seat comfort and Type of Travel

[154]:
```python
cross3 = cross_t('Seat comfort','Type of Travel')
cross3
```

[154]:

Type of Travel	Business travel	Personal Travel
Seat comfort		
0	1	0
1	6896	5135
2	9260	5586
3	12334	6307
4	23629	8053
5	19345	7048

count the occurrences of each combination of Seat comfort and Class

[155]:
```python
cross4 = cross_t('Seat comfort','Class')
cross4
```

[155]:

Class	Business	Eco	Eco Plus
Seat comfort			
0	1	0	0
1	3490	7448	1093
2	4843	8667	1336
3	7224	9782	1635
4	18440	11334	1908
5	15535	9362	1496

Visualization

[156]:
```python
Pie('Seat comfort','Seat comfort','Seat comfort Distribution')
```

[157]:
```python
Bar_hue('Seat comfort','satisfaction','Seat comfort','Satisfaction','Seat␣
↪comfort Distribution')
```

[158]:
```python
Bar_2hue('Seat comfort','Gender','Seat comfort','Gender',title='Seat comfort␣
↪Distribution',hue2='Customer Type',title_h2='Customer')
```

[159]:
```python
Bar_2hue('Seat comfort','Type of Travel','Seat comfort','Type of␣
↪Travel',title='Seat comfort Distribution',hue2='Class',title_h2='Class')
```

[160]:
```python
Heatmap(cross,'Seat comfort Distribution','Seat␣
↪comfort','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[161]:
```python
Heatmap(cross2,'Seat comfort Distribution','Seat comfort','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

```
[162]: Heatmap(cross4,'Seat comfort Vs Class Categories','Seat␣
         ↪comfort','Class',make_subplot=False)
```

What is Type of Inflight entertainment distribution?

calculate the value counts for the "Inflight entertainment" column

```
[163]: data['Inflight entertainment'].value_counts().to_frame()
```

```
[163]:                         count
       Inflight entertainment
       4                       29335
       5                       25145
       3                       19080
       2                       17579
       1                       12441
       0                          14
```

count the occurrences of each combination of Inflight entertainment and satisfaction

```
[164]: cross = cross_t('Inflight entertainment','satisfaction')
       cross
```

```
[164]: satisfaction            neutral or dissatisfied  satisfied
       Inflight entertainment
       0                                            14          0
       1                                         10701       1740
       2                                         13829       3750
       3                                         13934       5146
       4                                         11381      17954
       5                                          8838      16307
```

count the occurrences of each combination of Inflight entertainment and Gender

```
[165]: cross1 = cross_t('Inflight entertainment','Gender')
       cross1
```

```
[165]: Gender                  Female   Male
       Inflight entertainment
       0                            7      7
       1                         6365   6076
       2                         9011   8568
       3                         9748   9332
       4                        14707  14628
       5                        12738  12407
```

count the occurrences of each combination of Inflight entertainment and Customer Type

```
[166]: cross2 = cross_t('Inflight entertainment','Customer Type')
       cross2
```

[166]:

Customer Type	Loyal Customer	disloyal Customer
Inflight entertainment		
0	14	0
1	9059	3382
2	13750	3829
3	15105	3975
4	25344	3991
5	21390	3755

count the occurrences of each combination of Inflight entertainment and Type of Travel

[167]:
```
cross3 = cross_t('Inflight entertainment','Type of Travel')
cross3
```

[167]:

Type of Travel	Business travel	Personal Travel
Inflight entertainment		
0	14	0
1	6886	5555
2	11002	6577
3	12322	6758
4	22605	6730
5	18636	6509

count the occurrences of each combination of Inflight entertainment and Class

[168]:
```
cross4 = cross_t('Inflight entertainment','Class')
cross4
```

[168]:

Class	Business	Eco	Eco Plus
Inflight entertainment			
0	6	3	5
1	3836	7486	1119
2	6567	9534	1478
3	7722	9763	1595
4	17074	10511	1750
5	14328	9296	1521

Visualization

[169]:
```
Pie('Inflight entertainment','Inflight entertainment','Inflight entertainment␣
↪Distribution')
```

[170]:
```
Bar_hue('Inflight entertainment','satisfaction','Inflight␣
↪entertainment','Satisfaction','Inflight entertainment Distribution')
```

[171]:
```
Bar_2hue('Inflight␣
↪entertainment','Gender','Entertainment','Gender',title='Inflight␣
↪entertainment Distribution',hue2='Customer Type',title_h2='Customer')
```

[172]:
```
Bar_2hue('Inflight entertainment','Type of Travel','Entertainment','Type of␣
↪Travel',title='Inflight entertainment␣
↪Distribution',hue2='Class',title_h2='Class')
```

[173]:
```
Heatmap(cross,'Inflight entertainment Distribution','Inflight␣
↪entertainment','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[174]:
```
Heatmap(cross2,'Inflight entertainment Distribution','Inflight␣
↪entertainment','Customer Type',make_subplot=True,feature_h2='Type of␣
↪Travel',pivot2=cross3)
```

[175]:
```
Heatmap(cross4,'Inflight entertainment Vs Class Categories','Inflight␣
↪entertainment','Class',make_subplot=False)
```

What is On-board service distribution?

calculate the value counts for the "On-board service" column

[176]:
```
data['On-board service'].value_counts().to_frame()
```

[176]:

	count
On-board service	
4	30773
5	23584
3	22770
2	14632
1	11832
0	3

count the occurrences of each combination of On-board service and satisfaction

[177]:
```
cross = cross_t('On-board service','satisfaction')
cross
```

[177]:

satisfaction	neutral or dissatisfied	satisfied
On-board service		
0	3	0
1	9541	2291
2	10890	3742
3	15583	7187
4	14246	16527
5	8434	15150

count the occurrences of each combination of On-board service and Gender

[178]:
```
cross1 = cross_t('On-board service','Gender')
cross1
```

[178]:
```
Gender           Female   Male
On-board service
0                     2      1
1                  6039   5793
2                  7783   6849
3                 11352  11418
4                 15352  15421
5                 12048  11536
```

count the occurrences of each combination of On-board service and Customer Type

[179]:
```
cross2 = cross_t('On-board service','Customer Type')
cross2
```

[179]:
```
Customer Type     Loyal Customer  disloyal Customer
On-board service
0                              3                  0
1                           9269               2563
2                          12005               2627
3                          17639               5131
4                          25640               5133
5                          20106               3478
```

count the occurrences of each combination of On-board service and Type of Travel

[180]:
```
cross3 = cross_t('On-board service','Type of Travel')
cross3
```

[180]:
```
Type of Travel    Business travel  Personal Travel
On-board service
0                               3                0
1                            7619             4213
2                           10138             4494
3                           14376             8394
4                           22444             8329
5                           16885             6699
```

count the occurrences of each combination of On-board service and Class

[181]:
```
cross4 = cross_t('On-board service','Class')
cross4
```

[181]:
```
Class             Business    Eco  Eco Plus
On-board service
0                        3      0         0
1                     3337   7246      1249
2                     5417   7835      1380
3                     9331  11624      1815
4                    17127  11819      1827
```

```
5                    14318    8069      1197
```

Visualization

[182]:
```python
Pie('On-board service','On-board service','On-board service Distribution')
```

[183]:
```python
Bar_hue('On-board service','satisfaction','On-board␣
↪service','Satisfaction','On-board service Distribution')
```

[184]:
```python
Bar_2hue('On-board service','Gender','On-board␣
↪service','Gender',title='On-board service Distribution',hue2='Customer␣
↪Type',title_h2='Customer')
```

[185]:
```python
Bar_2hue('On-board service','Type of Travel','On-board service','Type of␣
↪Travel',title='On-board service Distribution',hue2='Class',title_h2='Class')
```

[186]:
```python
Heatmap(cross,'On-board service Distribution','On-board␣
↪service','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[187]:
```python
Heatmap(cross2,'On-board service Distribution','On-board service','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[188]:
```python
Heatmap(cross4,'On-board service Vs Class Categories','On-board␣
↪service','Class',make_subplot=False)
```

What is Type of Leg room service distribution?

calculate the value counts for the "Leg room service" column

[189]:
```python
data['Leg room service'].value_counts().to_frame()
```

[189]:

	count
Leg room service	
4	28704
5	24599
3	20042
2	19469
1	10310
0	470

count the occurrences of each combination of Leg room service and satisfaction

[190]:
```python
cross = cross_t('Leg room service','satisfaction')
cross
```

[190]:

satisfaction	neutral or dissatisfied	satisfied
Leg room service		
0	304	166
1	8221	2089
2	14124	5345

```
3                                    14580      5462
4                                    11980     16724
5                                     9488     15111
```

count the occurrences of each combination of Leg room service and Gender

[191]:
```
cross1 = cross_t('Leg room service','Gender')
cross1
```

[191]:
```
Gender            Female   Male
Leg room service
0                    406     64
1                   5363   4947
2                  10120   9349
3                  10273   9769
4                  14458  14246
5                  11956  12643
```

count the occurrences of each combination of Leg room service and Customer Type

[192]:
```
cross2 = cross_t('Leg room service','Customer Type')
cross2
```

[192]:
```
Customer Type     Loyal Customer  disloyal Customer
Leg room service
0                            470                  0
1                           8088               2222
2                          15407               4062
3                          15852               4190
4                          24429               4275
5                          20416               4183
```

count the occurrences of each combination of Leg room service and Type of Travel

[193]:
```
cross3 = cross_t('Leg room service','Type of Travel')
cross3
```

[193]:
```
Type of Travel    Business travel  Personal Travel
Leg room service
0                              71              399
1                            6623             3687
2                           11964             7505
3                           12289             7753
4                           21759             6945
5                           18759             5840
```

count the occurrences of each combination of Leg room service and Class

[194]:
```
cross4 = cross_t('Leg room service','Class')
cross4
```

```
[194]: Class             Business    Eco  Eco Plus
       Leg room service
       0                      124    306        40
       1                     2867   6343      1100
       2                     7538  10293      1638
       3                     7793  10567      1682
       4                    16846  10258      1600
       5                    14365   8826      1408
```

Visualization

```
[195]: Pie('Leg room service','Leg room service','Leg room service Distribution')
```

```
[196]: Bar_hue('Leg room service','satisfaction','Leg room␣
        ↪service','Satisfaction','Leg room service Distribution')
```

```
[197]: Bar_2hue('Leg room service','Gender','Leg room service','Gender',title='Leg␣
        ↪room service Distribution',hue2='Customer Type',title_h2='Customer')
```

```
[198]: Bar_2hue('Leg room service','Type of Travel','Leg room service','Type of␣
        ↪Travel',title='Leg room service Distribution',hue2='Class',title_h2='Class')
```

```
[199]: Heatmap(cross,'Leg room service Distribution','Leg room␣
        ↪service','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

```
[200]: Heatmap(cross2,'Leg room service Distribution','Leg room service','Customer␣
        ↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

```
[201]: Heatmap(cross4,'Leg room service Vs Class Categories','Leg room␣
        ↪service','Class',make_subplot=False)
```

What is Type of Baggage handling distribution?

calculate the value counts for the "Baggage handling" column

```
[202]: data['Baggage handling'].value_counts().to_frame()
```

```
[202]:                  count
       Baggage handling
       4                37274
       5                27047
       3                20567
       2                11483
       1                 7223
```

count the occurrences of each combination of Baggage handling and satisfaction

```
[203]: cross = cross_t('Baggage handling','satisfaction')
       cross
```

[203]:
satisfaction	neutral or dissatisfied	satisfied
Baggage handling		
1	5075	2148
2	8086	3397
3	15719	4848
4	19345	17929
5	10472	16575

count the occurrences of each combination of Baggage handling and Gender

[204]:
```
cross1 = cross_t('Baggage handling','Gender')
cross1
```

[204]:
Gender	Female	Male
Baggage handling		
1	4144	3079
2	6257	5226
3	10313	10254
4	18251	19023
5	13611	13436

count the occurrences of each combination of Baggage handling and Customer Type

[205]:
```
cross2 = cross_t('Baggage handling','Customer Type')
cross2
```

[205]:
Customer Type	Loyal Customer	disloyal Customer
Baggage handling		
1	6207	1016
2	9953	1530
3	16232	4335
4	29870	7404
5	22400	4647

count the occurrences of each combination of Baggage handling and Type of Travel

[206]:
```
cross3 = cross_t('Baggage handling','Type of Travel')
cross3
```

[206]:
Type of Travel	Business travel	Personal Travel
Baggage handling		
1	4419	2804
2	7825	3658
3	14215	6352
4	26431	10843
5	18575	8472

count the occurrences of each combination of Baggage handling and Class

```
[207]: cross4 = cross_t('Baggage handling','Class')
cross4
```

```
[207]: Class              Business    Eco  Eco Plus
Baggage handling
1                      2416   4092       715
2                      4616   5876       991
3                      7227  11354      1986
4                     19353  15508      2413
5                     15921   9763      1363
```

Visualization

```
[208]: Pie('Baggage handling','Baggage handling','Baggage handling Distribution')
```

```
[209]: Bar_hue('Baggage handling','satisfaction','Baggage␣
 ↪handling','Satisfaction','Baggage handling Distribution')
```

```
[210]: Bar_2hue('Baggage handling','Gender','Baggage handling','Gender',title='Baggage␣
 ↪handling Distribution',hue2='Customer Type',title_h2='Customer')
```

```
[211]: Bar_2hue('Baggage handling','Type of Travel','Baggage handling','Type of␣
 ↪Travel',title='Baggage handling Distribution',hue2='Class',title_h2='Class')
```

```
[212]: Heatmap(cross,'Baggage handling Distribution','Baggage␣
 ↪handling','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

```
[213]: Heatmap(cross2,'Baggage handling Distribution','Baggage handling','Customer␣
 ↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

```
[214]: Heatmap(cross4,'Baggage handling Vs Class Categories','Baggage␣
 ↪handling','Class',make_subplot=False)
```

What is Type of Checkin service distribution?

calculate the value counts for the Checkin service column

```
[215]: data['Checkin service'].value_counts().to_frame()
```

```
[215]:                  count
Checkin service
4                 28975
3                 28356
5                 20556
2                 12854
1                 12852
0                     1
```

count the occurrences of each combination of Checkin service and satisfaction

```
[216]: cross = cross_t('Checkin service','satisfaction')
       cross
```

```
[216]: satisfaction     neutral or dissatisfied  satisfied
       Checkin service
       0                                      1          0
       1                                   9776       3076
       2                                   9606       3248
       3                                  15639      12717
       4                                  15651      13324
       5                                   8024      12532
```

count the occurrences of each combination of Checkin service and Gender

```
[217]: cross1 = cross_t('Checkin service','Gender')
       cross1
```

```
[217]: Gender           Female   Male
       Checkin service
       0                     1      0
       1                  6580   6272
       2                  6670   6184
       3                 14389  13967
       4                 14723  14252
       5                 10213  10343
```

count the occurrences of each combination of Checkin service and Customer Type

```
[218]: cross2 = cross_t('Checkin service','Customer Type')
       cross2
```

```
[218]: Customer Type    Loyal Customer  disloyal Customer
       Checkin service
       0                             1                  0
       1                         10205               2647
       2                         10243               2611
       3                         23238               5118
       4                         23905               5070
       5                         17070               3486
```

count the occurrences of each combination of Checkin service and Type of Travel

```
[219]: cross3 = cross_t('Checkin service','Type of Travel')
       cross3
```

```
[219]: Type of Travel   Business travel  Personal Travel
       Checkin service
       0                              1                0
       1                           9050             3802
```

```
2                        9104            3750
3                       19418            8938
4                       19862            9113
5                       14030            6526
```

count the occurrences of each combination of Checkin service and Class

[220]:
```python
cross4 = cross_t('Checkin service','Class')
cross4
```

[220]:
```
Class            Business    Eco  Eco Plus
Checkin service
0                       1      0         0
1                    4174   7356      1322
2                    4297   7215      1342
3                   14458  12062      1836
4                   14851  12297      1827
5                   11752   7663      1141
```

Visualization

[221]:
```python
Pie('Checkin service','Checkin service','Checkin service Distribution')
```

[222]:
```python
Bar_hue('Checkin service','satisfaction','Checkin service','Satisfaction','Checkin service Distribution')
```

[223]:
```python
Bar_2hue('Checkin service','Gender','Checkin service','Gender',title='Checkin service Distribution',hue2='Customer Type',title_h2='Customer')
```

[224]:
```python
Bar_2hue('Checkin service','Type of Travel','Checkin service','Type of Travel',title='Checkin service Distribution',hue2='Class',title_h2='Class')
```

[225]:
```python
Heatmap(cross,'Checkin service Distribution','Checkin service','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[226]:
```python
Heatmap(cross2,'Checkin service Distribution','Checkin service','Customer Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[227]:
```python
Heatmap(cross4,'Checkin service VS Class Categories','Checkin service','Class',make_subplot=False)
```

What is Type of Inflight service distribution?

calculate the value counts for the Inflight service column

[228]:
```python
data['Inflight service'].value_counts().to_frame()
```

[228]:
```
                  count
Inflight service
4                 37846
```

```
5                 27041
3                 20227
2                 11414
1                  7063
0                     3
```

count the occurrences of each combination of Inflight service and satisfaction

[229]:
```
cross = cross_t('Inflight service','satisfaction')
cross
```

[229]:
```
satisfaction      neutral or dissatisfied  satisfied
Inflight service
0                                       3          0
1                                    5017       2046
2                                    7975       3439
3                                   15394       4833
4                                   19764      18082
5                                   10544      16497
```

count the occurrences of each combination of Inflight service and Gender

[230]:
```
cross1 = cross_t('Inflight service','Gender')
cross1
```

[230]:
```
Gender            Female   Male
Inflight service
0                      2      1
1                   3976   3087
2                   6270   5144
3                  10254   9973
4                  18602  19244
5                  13472  13569
```

count the occurrences of each combination of Inflight service and Customer Type

[231]:
```
cross2 = cross_t('Inflight service','Customer Type')
cross2
```

[231]:
```
Customer Type     Loyal Customer  disloyal Customer
Inflight service
0                              3                  0
1                           6005               1058
2                           9835               1579
3                          16090               4137
4                          30441               7405
5                          22288               4753
```

count the occurrences of each combination of Inflight service and Type of Travel

[232]:
```
cross3 = cross_t('Inflight service','Type of Travel')
cross3
```

[232]:

Type of Travel	Business travel	Personal Travel
Inflight service		
0	3	0
1	4394	2669
2	7877	3537
3	14045	6182
4	26559	11287
5	18587	8454

count the occurrences of each combination of Inflight service and Class

[233]:
```
class4 = cross_t('Inflight service','Class')
class4
```

[233]:

Class	Business	Eco	Eco Plus
Inflight service			
0	3	0	0
1	2399	3976	688
2	4608	5856	950
3	7173	11091	1963
4	19457	15876	2513
5	15893	9794	1354

Visualization

[234]:
```
Pie('Inflight service','Inflight service','Inflight service Distribution')
```

[235]:
```
Bar_hue('Inflight service','satisfaction','Inflight␣
↪service','Satisfaction','Inflight service Distribution')
```

[236]:
```
Bar_2hue('Inflight service','Gender','Inflight␣
↪service','Gender',title='Inflight service Distribution',hue2='Customer␣
↪Type',title_h2='Customer')
```

[237]:
```
Bar_2hue('Inflight service','Type of Travel','Inflight service','Type of␣
↪Travel',title='Inflight service Distribution',hue2='Class',title_h2='Class')
```

[238]:
```
Heatmap(cross,'Inflight service Distribution','Inflight␣
↪service','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cross1)
```

[239]:
```
Heatmap(cross2,'Inflight service Distribution','Inflight service','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[240]:
```
Heatmap(cross4,'Inflight service VS Class Categories','Inflight␣
↪service','Class',make_subplot=False)
```

What is Type of Cleanliness distribution?

calculate the value counts for the Cleanliness column

[241]:
```
data['Cleanliness'].value_counts().to_frame()
```

[241]:
```
             count
Cleanliness
4            27100
3            24506
5            22619
2            16081
1            13276
0               12
```

count the occurrences of each combination of Cleanliness and satisfaction

[242]:
```
cross = cross_t('Cleanliness','satisfaction')
cross
```

[242]:
```
satisfaction  neutral or dissatisfied  satisfied
Cleanliness
0                                  12          0
1                               10669       2607
2                               12653       3428
3                               13925      10581
4                               12587      14513
5                                8851      13768
```

count the occurrences of each combination of Cleanliness and Gender

[243]:
```
cross1 = cross_t('Cleanliness','Gender')
cross1
```

[243]:
```
Gender       Female   Male
Cleanliness
0                 6      6
1              6836   6440
2              7959   8122
3             12731  11775
4             13819  13281
5             11225  11394
```

count the occurrences of each combination of Cleanliness and Customer Type

[244]:
```
cross2 = cross_t('Cleanliness','Customer Type')
cross2
```

[244]:
```
Customer Type  Loyal Customer  disloyal Customer
Cleanliness
```

```
0                        12             0
1                      9922          3354
2                     12210          3871
3                     20584          3922
4                     23131          3969
5                     18803          3816
```

count the occurrences of each combination of Cleanliness and Type of Travel

[245]:
```python
cross3 = cross_t('Cleanliness','Type of Travel')
cross3
```

[245]:
```
Type of Travel  Business travel  Personal Travel
Cleanliness
0                            12                0
1                          8178             5098
2                         10133             5948
3                         17262             7244
4                         19815             7285
5                         16065             6554
```

count the occurrences of each combination of Cleanliness and Class

[246]:
```python
cross4 = cross_t('Cleanliness','Class')
cross4
```

[246]:
```
Class        Business    Eco  Eco Plus
Cleanliness
0                   4      3         5
1                4720   7423      1133
2                5544   9107      1430
3               12653  10172      1681
4               14579  10769      1752
5               12033   9119      1467
```

Visualization

[247]:
```python
Pie('Cleanliness','Cleanliness','Cleanliness Distribution')
```

[248]:
```python
Bar_hue('Cleanliness','satisfaction','Cleanliness','Satisfaction','Cleanliness␣
↪Distribution')
```

[249]:
```python
Bar_2hue('Cleanliness','Gender','Cleanliness','Gender',title='Cleanliness␣
↪Distribution',hue2='Customer Type',title_h2='Customer')
```

[250]:
```python
Bar_2hue('Cleanliness','Type of Travel','Cleanliness','Type of␣
↪Travel',title='Cleanliness Distribution',hue2='Class',title_h2='Class')
```

[251]:
```python
Heatmap(cross,'Cleanliness␣
↪Distribution','Cleanliness','Satisfaction',make_subplot=True,feature_h2='Gender',pivot2=cro
```

[252]:
```python
Heatmap(cross2,'Cleanliness Distribution','Cleanliness','Customer␣
↪Type',make_subplot=True,feature_h2='Type of Travel',pivot2=cross3)
```

[253]:
```python
Heatmap(cross4,'Cleanliness VS Class␣
↪Categories','Cleanliness','Class',make_subplot=False)
```

What is Type of Departure Delay in Minutes distribution?

Find the minimum Departure Delay in Minutes

[254]:
```python
data['Departure Delay in Minutes'].min()
```

[254]: 0

Find the maximum Departure Delay in Minutes

[255]:
```python
data['Departure Delay in Minutes'].max()
```

[255]: 1592

average the occurrences of each combination of Departure Delay in Minutes and Type of Travel

[256]:
```python
pivot_table = pivot('Departure Delay in Minutes','Type of Travel')
pivot_table
```

[256]:

	Departure Delay in Minutes
Type of Travel	
Business travel	14.902470
Personal Travel	14.404214

average the occurrences of each combination of Departure Delay in Minutes and Class

[257]:
```python
pivot_table1 = pivot('Departure Delay in Minutes','Class')
pivot_table1
```

[257]:

	Departure Delay in Minutes
Class	
Business	14.335554
Eco	15.093147
Eco Plus	15.329405

Visualization

[258]:
```python
Boxplot_outlier('Departure Delay in Minutes','Departure Delay Distribution')
```

[259]:
```python
mean(pivot_table,pivot_table1,'Departure Delay in Minutes','Type of␣
↪Travel','Class','Average Departure Delay',title_f='Departure Delay')
```

What is Arrival Delay in Minutes distribution?

Find the minimum Arrival Delay in Minutes

[260]:
```
data['Arrival Delay in Minutes'].min()
```

[260]: 0.0

Find the maximum Arrival Delay in Minutes

[261]:
```
data['Arrival Delay in Minutes'].max()
```

[261]: 1584.0

average the occurrences of each combination of Arrival Delay in Minutes and Type of Travel

[262]:
```
pivot_table = pivot('Arrival Delay in Minutes','Type of Travel')
pivot_table
```

[262]:

	Arrival Delay in Minutes
Type of Travel	
Business travel	15.326146
Personal Travel	14.850665

average the occurrences of each combination of Arrival Delay in Minutes and Class

[263]:
```
pivot_table1 = pivot('Arrival Delay in Minutes','Class')
pivot_table1
```

[263]:

	Arrival Delay in Minutes
Class	
Business	14.577272
Eco	15.672183
Eco Plus	16.088645

Visualization

[264]:
```
Boxplot_outlier('Arrival Delay in Minutes','Arrival Delay Distribution')
```

[265]:
```
mean(pivot_table,pivot_table1,'Arrival Delay in Minutes','Type of␣
↪Travel','Class','Average Arrival Delay',title_f='Arrival Delay')
```

What is satisfaction distribution?

calculate the value counts for the satisfaction column

[266]:
```
data['satisfaction'].value_counts().to_frame().head()
```

[266]:

	count
satisfaction	
neutral or dissatisfied	58697
satisfied	44897

Visualization

[267]:
```python
Pie('satisfaction','Traget','Traget Distribution')
```

Remove Outliers

[268]:
```python
cols = ['Flight Distance', 'Departure Delay in Minutes', 'Arrival Delay in␣
↪Minutes']
fig = make_subplots(rows=2, cols=2, subplot_titles=cols)
for i, col in enumerate(cols, start=1):
    q1 = data[col].quantile(0.25)
    q3 = data[col].quantile(0.75)
    iqr = q3 - q1
    upper = q3 + (1.5 * iqr)
    lower = q1 - (1.5 * iqr)
    data[col][data[col]>upper] = upper
    data[col][data[col]<lower] = lower
    trace = go.Box(y=data[col], name=col)
    fig.add_trace(trace, row=(i - 1) // 2 + 1, col=(i - 1) % 2 + 1)
fig.update_layout(title_text='Box Plot of Columns without Outliers',title_x=0.
↪5, title_y=0.95,
                  height=800, width=1000, template='plotly_dark')
fig.show()
```

Observation based on figure the dataset is almost banlanced

** #

PreProcessing

Tabel of Contents

Transform Object Columns

[269]:
```python
data2=data.iloc[:,1:].copy()
object=data2.select_dtypes(include='object').columns
label=LabelEncoder()
for col in object:
    data2[col] = label.fit_transform(data2[col])
data2.head()
```

[269]:
```
   Gender  Customer Type  Age  Type of Travel  Class  Flight Distance  \
0       1              0   13               1      2            460.0
1       1              1   25               0      0            235.0
2       0              0   26               0      0           1142.0
3       0              0   25               0      0            562.0
4       1              0   61               0      0            214.0

   Inflight wifi service  Departure/Arrival time convenient  \
0                      3                                  4
1                      3                                  2
2                      2                                  2
```

```
3                   2                                 5
4                   3                                 3

   Ease of Online booking  Gate location  …  Inflight entertainment  \
0                       3              1  …                       5
1                       3              3  …                       1
2                       2              2  …                       5
3                       5              5  …                       2
4                       3              3  …                       3

   On-board service  Leg room service  Baggage handling  Checkin service  \
0                 4                 3                 4                4
1                 1                 5                 3                1
2                 4                 3                 4                4
3                 2                 5                 3                1
4                 3                 4                 4                3

   Inflight service  Cleanliness  Departure Delay in Minutes  \
0                 5            5                          25
1                 4            1                           1
2                 4            5                           0
3                 4            2                          11
4                 3            3                           0

   Arrival Delay in Minutes  satisfaction
0                      18.0             0
1                       6.0             0
2                       0.0             1
3                       9.0             0
4                       0.0             1

[5 rows x 23 columns]
```

Show Correlation

[270]:
```
data2.corr()
```

[270]:
```
                                     Gender  Customer Type       Age  \
Gender                             1.000000      -0.031558  0.008921
Customer Type                     -0.031558       1.000000 -0.281821
Age                                0.008921      -0.281821  1.000000
Type of Travel                     0.006808      -0.308268 -0.048593
Class                             -0.012840       0.042589 -0.117423
Flight Distance                    0.006185      -0.226003  0.099990
Inflight wifi service              0.008964      -0.007706  0.017470
Departure/Arrival time convenient  0.008846      -0.207007  0.038038
Ease of Online booking             0.007166      -0.019627  0.024461
Gate location                      0.000213       0.006294 -0.001558
```

Food and drink	0.005707	-0.059554	0.022920
Online boarding	-0.042151	-0.189477	0.208681
Seat comfort	-0.026643	-0.159722	0.160302
Inflight entertainment	0.006071	-0.110106	0.076380
On-board service	0.008019	-0.056374	0.057123
Leg room service	0.031842	-0.047809	0.040498
Baggage handling	0.037333	0.024890	-0.047619
Checkin service	0.010438	-0.032065	0.035003
Inflight service	0.038936	0.023055	-0.049899
Cleanliness	0.006439	-0.083757	0.053493
Departure Delay in Minutes	0.001561	0.004311	-0.008581
Arrival Delay in Minutes	0.000190	0.005811	-0.011870
satisfaction	0.012356	-0.187558	0.137040

	Type of Travel	Class	Flight Distance \
Gender	0.006808	-0.012840	0.006185
Customer Type	-0.308268	0.042589	-0.226003
Age	-0.048593	-0.117423	0.099990
Type of Travel	1.000000	0.487001	-0.268305
Class	0.487001	1.000000	-0.428742
Flight Distance	-0.268305	-0.428742	1.000000
Inflight wifi service	-0.104879	-0.023046	0.007106
Departure/Arrival time convenient	0.259829	0.089793	-0.019844
Ease of Online booking	-0.133399	-0.094323	0.065992
Gate location	-0.030802	-0.004532	0.004647
Food and drink	-0.063124	-0.076834	0.057217
Online boarding	-0.224620	-0.296949	0.215819
Seat comfort	-0.123994	-0.209955	0.158055
Inflight entertainment	-0.147978	-0.178928	0.128960
On-board service	-0.056468	-0.207922	0.109964
Leg room service	-0.138680	-0.197331	0.134063
Baggage handling	-0.031355	-0.164016	0.063324
Checkin service	0.017043	-0.157084	0.073548
Inflight service	-0.022492	-0.158457	0.057738
Cleanliness	-0.078767	-0.125933	0.093425
Departure Delay in Minutes	-0.003935	0.010379	0.001499
Arrival Delay in Minutes	-0.005489	0.021780	-0.006758
satisfaction	-0.448995	-0.449466	0.299538

	Inflight wifi service \
Gender	0.008964
Customer Type	-0.007706
Age	0.017470
Type of Travel	-0.104879
Class	-0.023046
Flight Distance	0.007106
Inflight wifi service	1.000000

```
Departure/Arrival time convenient           0.343758
Ease of Online booking                      0.715848
Gate location                               0.336127
Food and drink                              0.134603
Online boarding                             0.457002
Seat comfort                                0.122617
Inflight entertainment                      0.209513
On-board service                            0.121484
Leg room service                            0.160485
Baggage handling                            0.121060
Checkin service                             0.043178
Inflight service                            0.110626
Cleanliness                                 0.132652
Departure Delay in Minutes                 -0.027663
Arrival Delay in Minutes                   -0.032194
satisfaction                                0.284163

                                   Departure/Arrival time convenient  \
Gender                                                      0.008846
Customer Type                                              -0.207007
Age                                                         0.038038
Type of Travel                                              0.259829
Class                                                       0.089793
Flight Distance                                            -0.019844
Inflight wifi service                                       0.343758
Departure/Arrival time convenient                           1.000000
Ease of Online booking                                      0.437021
Gate location                                               0.444601
Food and drink                                              0.005189
Online boarding                                             0.069990
Seat comfort                                                0.011416
Inflight entertainment                                     -0.004683
On-board service                                            0.068604
Leg room service                                            0.012461
Baggage handling                                            0.071901
Checkin service                                             0.093329
Inflight service                                            0.073227
Cleanliness                                                 0.014337
Departure Delay in Minutes                                 -0.001442
Arrival Delay in Minutes                                   -0.003062
satisfaction                                               -0.051718

                                   Ease of Online booking  Gate location  …  \
Gender                                           0.007166       0.000213  …
Customer Type                                   -0.019627       0.006294  …
Age                                              0.024461      -0.001558  …
Type of Travel                                  -0.133399      -0.030802  …
```

Class	-0.094323	-0.004532	…
Flight Distance	0.065992	0.004647	…
Inflight wifi service	0.715848	0.336127	…
Departure/Arrival time convenient	0.437021	0.444601	…
Ease of Online booking	1.000000	0.458746	…
Gate location	0.458746	1.000000	…
Food and drink	0.031940	-0.001170	…
Online boarding	0.404093	0.001451	…
Seat comfort	0.030021	0.003383	…
Inflight entertainment	0.047185	0.003564	…
On-board service	0.038759	-0.028532	…
Leg room service	0.107431	-0.005868	…
Baggage handling	0.038851	0.002421	…
Checkin service	0.010957	-0.035451	…
Inflight service	0.035330	0.001742	…
Cleanliness	0.016192	-0.004015	…
Departure Delay in Minutes	-0.008119	0.003713	…
Arrival Delay in Minutes	-0.010832	0.004882	…
satisfaction	0.171507	0.000449	…

	Inflight entertainment	On-board service	\
Gender	0.006071	0.008019	
Customer Type	-0.110106	-0.056374	
Age	0.076380	0.057123	
Type of Travel	-0.147978	-0.056468	
Class	-0.178928	-0.207922	
Flight Distance	0.128960	0.109964	
Inflight wifi service	0.209513	0.121484	
Departure/Arrival time convenient	-0.004683	0.068604	
Ease of Online booking	0.047185	0.038759	
Gate location	0.003564	-0.028532	
Food and drink	0.622374	0.058999	
Online boarding	0.285194	0.155345	
Seat comfort	0.610614	0.132030	
Inflight entertainment	1.000000	0.420352	
On-board service	0.420352	1.000000	
Leg room service	0.299850	0.355657	
Baggage handling	0.378361	0.519252	
Checkin service	0.120812	0.243852	
Inflight service	0.405247	0.550725	
Cleanliness	0.691735	0.123236	
Departure Delay in Minutes	-0.031218	-0.034174	
Arrival Delay in Minutes	-0.042152	-0.046057	
satisfaction	0.398203	0.322450	

	Leg room service	Baggage handling	\
Gender	0.031842	0.037333	

```
Customer Type                          -0.047809          0.024890
Age                                     0.040498         -0.047619
Type of Travel                         -0.138680         -0.031355
Class                                  -0.197331         -0.164016
Flight Distance                         0.134063          0.063324
Inflight wifi service                   0.160485          0.121060
Departure/Arrival time convenient       0.012461          0.071901
Ease of Online booking                  0.107431          0.038851
Gate location                          -0.005868          0.002421
Food and drink                          0.032415          0.034811
Online boarding                         0.123780          0.083299
Seat comfort                            0.105447          0.074553
Inflight entertainment                  0.299850          0.378361
On-board service                        0.355657          0.519252
Leg room service                        1.000000          0.369674
Baggage handling                        0.369674          1.000000
Checkin service                         0.153079          0.233326
Inflight service                        0.368925          0.628944
Cleanliness                             0.096401          0.095783
Departure Delay in Minutes             -0.007546         -0.016931
Arrival Delay in Minutes               -0.015937         -0.028522
satisfaction                            0.313182          0.247819

                                   Checkin service  Inflight service  \
Gender                                    0.010438          0.038936
Customer Type                            -0.032065          0.023055
Age                                       0.035003         -0.049899
Type of Travel                            0.017043         -0.022492
Class                                    -0.157084         -0.158457
Flight Distance                           0.073548          0.057738
Inflight wifi service                     0.043178          0.110626
Departure/Arrival time convenient         0.093329          0.073227
Ease of Online booking                    0.010957          0.035330
Gate location                            -0.035451          0.001742
Food and drink                            0.087055          0.034077
Online boarding                           0.204208          0.074390
Seat comfort                              0.191545          0.069193
Inflight entertainment                    0.120812          0.405247
On-board service                          0.243852          0.550725
Leg room service                          0.153079          0.368925
Baggage handling                          0.233326          0.628944
Checkin service                           1.000000          0.237256
Inflight service                          0.237256          1.000000
Cleanliness                               0.179431          0.088891
Departure Delay in Minutes               -0.025473         -0.037469
Arrival Delay in Minutes                 -0.035619         -0.052510
satisfaction                              0.235914          0.244852
```

	Cleanliness	Departure Delay in Minutes \
Gender	0.006439	0.001561
Customer Type	-0.083757	0.004311
Age	0.053493	-0.008581
Type of Travel	-0.078767	-0.003935
Class	-0.125933	0.010379
Flight Distance	0.093425	0.001499
Inflight wifi service	0.132652	-0.027663
Departure/Arrival time convenient	0.014337	-0.001442
Ease of Online booking	0.016192	-0.008119
Gate location	-0.004015	0.003713
Food and drink	0.657648	-0.025419
Online boarding	0.331498	-0.031357
Seat comfort	0.678478	-0.026276
Inflight entertainment	0.691735	-0.031218
On-board service	0.123236	-0.034174
Leg room service	0.096401	-0.007546
Baggage handling	0.095783	-0.016931
Checkin service	0.179431	-0.025473
Inflight service	0.088891	-0.037469
Cleanliness	1.000000	-0.021401
Departure Delay in Minutes	-0.021401	1.000000
Arrival Delay in Minutes	-0.031961	0.842063
satisfaction	0.305050	-0.074516

	Arrival Delay in Minutes	satisfaction
Gender	0.000190	0.012356
Customer Type	0.005811	-0.187558
Age	-0.011870	0.137040
Type of Travel	-0.005489	-0.448995
Class	0.021780	-0.449466
Flight Distance	-0.006758	0.299538
Inflight wifi service	-0.032194	0.284163
Departure/Arrival time convenient	-0.003062	-0.051718
Ease of Online booking	-0.010832	0.171507
Gate location	0.004882	0.000449
Food and drink	-0.034661	0.209659
Online boarding	-0.043459	0.503447
Seat comfort	-0.036607	0.349112
Inflight entertainment	-0.042152	0.398203
On-board service	-0.046057	0.322450
Leg room service	-0.015937	0.313182
Baggage handling	-0.028522	0.247819
Checkin service	-0.035619	0.235914
Inflight service	-0.052510	0.244852
Cleanliness	-0.031961	0.305050

```
Departure Delay in Minutes                              0.842063     -0.074516
Arrival Delay in Minutes                                1.000000     -0.097349
satisfaction                                           -0.097349      1.000000

[23 rows x 23 columns]
```

[271]:

```python
corr = data2.corr()
corr=corr.round(2)
fig = ff.create_annotated_heatmap(z=corr.values,
                                  x=corr.columns.tolist(),
                                  y=corr.columns.tolist(),
                                  colorscale='RdBu',
                                  hoverinfo='none',
                                  showscale=True,
                                  ygap=1,
                                  xgap=1
                                 )
fig.update_xaxes(side='bottom')
fig.update_layout(
    title_text='Heatmap',
    title_x=0.5,
    width=1100,
    height=1000,
    xaxis=dict(showgrid=True),
    yaxis=dict(showgrid=True, autorange='reversed'),
    template='plotly_dark'
)
fig.show()
```

[272]:

```python
mask = np.triu(np.ones_like(corr, dtype=bool))
df_mask = corr.mask(mask)
df_mask_rounded = df_mask.round(2)
fig = ff.create_annotated_heatmap(z=df_mask_rounded.values,
                                  x=df_mask_rounded.columns.tolist(),
                                  y=df_mask_rounded.columns.tolist(),
                                  colorscale='RdBu',
                                  hoverinfo='none',
                                  showscale=True,
                                  ygap=1,
                                  xgap=1
                                 )
fig.update_xaxes(side='bottom')
fig.update_layout(
    title_text='Heatmap',
    title_x=0.5,
    width=1100,
    height=1000,
```

```
    xaxis=dict(showgrid=True),
    yaxis=dict(showgrid=True, autorange='reversed'),
    template='plotly_dark'
)
for annotation in fig.layout.annotations:
    if annotation.text == 'nan':
        annotation.text = ""
fig.show()
```

Classification

[273]:
```
X_classification = data2.iloc[:,:-1]
y_classification = data2.iloc[:,-1]
key = X_classification.keys()
X_classification.head()
```

[273]:
```
   Gender  Customer Type  Age  Type of Travel  Class  Flight Distance  \
0       1              0   13               1      2            460.0
1       1              1   25               0      0            235.0
2       0              0   26               0      0           1142.0
3       0              0   25               0      0            562.0
4       1              0   61               0      0            214.0

   Inflight wifi service  Departure/Arrival time convenient  \
0                      3                                  4
1                      3                                  2
2                      2                                  2
3                      2                                  5
4                      3                                  3

   Ease of Online booking  Gate location  …  Seat comfort  \
0                       3              1  …             5
1                       3              3  …             1
2                       2              2  …             5
3                       5              5  …             2
4                       3              3  …             5

   Inflight entertainment  On-board service  Leg room service  \
0                       5                 4                 3
1                       1                 1                 5
2                       5                 4                 3
3                       2                 2                 5
4                       3                 3                 4

   Baggage handling  Checkin service  Inflight service  Cleanliness  \
0                 4                4                 5            5
1                 3                1                 4            1
2                 4                4                 4            5
```

```
3                  3                 1                 4            2
4                  4                 3                 3            3

   Departure Delay in Minutes  Arrival Delay in Minutes
0                          25                      18.0
1                           1                       6.0
2                           0                       0.0
3                          11                       9.0
4                           0                       0.0

[5 rows x 22 columns]
```

[274]:
```
y_classification.head()
```

[274]:
```
0    0
1    0
2    1
3    0
4    1
Name: satisfaction, dtype: int64
```

** #

ML Models

Tabel of Contents

Classification Models

RandomForestClassifier

[275]:
```
def Split(X,y):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1,␣
 ↪random_state=44, shuffle=True, stratify=y)
    print('X_train shape is ', X_train.shape)
    print('X_test shape is ', X_test.shape)
    print('y_train shape is ', y_train.shape)
    print('y_test shape is ', y_test.shape)
    return X_train, y_train, X_test, y_test

def SelectFeature(model, X_train, y_train):
    FeatureSelection = SelectFromModel(estimator=model)
    FeatureSelection.fit(X_train, y_train)
    return X_train.iloc[:, FeatureSelection.get_support()].columns

def Search(model, parameters, X_train, y_train):
    GridSearchModel = GridSearchCV(model, parameters, cv=5,␣
 ↪return_train_score=True)
    GridSearchModel.fit(X_train, y_train)
    return GridSearchModel.best_estimator_
```

```python
def cross_validation(model, X_train, y_train):
    CrossValidateValues1 = cross_validate(model, X_train, y_train, cv=5,␣
 ↪return_train_score=True)
    print('Train Score Value : ', CrossValidateValues1['train_score'], "\t␣
 ↪Mean", CrossValidateValues1['train_score'].mean())
    print('Test Score Value : ', CrossValidateValues1['test_score'], "\t Mean",␣
 ↪CrossValidateValues1['test_score'].mean())

def PipeLine(model, X_train, y_train, flage=0):
    if flage == 0:
        steps = [('model', model)]
    elif flage == 1:
        steps = [('scaling', MinMaxScaler()), ('model', model)]
    elif flage == 2:
        steps = [('scaling', Normalizer()), ('model', model)]
    elif flage == 3:
        steps = [('pca', PCA()), ('model', model)]
    elif flage == 4:
        steps = [('scaling', MinMaxScaler()), ('pca', PCA()), ('model', model)]
    elif flage==5:
        steps = [('scaling', Normalizer()), ('pca', PCA()), ('model', model)]
    else:
        steps = [('scaling', MinMaxScaler()), ('poly',␣
 ↪PolynomialFeatures(degree=2)), ('model', model)]
    return Pipeline(steps).fit(X_train, y_train)

def Area(fprValue2, tprValue2, AUCValue):
    fig = go.Figure()
    fig.add_trace(go.Scatter(x=fprValue2, y=tprValue2,
                    mode='lines',
                    name='ROC curve (AUC = {:.2f})'.format(AUCValue),␣
 ↪line=dict(color='red')))
    fig.add_shape(type='line',
        x0=0, y0=0, x1=1, y1=1,
        line=dict(color='orange', width=2, dash='dash'),
        name='Random Guessing')
    fig.update_layout(
                      title='Receiver Operating Characteristic (ROC) Curve',
                      title_x=.5,
                      xaxis_title='False Positive Rate',
                      yaxis_title='True Positive Rate',
                      xaxis=dict(range=[0, 1], constrain='domain'),
                      yaxis=dict(range=[0, 1]),
                      legend=dict(x=0.01, y=0.99),
                      showlegend=True,
                      template='plotly_dark'
```

```
                     )
    fig.update_annotations(font=dict(size=20))
    fig.show()

def Check(model, X_train, y_train, X_test, y_test):
    y_pred = model.predict(X_test)
    train = accuracy_score(y_train, model.predict(X_train))
    test = accuracy_score(y_test, y_pred)
    print('Model Train Score is : ', train)
    print('Model Test Score is : ', test)
    F1Score = f1_score(y_test, y_pred)
    print('F1 Score is : ', F1Score)
    RecallScore = recall_score(y_test, y_pred)
    print('Recall Score is : ', RecallScore)
    PrecisionScore = precision_score(y_test, y_pred)
    print('Precision Score is : ', PrecisionScore)
    fprValue2, tprValue2, thresholdsValue2 = roc_curve(y_test, y_pred)
    AUCValue = auc(fprValue2, tprValue2)
    print('AUC Value  : ', AUCValue)
    Area(fprValue2, tprValue2, AUCValue)
    ClassificationReport = classification_report(y_test, y_pred)
    print('\nClassification Report is : ', ClassificationReport)
    CM = confusion_matrix(y_test, y_pred)
    print('\nConfusion Matrix is : \n', CM)
    disp = ConfusionMatrixDisplay(confusion_matrix=CM, display_labels=[0, 1])
    disp.plot(cmap='Blues')
    values = [train, test, F1Score, RecallScore, PrecisionScore, AUCValue]
    return values

def Models(models, X_train, y_train, X_test, y_test):
    print('Apply Model With Normal Data : \n')
    model = PipeLine(models, X_train, y_train)
    value1 = Check(model, X_train, y_train, X_test, y_test)
    print("\n\n Apply Model With Feature Selection :\n")
    try:
        feature = SelectFeature(model, X_train, y_train)
    except:
        feature = SelectFeature(RandomForestClassifier(max_depth=20), X_train,␣
 ↪y_train)
    X_train1 = X_train.loc[:, feature]
    X_test1 = X_test.loc[:, feature]
    model = PipeLine(models, X_train1, y_train, flage=1)
    value2 = Check(model, X_train1, y_train, X_test1, y_test)
    print("\n\n Apply Model With Normal Data With Scaling :\n")
    model = PipeLine(models, X_train, y_train, flage=1)
    value3 = Check(model, X_train, y_train, X_test, y_test)
    print("\n\n Apply Model With Normal Data With Normalize :\n")
```

```
    model = PipeLine(models, X_train, y_train, flage=2)
    value4 = Check(model, X_train, y_train, X_test, y_test)
    print("\n\n Apply Model With Normal Data With PCA :\n")
    model = PipeLine(models, X_train, y_train, flage=3)
    value5 = Check(model, X_train, y_train, X_test, y_test)
    print("\n\n Apply Model With Normal Data With PCA and Scaling :\n")
    model = PipeLine(models, X_train, y_train, flage=4)
    value6 = Check(model, X_train, y_train, X_test, y_test)
    print("\n\n Apply Model With Normal Data With PCA and Normalize :\n")
    model = PipeLine(models, X_train, y_train, flage=5)
    value7 = Check(model, X_train, y_train, X_test, y_test)
    print("\n\n Apply Model With Normal Data With Feature Selection and Poly␣
 ↪and Scaling :\n")
    model = PipeLine(models, X_train1, y_train, flage=6)
    value8 = Check(model, X_train1, y_train, X_test1, y_test)
    return [value1, value2, value3, value4, value5, value6, value7,value8]
def models_draw(df):
    figure = go.Figure()
    for column in df.columns:
        trace = go.Bar(
            x=df.index,
            y=df[column],
            name=column,
            text=df[column].values.round(2),
            textposition='inside'
        )
        figure.add_trace(trace)
    figure.update_layout(
        barmode='group',
        title='Performance Metrics Comparison',
        title_x=.5,
        xaxis=dict(title='Models'),
        yaxis=dict(title='Score'),
        template='plotly_dark',
        width=1100,
        height=700
    )
    figure.show()
```

[276]:
```
X_train,y_train,X_test,y_test=Split(X_classification,y_classification)
```

```
X_train shape is  (93234, 22)
X_test shape is  (10360, 22)
y_train shape is  (93234,)
y_test shape is  (10360,)
```

[277]:
```
Search(RandomForestClassifier(max_depth=20),{'max_depth':
 ↪[5,10,15,20,25,30,35,40]},X_train,y_train)
```

[277]:
```
RandomForestClassifier(max_depth=35)
```

[278]:
```
cross_validation(RandomForestClassifier(max_depth=40),X_train,y_train)
```

```
Train Score Value :  [0.99998659 0.99998659 0.99998659 1.         1.        ]
Mean 0.9999919557027365
Test Score Value :  [0.9610125  0.96106612 0.96229957 0.96122701 0.96176124]
Mean 0.9614732853674657
```

[279]:
```
Values =␣
 ↪Models(RandomForestClassifier(max_depth=40),X_train,y_train,X_test,y_test)
```

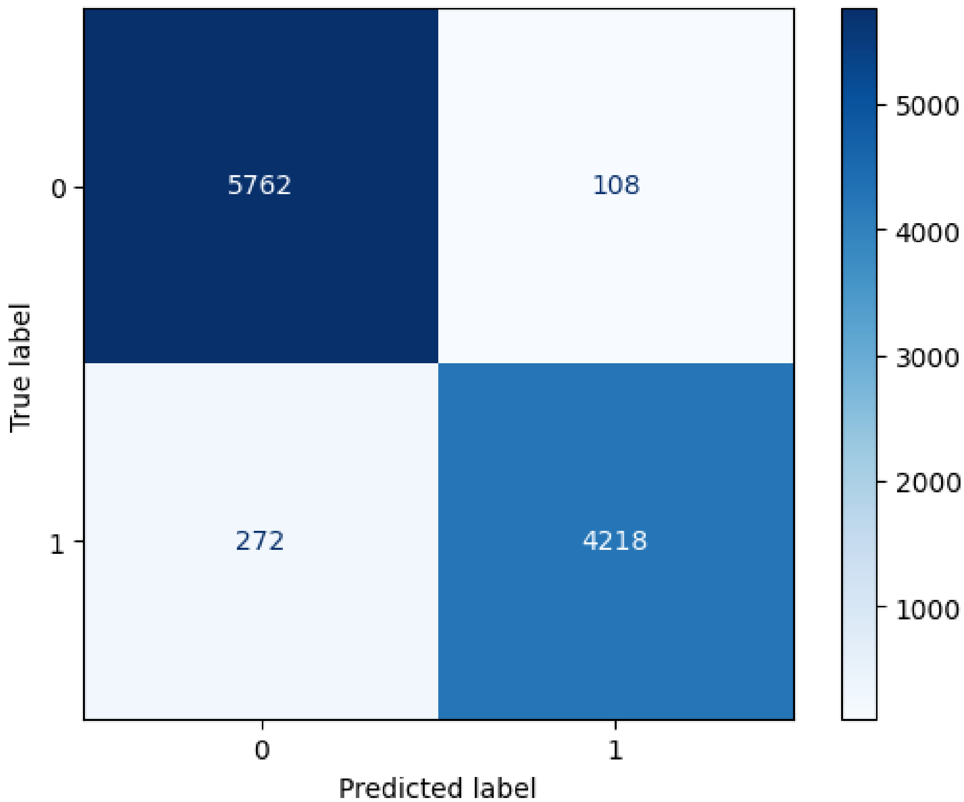
```
Apply Model With Normal Data :

Model Train Score is :  1.0
Model Test Score is :  0.9633204633204633
F1 Score is :  0.956896551724138
Recall Score is :  0.9394209354120268
Precision Score is :  0.9750346740638003
AUC Value  :  0.9605111491370185


Classification Report is :                precision    recall  f1-score
support

           0       0.95      0.98      0.97      5870
           1       0.98      0.94      0.96      4490

    accuracy                           0.96     10360
   macro avg       0.96      0.96      0.96     10360
weighted avg       0.96      0.96      0.96     10360


Confusion Matrix is :
 [[5762  108]
 [ 272 4218]]


 Apply Model With Feature Selection :

Model Train Score is :  0.9348199154814767
Model Test Score is :  0.9355212355212356
F1 Score is :  0.924994385807321
Recall Score is :  0.9173719376391982
Precision Score is :  0.9327445652173914
AUC Value  :  0.9333878427548631
```

```
Classification Report is :                precision    recall  f1-score
support

           0       0.94      0.95      0.94      5870
           1       0.93      0.92      0.92      4490

    accuracy                           0.94     10360
   macro avg       0.94      0.93      0.93     10360
weighted avg       0.94      0.94      0.94     10360


Confusion Matrix is :
 [[5573  297]
 [ 371 4119]]


 Apply Model With Normal Data With Scaling :

Model Train Score is :  1.0
Model Test Score is :  0.9632239382239383
F1 Score is :  0.9568369774555342
Recall Score is :  0.9405345211581292
Precision Score is :  0.9737145492275767
AUC Value  :  0.9605568687562366

Classification Report is :                precision    recall  f1-score
support

           0       0.96      0.98      0.97      5870
           1       0.97      0.94      0.96      4490

    accuracy                           0.96     10360
   macro avg       0.96      0.96      0.96     10360
weighted avg       0.96      0.96      0.96     10360


Confusion Matrix is :
 [[5756  114]
 [ 267 4223]]


 Apply Model With Normal Data With Normalize :

Model Train Score is :  1.0
Model Test Score is :  0.9445945945945946
F1 Score is :  0.9350090579710144
```

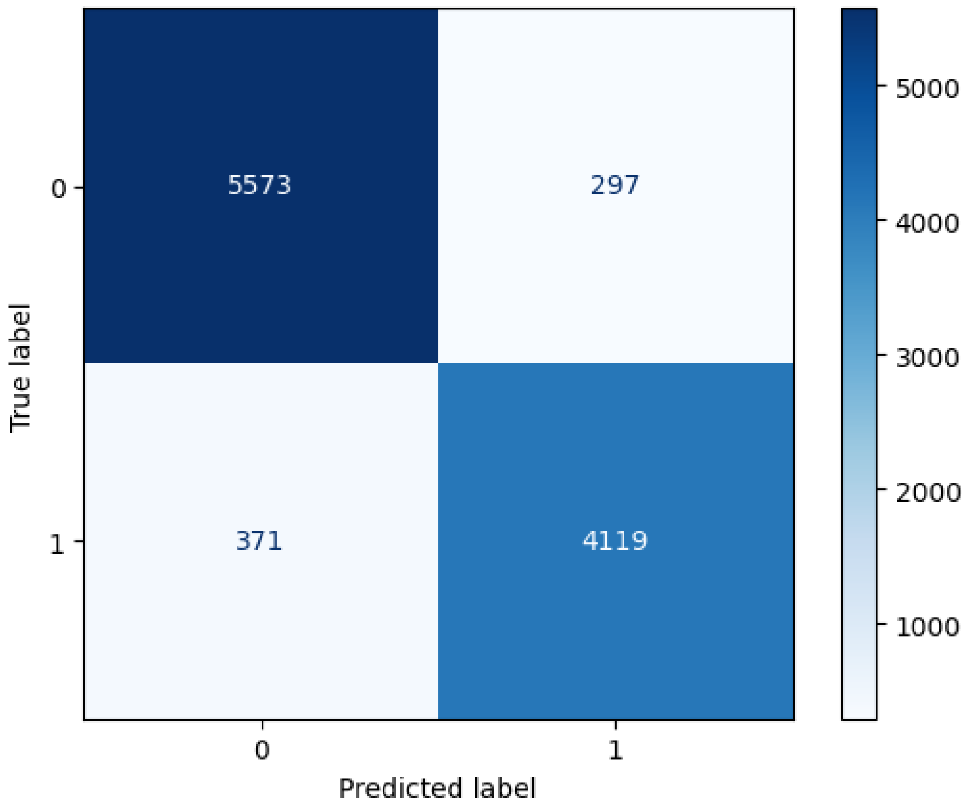
```
Recall Score is :  0.9195991091314031
Precision Score is :  0.9509442653155228
AUC Value  :  0.9416564540546283

Classification Report is :                precision    recall  f1-score
support

           0       0.94      0.96      0.95      5870
           1       0.95      0.92      0.94      4490

    accuracy                           0.94     10360
   macro avg       0.95      0.94      0.94     10360
weighted avg       0.94      0.94      0.94     10360


Confusion Matrix is :
 [[5657  213]
 [ 361 4129]]


 Apply Model With Normal Data With PCA :

Model Train Score is :  1.0
Model Test Score is :  0.9424710424710425
F1 Score is :  0.9315414656558695
Recall Score is :  0.9031180400890868
Precision Score is :  0.9618121442125237
AUC Value  :  0.9378452210666899

Classification Report is :                precision    recall  f1-score
support

           0       0.93      0.97      0.95      5870
           1       0.96      0.90      0.93      4490

    accuracy                           0.94     10360
   macro avg       0.95      0.94      0.94     10360
weighted avg       0.94      0.94      0.94     10360


Confusion Matrix is :
 [[5709  161]
 [ 435 4055]]


 Apply Model With Normal Data With PCA and Scaling :
```

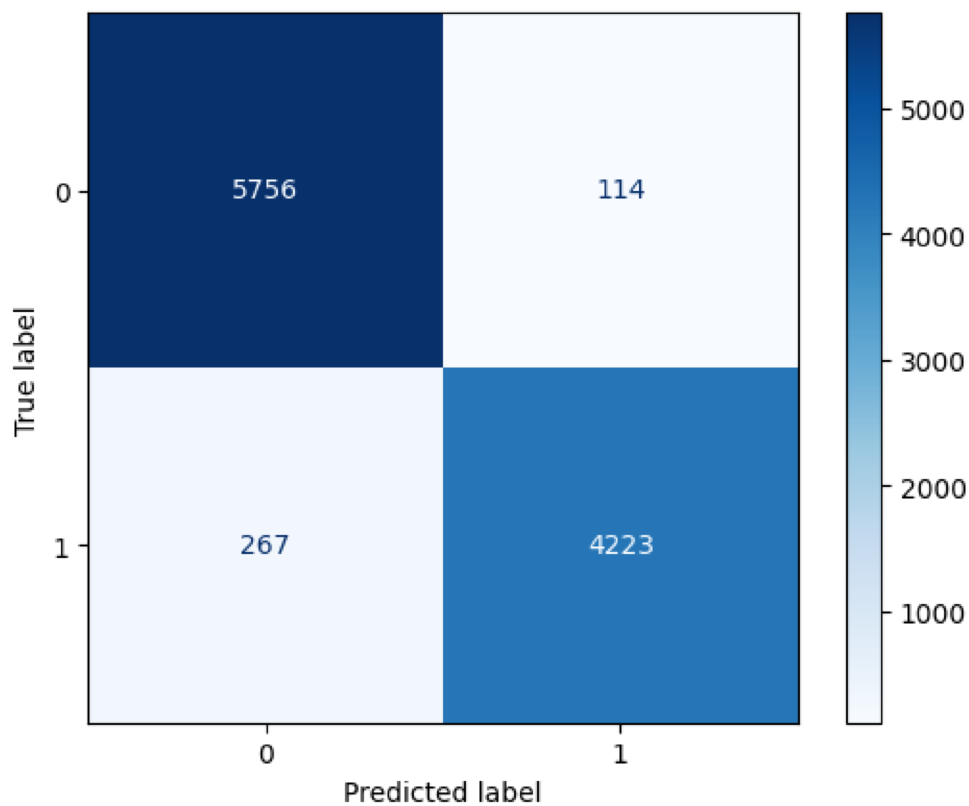
```
Model Train Score is :  0.9999892742990755
Model Test Score is :  0.9379343629343629
F1 Score is :  0.9260664596987467
Recall Score is :  0.8968819599109131
Precision Score is :  0.9572141668647492
AUC Value  :  0.933108782340465

Classification Report is :                precision    recall  f1-score
support

           0       0.92      0.97      0.95      5870
           1       0.96      0.90      0.93      4490

    accuracy                           0.94     10360
   macro avg       0.94      0.93      0.94     10360
weighted avg       0.94      0.94      0.94     10360


Confusion Matrix is :
 [[5690  180]
 [ 463 4027]]


 Apply Model With Normal Data With PCA and Normalize :

Model Train Score is :  0.9999892742990755
Model Test Score is :  0.9132239382239382
F1 Score is :  0.895233655751078
Recall Score is :  0.855456570155902
Precision Score is :  0.9388902468834026
AUC Value  :  0.9064335661682407

Classification Report is :                precision    recall  f1-score
support

           0       0.90      0.96      0.93      5870
           1       0.94      0.86      0.90      4490

    accuracy                           0.91     10360
   macro avg       0.92      0.91      0.91     10360
weighted avg       0.91      0.91      0.91     10360


Confusion Matrix is :
 [[5620  250]
 [ 649 3841]]
```

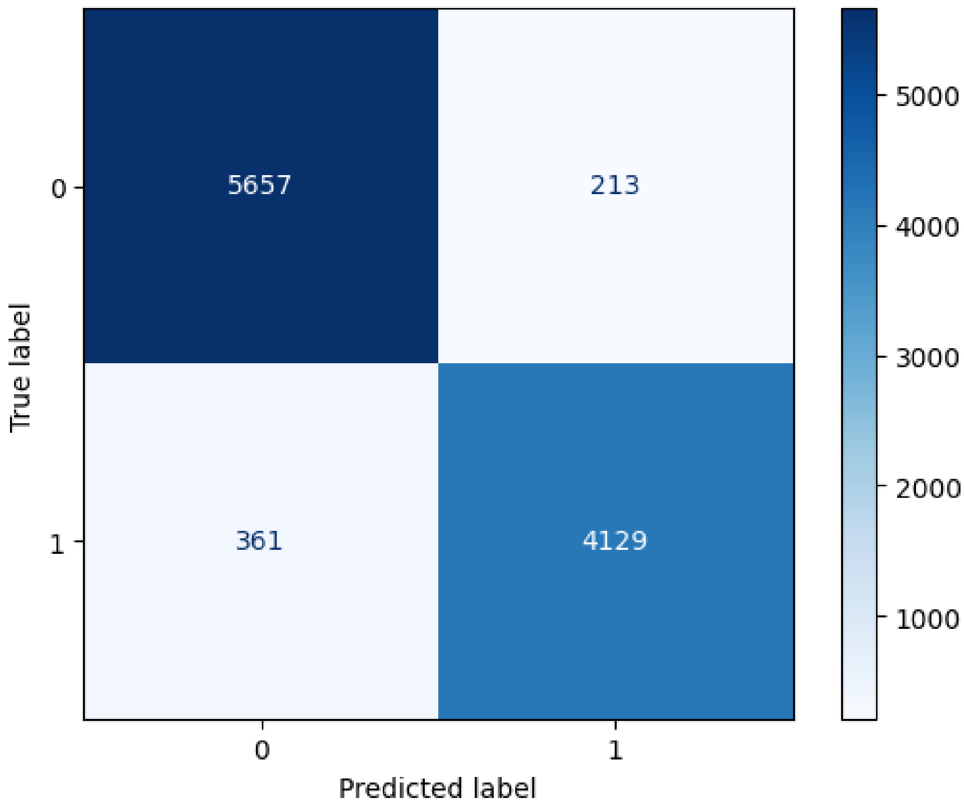
```
 Apply Model With Normal Data With Feature Selection and Poly and Scaling :

Model Train Score is :  0.9347984640796276
Model Test Score is :  0.9359073359073359
F1 Score is :  0.9253429278165056
Recall Score is :  0.9164810690423163
Precision Score is :  0.934377838328792
AUC Value  :  0.933623839461533


Classification Report is :                precision    recall  f1-score
support

           0       0.94      0.95      0.94      5870
           1       0.93      0.92      0.93      4490

    accuracy                           0.94     10360
   macro avg       0.94      0.93      0.93     10360
weighted avg       0.94      0.94      0.94     10360


Confusion Matrix is :
 [[5581  289]
 [ 375 4115]]
```

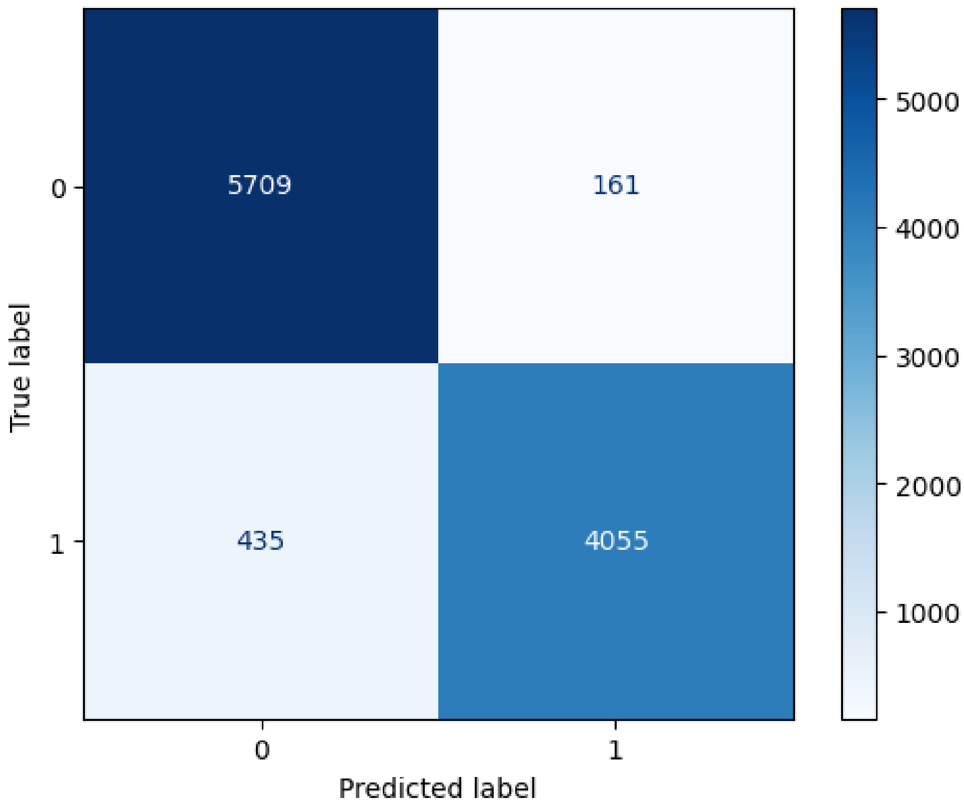


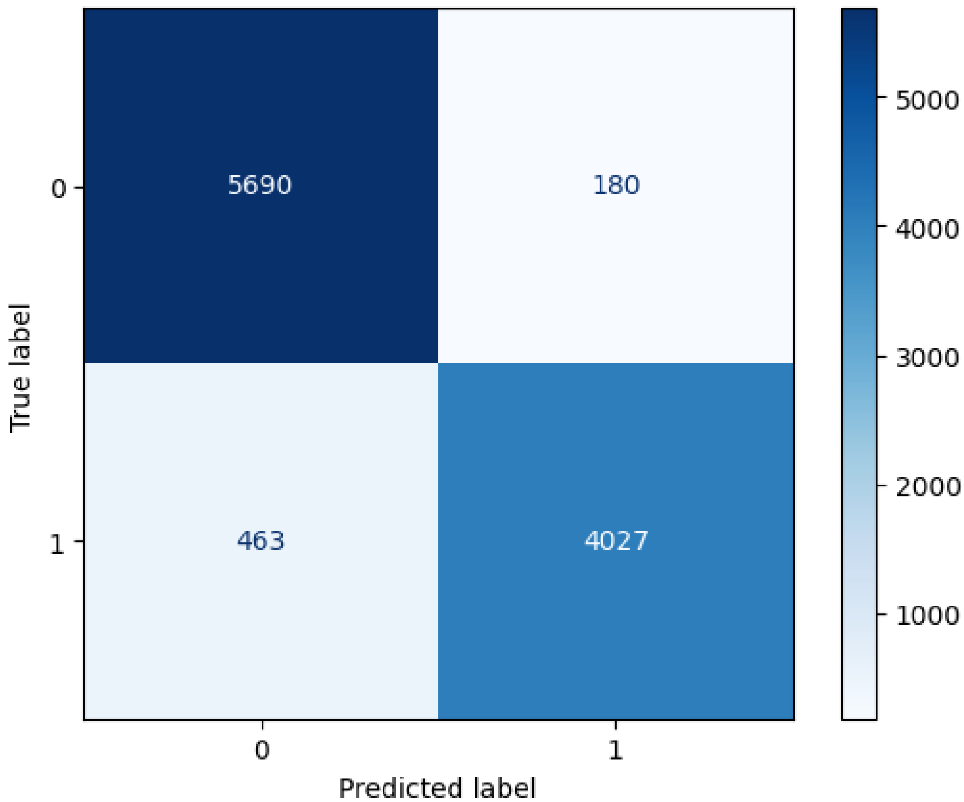
5762
108
272
4218
0
1
True label
Predicted label
5000
4000
3000
2000
1000

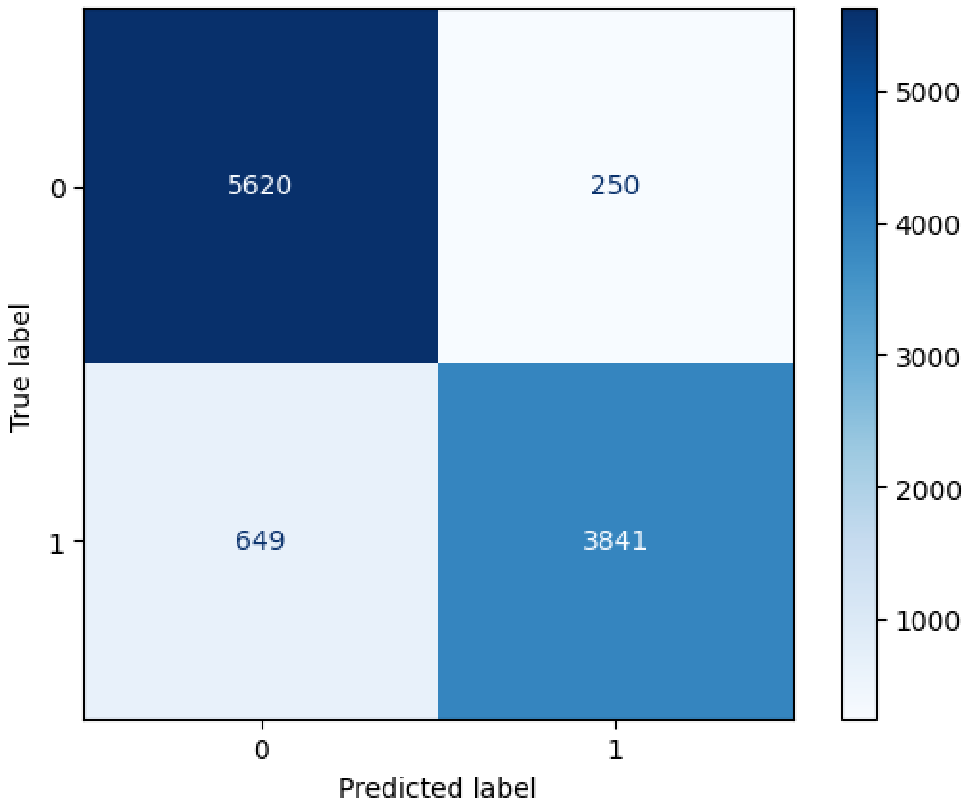

5573
297
371
4119
0
1
0
1
True label
Predicted label
5000
4000
3000
2000
1000

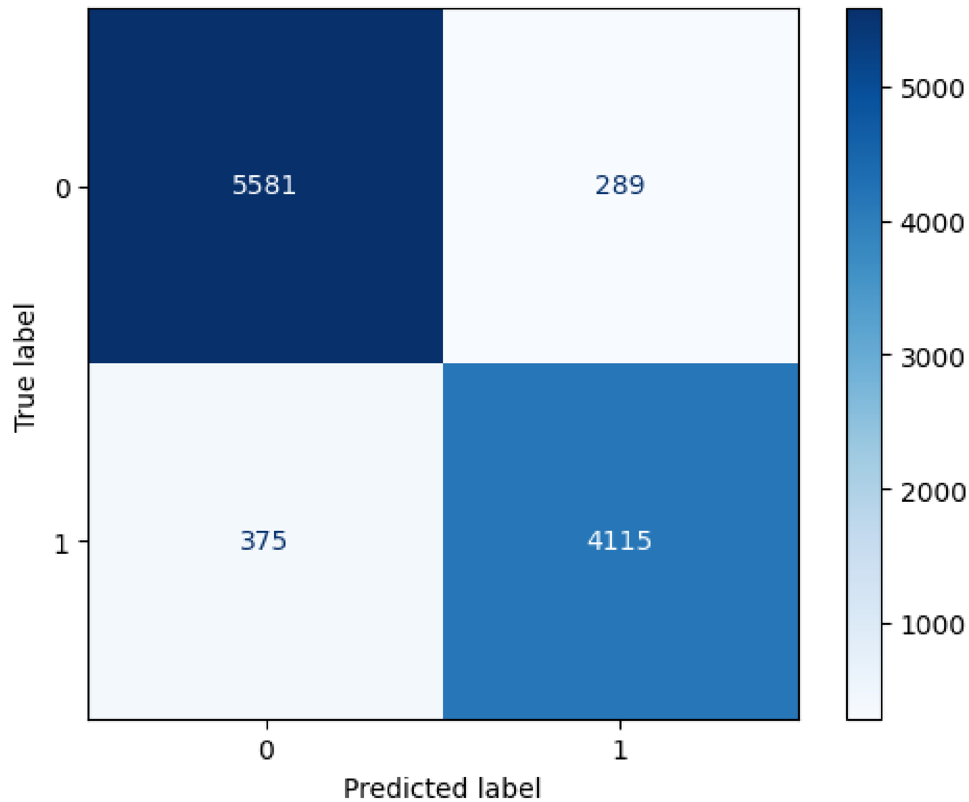

5756
114
267
4223
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5657
213
361
4129
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5709
161
435
4055
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5690
180
463
4027
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5620
250
649
3841
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000



[280]:
```
df = pd.DataFrame(Values,columns=['Train Accuracy','Test Accuracy','Test␣
↪F1','Test Recall','Test Precision','AUC'])
df['Models'] = ['Forest','Forest With Feature','Forest Scaling','Forest With␣
↪Normalize','Forest With PCA','Forest With PCA and Scaling',
               'Forest With PCA and Normalize','Forest With Feature and Poly␣
↪and Scaling']
df.set_index('Models', inplace=True)
df
```

[280]:
```
                                          Train Accuracy  Test Accuracy  \
Models
Forest                                          1.000000       0.963320
Forest With Feature                             0.934820       0.935521
Forest Scaling                                  1.000000       0.963224
Forest With Normalize                           1.000000       0.944595
Forest With PCA                                 1.000000       0.942471
Forest With PCA and Scaling                     0.999989       0.937934
Forest With PCA and Normalize                   0.999989       0.913224
Forest With Feature and Poly and Scaling        0.934798       0.935907

                                           Test F1  Test Recall  \
```

```
Models
Forest                                          0.956897     0.939421
Forest With Feature                             0.924994     0.917372
Forest Scaling                                  0.956837     0.940535
Forest With Normalize                           0.935009     0.919599
Forest With PCA                                 0.931541     0.903118
Forest With PCA and Scaling                     0.926066     0.896882
Forest With PCA and Normalize                   0.895234     0.855457
Forest With Feature and Poly and Scaling        0.925343     0.916481

                                          Test Precision       AUC
Models
Forest                                          0.975035  0.960511
Forest With Feature                             0.932745  0.933388
Forest Scaling                                  0.973715  0.960557
Forest With Normalize                           0.950944  0.941656
Forest With PCA                                 0.961812  0.937845
Forest With PCA and Scaling                     0.957214  0.933109
Forest With PCA and Normalize                   0.938890  0.906434
Forest With Feature and Poly and Scaling        0.934378  0.933624
```

[281]:
```
models_draw(df)
```

DecisionTreeClassifier

[282]:
```
Search(DecisionTreeClassifier(max_depth=20),{'max_depth':
 ↪[5,10,15,20,25,30,35,40]},X_train,y_train)
```

[282]:
```
DecisionTreeClassifier(max_depth=15)
```

[283]:
```
cross_validation(DecisionTreeClassifier(max_depth=15),X_train,y_train)
```

```
Train Score Value :  [0.97531741 0.97616207 0.97567941 0.97608162 0.97533115]
Mean 0.9757143327090446
Test Score Value :  [0.95291468 0.95087682 0.95076956 0.95119858 0.9512496 ]
Mean 0.9514018474778545
```

[284]:
```
Values =␣
 ↪Models(DecisionTreeClassifier(max_depth=15),X_train,y_train,X_test,y_test)
```

```
Apply Model With Normal Data :

Model Train Score is :  0.973196473389536
Model Test Score is :  0.9522200772200772
F1 Score is :  0.943922057324119
Recall Score is :  0.9278396436525612
Precision Score is :  0.960571823841365
AUC Value  :  0.9493542340920387
```

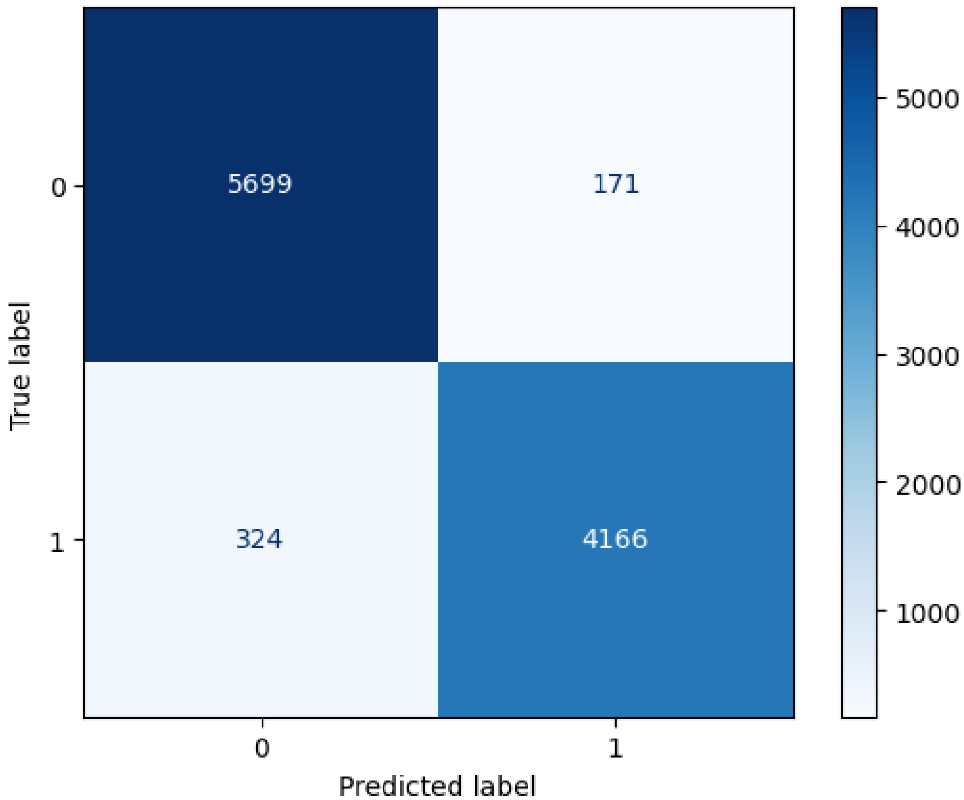
```
Classification Report is :                precision    recall  f1-score
support

           0       0.95      0.97      0.96      5870
           1       0.96      0.93      0.94      4490

    accuracy                           0.95     10360
   macro avg       0.95      0.95      0.95     10360
weighted avg       0.95      0.95      0.95     10360


Confusion Matrix is :
 [[5699  171]
 [ 324 4166]]


 Apply Model With Feature Selection :

Model Train Score is :  0.9263787888538516
Model Test Score is :  0.9301158301158301
F1 Score is :  0.9178206583427923
Recall Score is :  0.9004454342984409
Precision Score is :  0.9358796296296297
AUC Value  :  0.9266281685972613

Classification Report is :                precision    recall  f1-score
support

           0       0.93      0.95      0.94      5870
           1       0.94      0.90      0.92      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.93      0.93     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
 [[5593  277]
 [ 447 4043]]


 Apply Model With Normal Data With Scaling :

Model Train Score is :  0.9731321191839887
Model Test Score is :  0.9512548262548263
F1 Score is :  0.9428021293464719
```

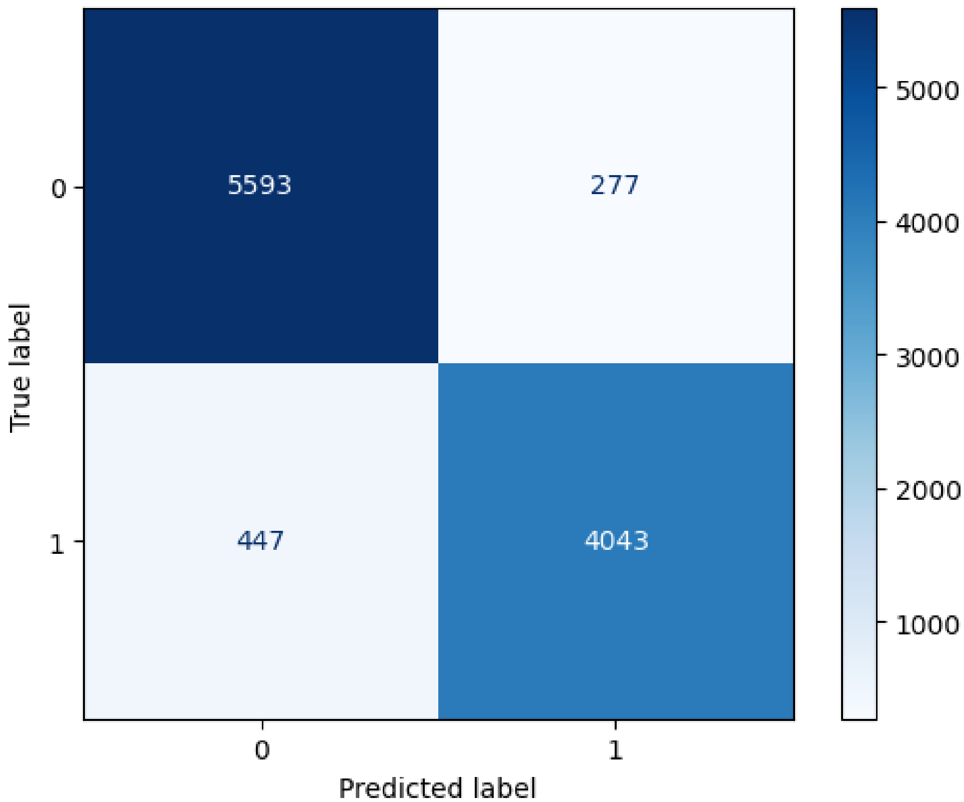
```
Recall Score is :  0.9269487750556793
Precision Score is :  0.9592071905969117
AUC Value  :  0.9483977265397647

Classification Report is :                precision    recall  f1-score
support

           0       0.95      0.97      0.96      5870
           1       0.96      0.93      0.94      4490

    accuracy                           0.95     10360
   macro avg       0.95      0.95      0.95     10360
weighted avg       0.95      0.95      0.95     10360


Confusion Matrix is :
 [[5693  177]
 [ 328 4162]]


 Apply Model With Normal Data With Normalize :

Model Train Score is :  0.9537936804170153
Model Test Score is :  0.9146718146718147
F1 Score is :  0.9025358324145535
Recall Score is :  0.9115812917594655
Precision Score is :  0.8936681222707423
AUC Value  :  0.914308533443617

Classification Report is :                precision    recall  f1-score
support

           0       0.93      0.92      0.92      5870
           1       0.89      0.91      0.90      4490

    accuracy                           0.91     10360
   macro avg       0.91      0.91      0.91     10360
weighted avg       0.91      0.91      0.91     10360


Confusion Matrix is :
 [[5383  487]
 [ 397 4093]]


 Apply Model With Normal Data With PCA :
```

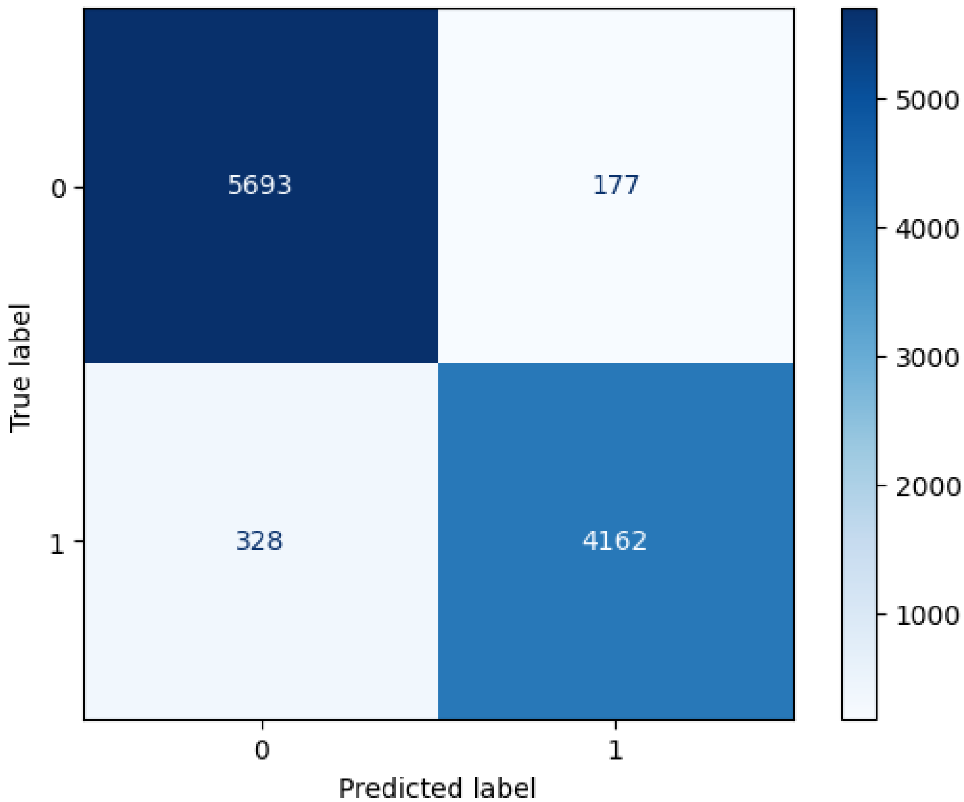
```
Model Train Score is :  0.9648518780702319
Model Test Score is :  0.9133204633204633
F1 Score is :  0.898093508851566
Recall Score is :  0.8812917594654789
Precision Score is :  0.9155483572420176
AUC Value  :  0.9095555901245623

Classification Report is :                precision    recall  f1-score
support

           0       0.91      0.94      0.92      5870
           1       0.92      0.88      0.90      4490

    accuracy                           0.91     10360
   macro avg       0.91      0.91      0.91     10360
weighted avg       0.91      0.91      0.91     10360


Confusion Matrix is :
 [[5505  365]
 [ 533 3957]]


 Apply Model With Normal Data With PCA and Scaling :

Model Train Score is :  0.9687667589076946
Model Test Score is :  0.9094594594594595
F1 Score is :  0.8929223744292238
Recall Score is :  0.8710467706013363
Precision Score is :  0.9159250585480093
AUC Value  :  0.904944168946324

Classification Report is :                precision    recall  f1-score
support

           0       0.90      0.94      0.92      5870
           1       0.92      0.87      0.89      4490

    accuracy                           0.91     10360
   macro avg       0.91      0.90      0.91     10360
weighted avg       0.91      0.91      0.91     10360


Confusion Matrix is :
 [[5511  359]
 [ 579 3911]]
```

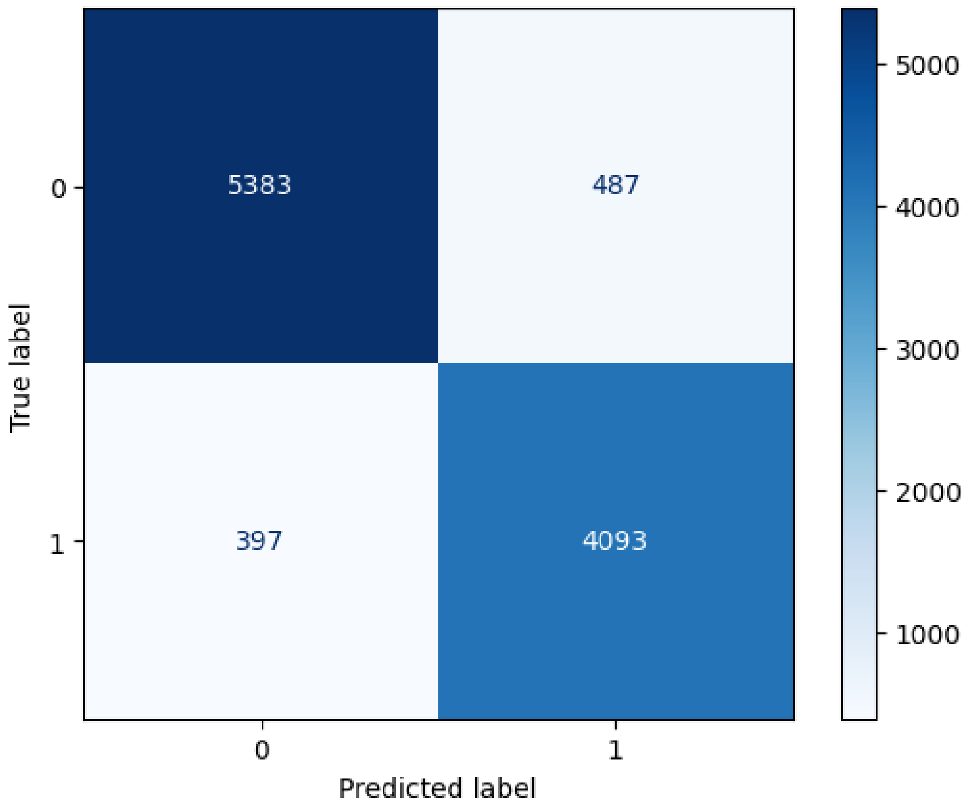
```
 Apply Model With Normal Data With PCA and Normalize :

Model Train Score is :  0.9709977047000021
Model Test Score is :  0.8657335907335907
F1 Score is :  0.8443897527687659
Recall Score is :  0.8405345211581292
Precision Score is :  0.8482805124747134
AUC Value  :  0.8627715195228465

Classification Report is :                precision    recall  f1-score
support

           0       0.88      0.89      0.88      5870
           1       0.85      0.84      0.84      4490

    accuracy                           0.87     10360
   macro avg       0.86      0.86      0.86     10360
weighted avg       0.87      0.87      0.87     10360


Confusion Matrix is :
 [[5195  675]
 [ 716 3774]]


 Apply Model With Normal Data With Feature Selection and Poly and Scaling :

Model Train Score is :  0.9263787888538516
Model Test Score is :  0.9301158301158301
F1 Score is :  0.9178019981834697
Recall Score is :  0.9002227171492205
Precision Score is :  0.936081519221862
AUC Value  :  0.9266019888982899

Classification Report is :                precision    recall  f1-score
support

           0       0.93      0.95      0.94      5870
           1       0.94      0.90      0.92      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.93      0.93     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
```

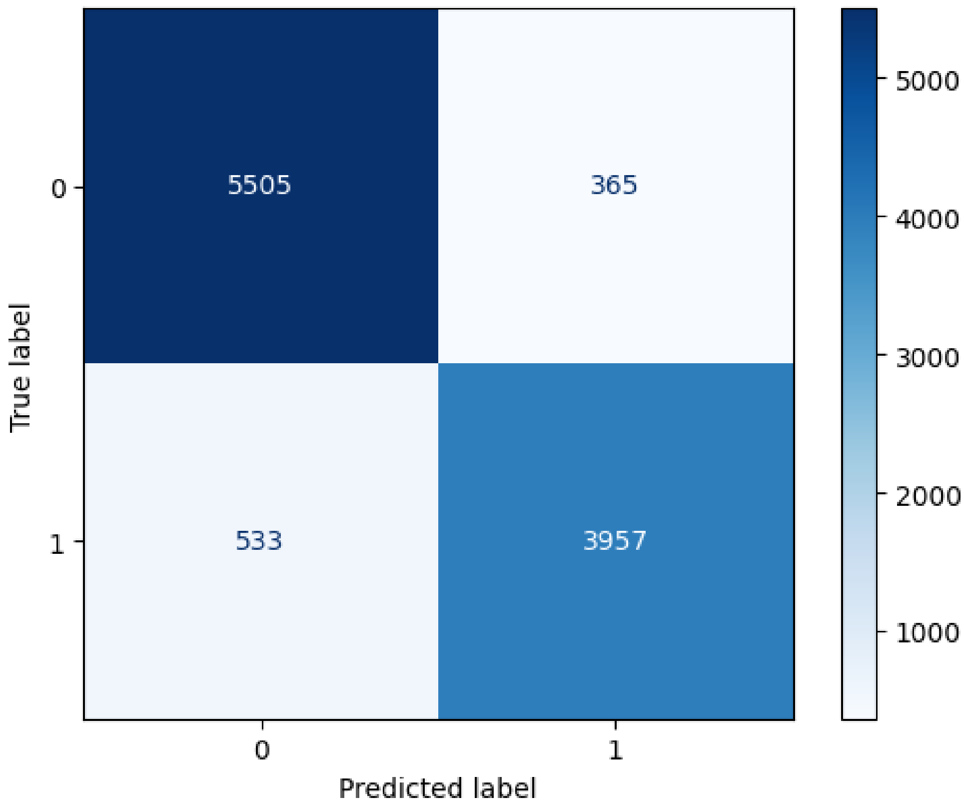
```
[[5594  276]
 [ 448 4042]]
```

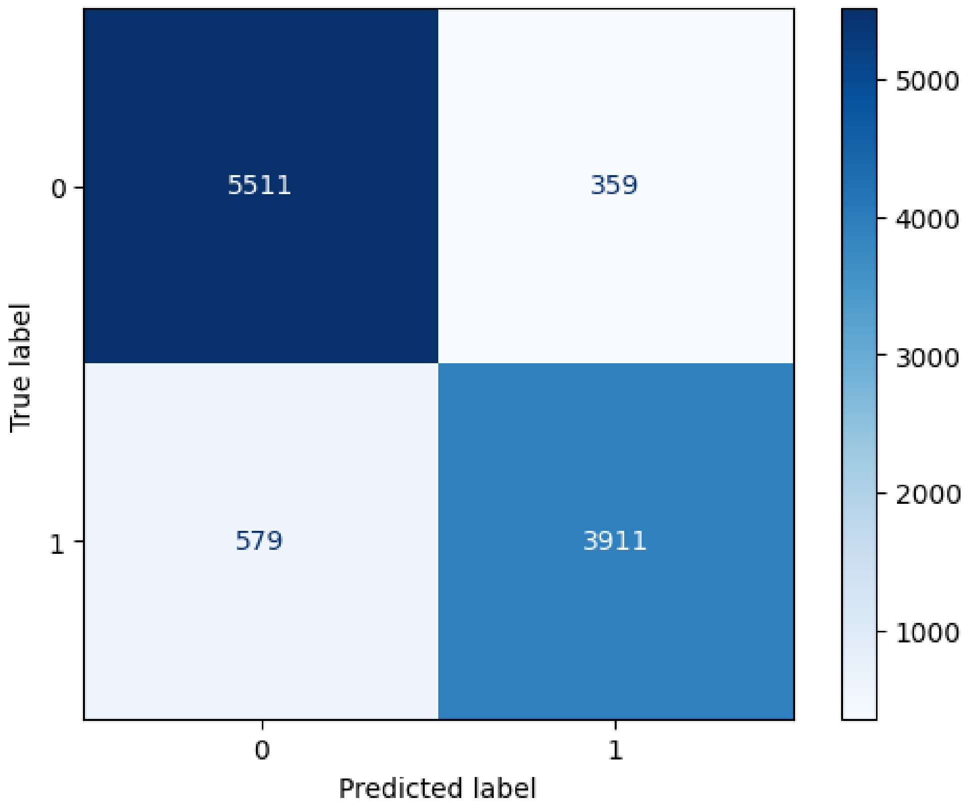


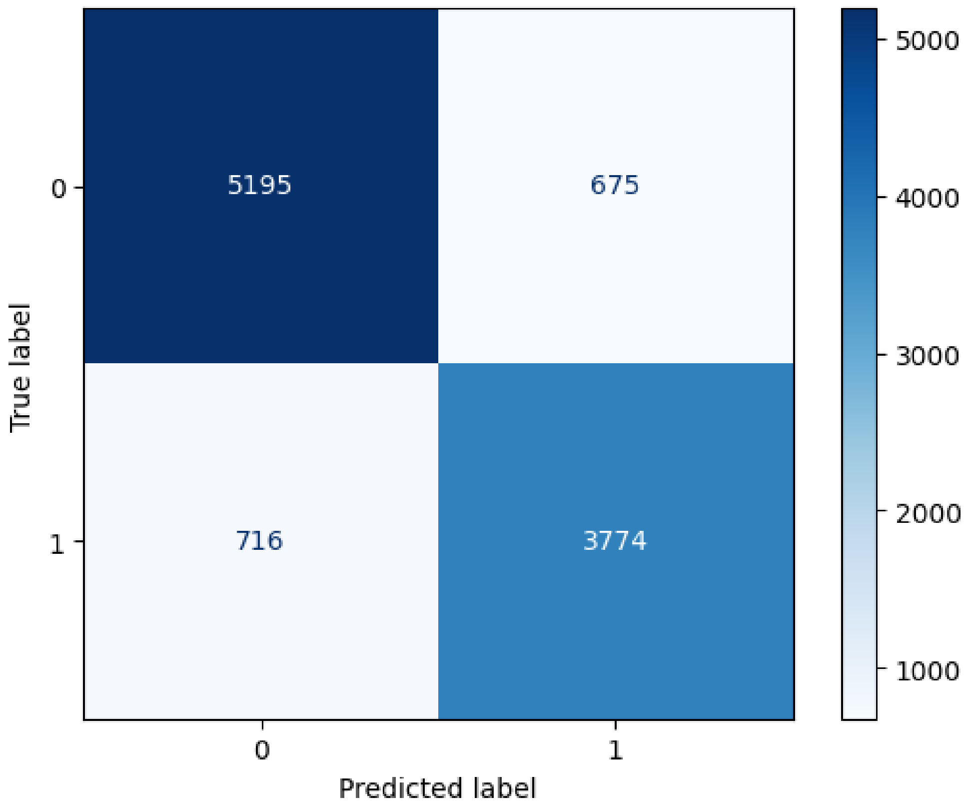

5593
277
447
4043
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000

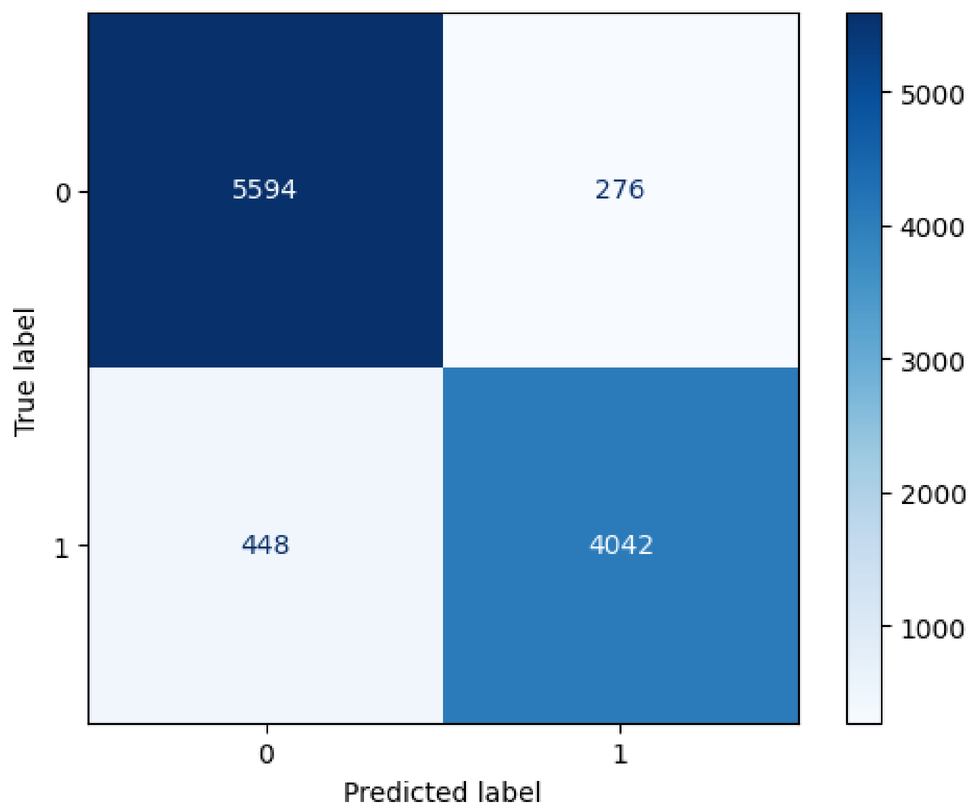

5693
177
328
4162
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5383
487
397
4093
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5505
365
533
3957
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5511
359
579
3911
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5195
675
716
3774
True label
Predicted label
0
1
5000
4000
3000
2000
1000



[285]:
```
df = pd.DataFrame(Values,columns=['Train Accuracy','Test Accuracy','Test␣
↪F1','Test Recall','Test Precision','AUC'])
df['Models'] = ['Decision','Decision With Feature','Decision Scaling','Decision␣
↪With Normalize','Decision With PCA','Decision With PCA and Scaling',
                'Decision With PCA and Normalize','Decision With Feature and␣
↪Poly and Scaling']
df.set_index('Models', inplace=True)
df
```

[285]:
```
                                            Train Accuracy  Test Accuracy  \
Models
Decision                                          0.973196       0.952220
Decision With Feature                             0.926379       0.930116
Decision Scaling                                  0.973132       0.951255
Decision With Normalize                           0.953794       0.914672
Decision With PCA                                 0.964852       0.913320
Decision With PCA and Scaling                     0.968767       0.909459
Decision With PCA and Normalize                   0.970998       0.865734
Decision With Feature and Poly and Scaling        0.926379       0.930116

                                             Test F1  Test Recall  \
```

```
Models
Decision                                       0.943922     0.927840
Decision With Feature                          0.917821     0.900445
Decision Scaling                               0.942802     0.926949
Decision With Normalize                        0.902536     0.911581
Decision With PCA                              0.898094     0.881292
Decision With PCA and Scaling                  0.892922     0.871047
Decision With PCA and Normalize                0.844390     0.840535
Decision With Feature and Poly and Scaling     0.917802     0.900223

                                            Test Precision       AUC
Models
Decision                                          0.960572  0.949354
Decision With Feature                             0.935880  0.926628
Decision Scaling                                  0.959207  0.948398
Decision With Normalize                           0.893668  0.914309
Decision With PCA                                 0.915548  0.909556
Decision With PCA and Scaling                     0.915925  0.904944
Decision With PCA and Normalize                   0.848281  0.862772
Decision With Feature and Poly and Scaling        0.936082  0.926602
```

[286]:
```
models_draw(df)
```

LogisticRegression

[287]:
```
Search(LogisticRegression(penalty='l2',solver='sag',C=1.0),{'C':[1,.
↪5,2,3,5,10,15,20]},X_train,y_train)
```

[287]:
```
LogisticRegression(C=1, solver='sag')
```

[288]:
```
cross_validation(LogisticRegression(penalty='l2',solver='sag',C=15),X_train,y_train)
```

```
Train Score Value :  [0.77411613 0.77390162 0.77451835 0.77415635 0.77517831]
Mean 0.7743741531947581
Test Score Value :  [0.77454818 0.77701507 0.77395828 0.77347563 0.77147914]
Mean 0.7740952590672775
```

[289]:
```
Values =␣
↪Models(LogisticRegression(penalty='l2',solver='sag',C=15),X_train,y_train,X_test,y_test)
```

```
Apply Model With Normal Data :

Model Train Score is :  0.7848209880515692
Model Test Score is :  0.7812741312741313
F1 Score is :  0.7499448245420437
Recall Score is :  0.7567928730512249
Precision Score is :  0.7432195975503062
AUC Value  :  0.7783964365256125
```

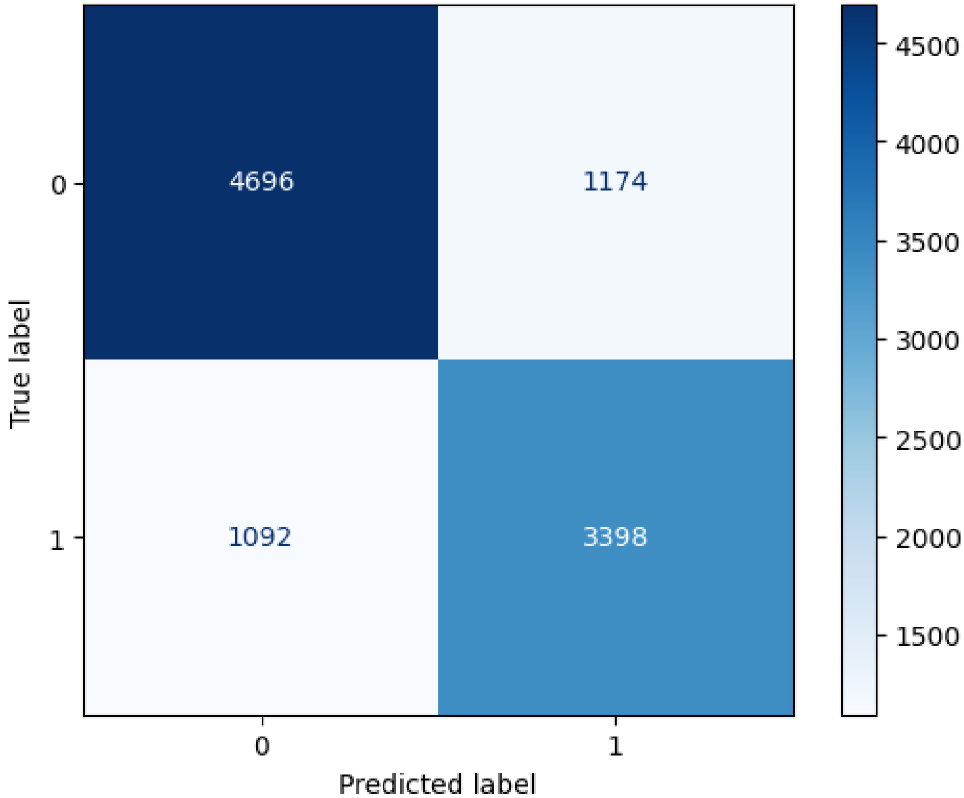
```
Classification Report is :                precision    recall  f1-score
support

           0       0.81      0.80      0.81      5870
           1       0.74      0.76      0.75      4490

    accuracy                           0.78     10360
   macro avg       0.78      0.78      0.78     10360
weighted avg       0.78      0.78      0.78     10360


Confusion Matrix is :
 [[4696 1174]
 [1092 3398]]


 Apply Model With Feature Selection :

Model Train Score is :  0.8365510436107
Model Test Score is :  0.8397683397683398
F1 Score is :  0.8139013452914798
Recall Score is :  0.8084632516703786
Precision Score is :  0.8194130925507901
AUC Value  :  0.8360885253241159

Classification Report is :                precision    recall  f1-score
support

           0       0.85      0.86      0.86      5870
           1       0.82      0.81      0.81      4490

    accuracy                           0.84     10360
   macro avg       0.84      0.84      0.84     10360
weighted avg       0.84      0.84      0.84     10360


Confusion Matrix is :
 [[5070  800]
 [ 860 3630]]


 Apply Model With Normal Data With Scaling :

Model Train Score is :  0.8747023617993436
Model Test Score is :  0.8814671814671815
F1 Score is :  0.8603910868576625
```

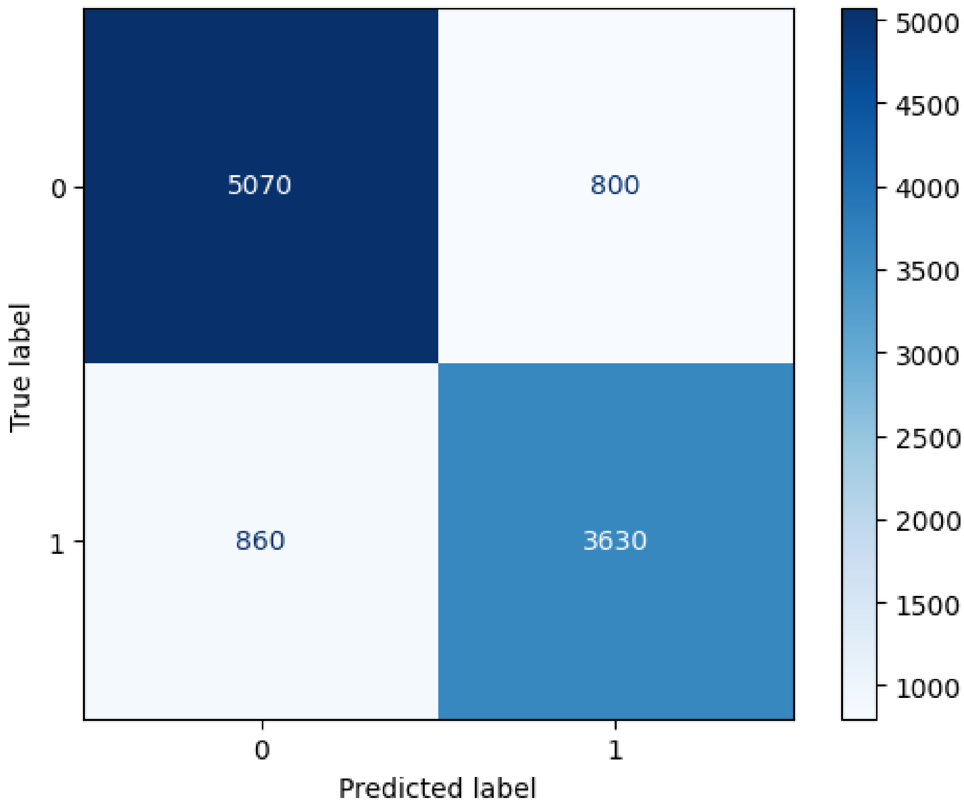
```
Recall Score is :  0.8427616926503341
Precision Score is :  0.8787738039944264
AUC Value  :  0.8769174732416917

Classification Report is :                precision    recall  f1-score
support

           0       0.88      0.91      0.90      5870
           1       0.88      0.84      0.86      4490

    accuracy                           0.88     10360
   macro avg       0.88      0.88      0.88     10360
weighted avg       0.88      0.88      0.88     10360


Confusion Matrix is :
 [[5348  522]
 [ 706 3784]]


 Apply Model With Normal Data With Normalize :

Model Train Score is :  0.8020893665401034
Model Test Score is :  0.8042471042471042
F1 Score is :  0.7706401266681746
Recall Score is :  0.7587973273942094
Precision Score is :  0.7828584558823529
AUC Value  :  0.7989046262183994

Classification Report is :                precision    recall  f1-score
support

           0       0.82      0.84      0.83      5870
           1       0.78      0.76      0.77      4490

    accuracy                           0.80     10360
   macro avg       0.80      0.80      0.80     10360
weighted avg       0.80      0.80      0.80     10360


Confusion Matrix is :
 [[4925  945]
 [1083 3407]]


 Apply Model With Normal Data With PCA :
```

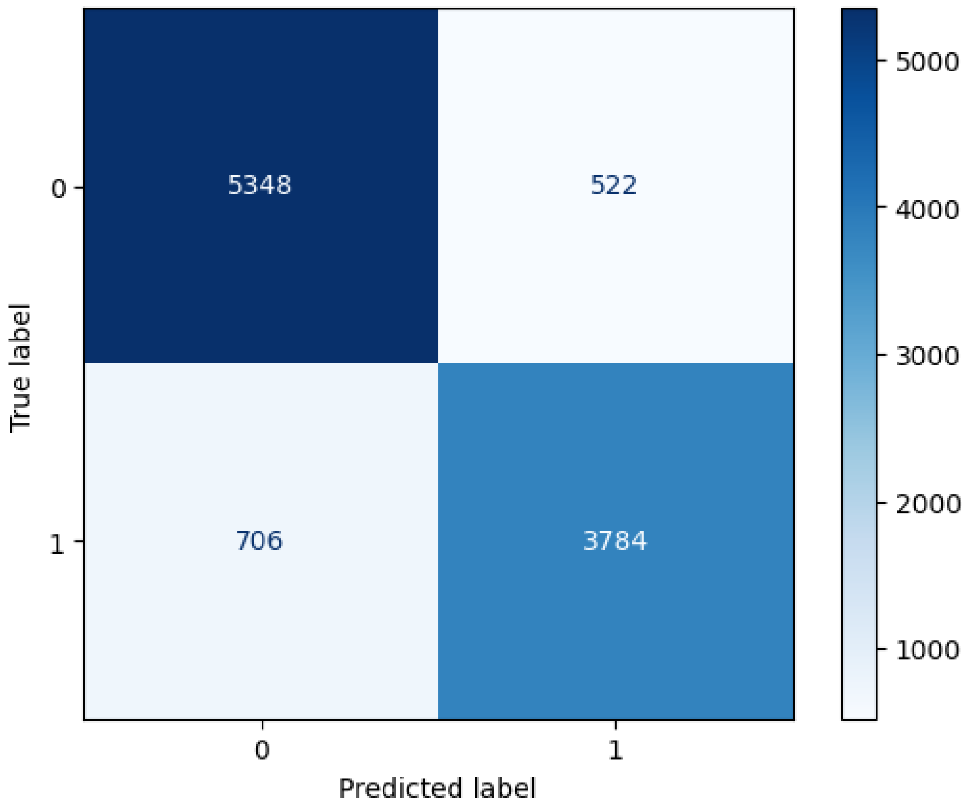
```
Model Train Score is :  0.8343415492202415
Model Test Score is :  0.8384169884169884
F1 Score is :  0.8153133274492497
Recall Score is :  0.8229398663697105
Precision Score is :  0.8078268473983384
AUC Value  :  0.8365977014983136

Classification Report is :                precision    recall  f1-score
support

           0       0.86      0.85      0.86      5870
           1       0.81      0.82      0.82      4490

    accuracy                           0.84     10360
   macro avg       0.84      0.84      0.84     10360
weighted avg       0.84      0.84      0.84     10360


Confusion Matrix is :
 [[4991  879]
 [ 795 3695]]


 Apply Model With Normal Data With PCA and Scaling :

Model Train Score is :  0.874691636098419
Model Test Score is :  0.8815637065637065
F1 Score is :  0.8604889141557703
Recall Score is :  0.8427616926503341
Precision Score is :  0.8789779326364692
AUC Value  :  0.8770026521173305

Classification Report is :                precision    recall  f1-score
support

           0       0.88      0.91      0.90      5870
           1       0.88      0.84      0.86      4490

    accuracy                           0.88     10360
   macro avg       0.88      0.88      0.88     10360
weighted avg       0.88      0.88      0.88     10360


Confusion Matrix is :
 [[5349  521]
 [ 706 3784]]
```

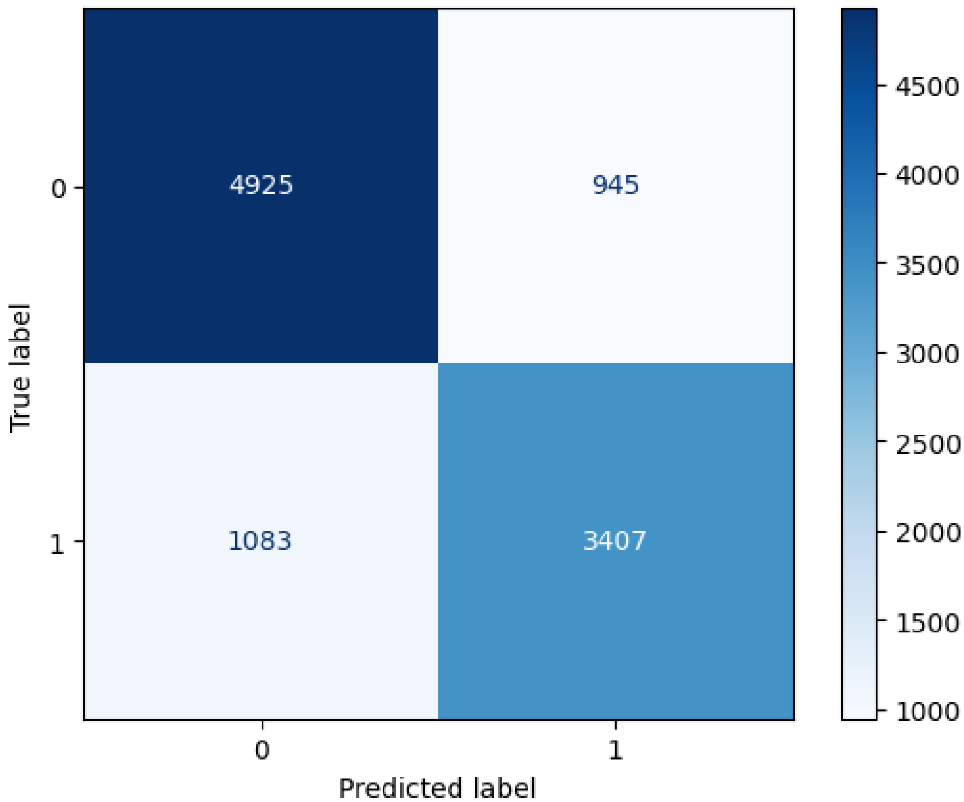
```
 Apply Model With Normal Data With PCA and Normalize :

Model Train Score is :  0.8020786408391788
Model Test Score is :  0.8042471042471042
F1 Score is :  0.7706401266681746
Recall Score is :  0.7587973273942094
Precision Score is :  0.7828584558823529
AUC Value  :  0.7989046262183994

Classification Report is :                precision    recall  f1-score
support

           0       0.82      0.84      0.83      5870
           1       0.78      0.76      0.77      4490

    accuracy                           0.80     10360
   macro avg       0.80      0.80      0.80     10360
weighted avg       0.80      0.80      0.80     10360


Confusion Matrix is :
 [[4925  945]
 [1083 3407]]


 Apply Model With Normal Data With Feature Selection and Poly and Scaling :

Model Train Score is :  0.9060857627045927
Model Test Score is :  0.9074324324324324
F1 Score is :  0.8924526185936974
Recall Score is :  0.8861915367483296
Precision Score is :  0.8988028009939011
AUC Value  :  0.9049356320879638

Classification Report is :                precision    recall  f1-score
support

           0       0.91      0.92      0.92      5870
           1       0.90      0.89      0.89      4490

    accuracy                           0.91     10360
   macro avg       0.91      0.90      0.91     10360
weighted avg       0.91      0.91      0.91     10360


Confusion Matrix is :
```

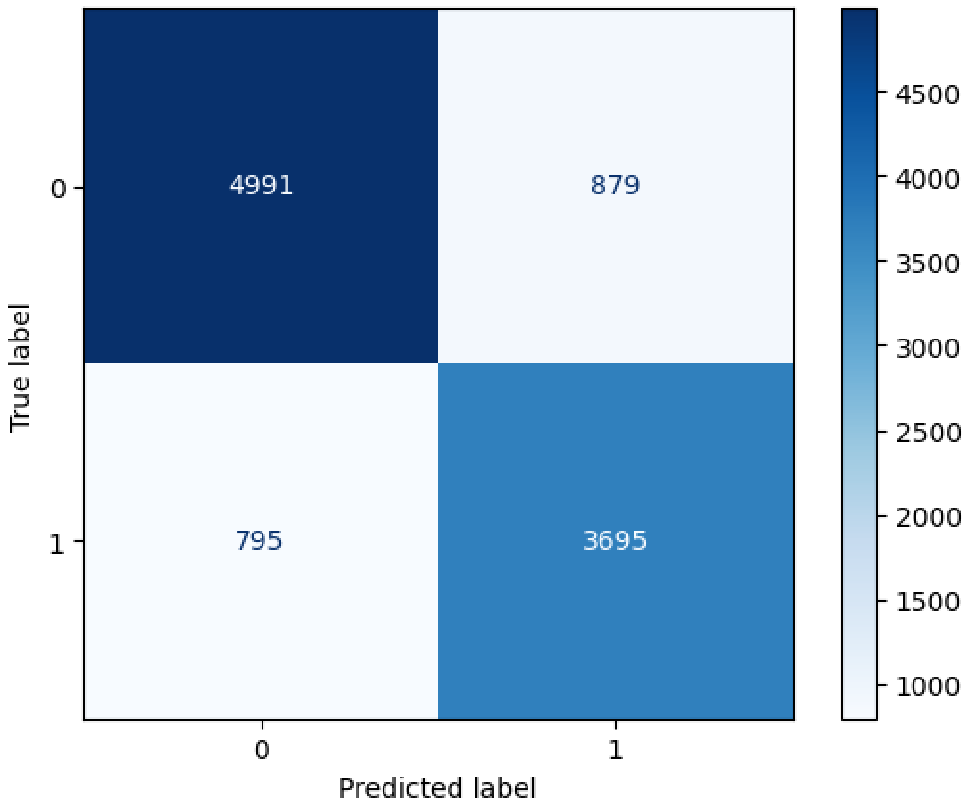
```
[[5422  448]
 [ 511 3979]]
```

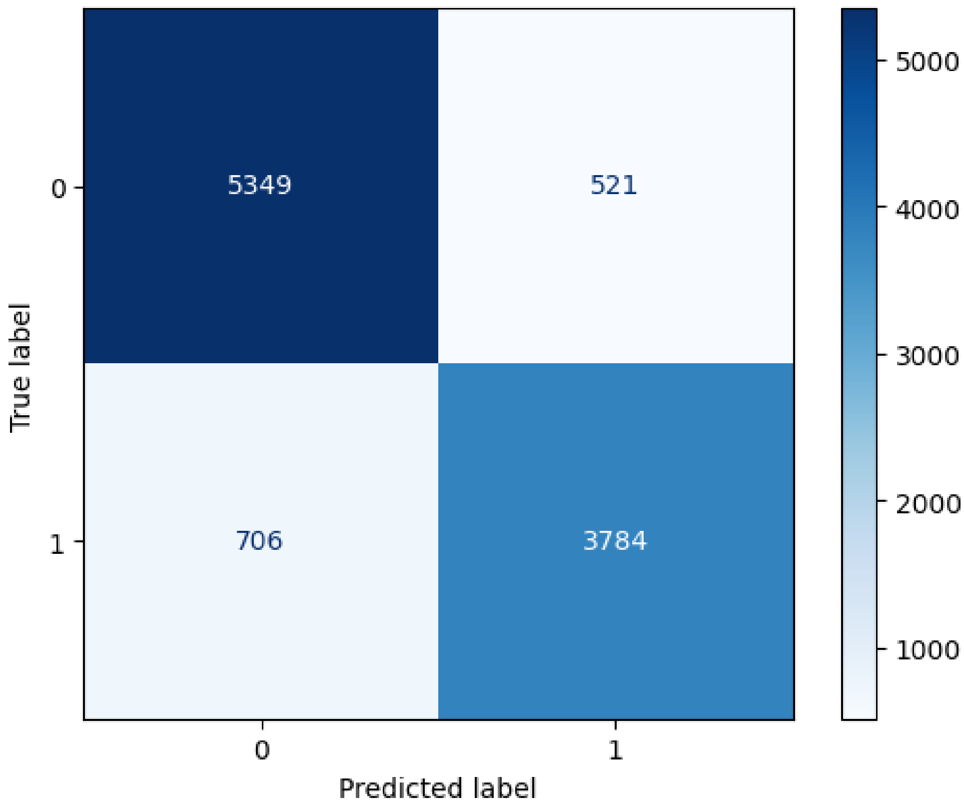



5070
800
860
3630
True label
0
1
Predicted label
5000
4500
4000
3500
3000
2500
2000
1500
1000

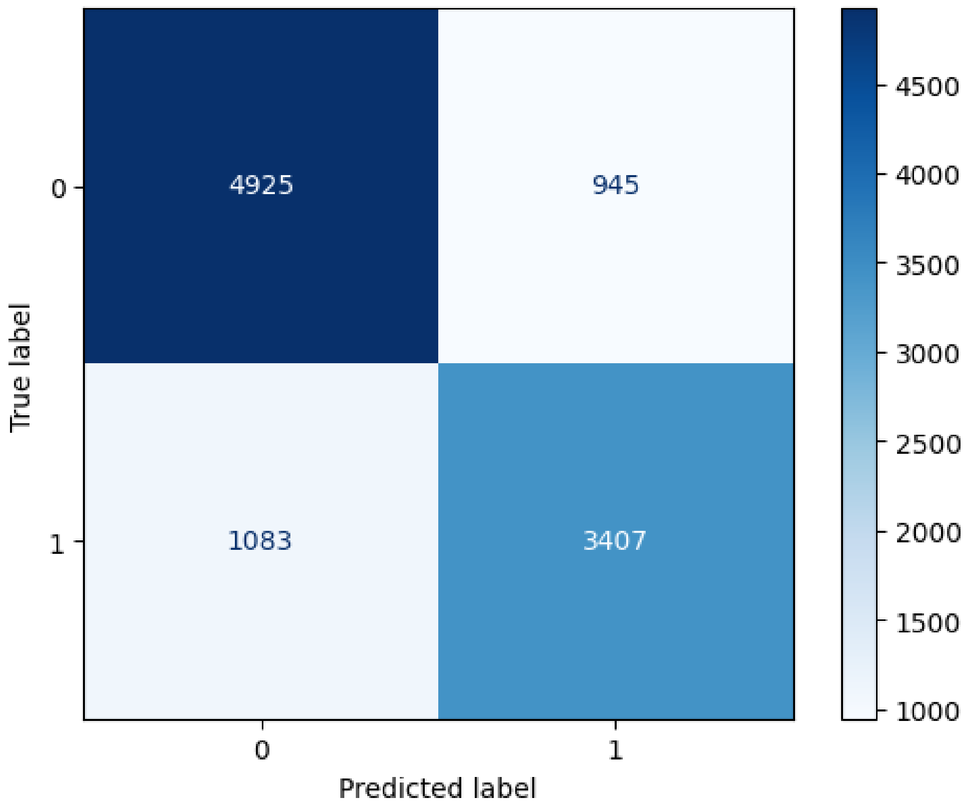

5348
522
706
3784
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000

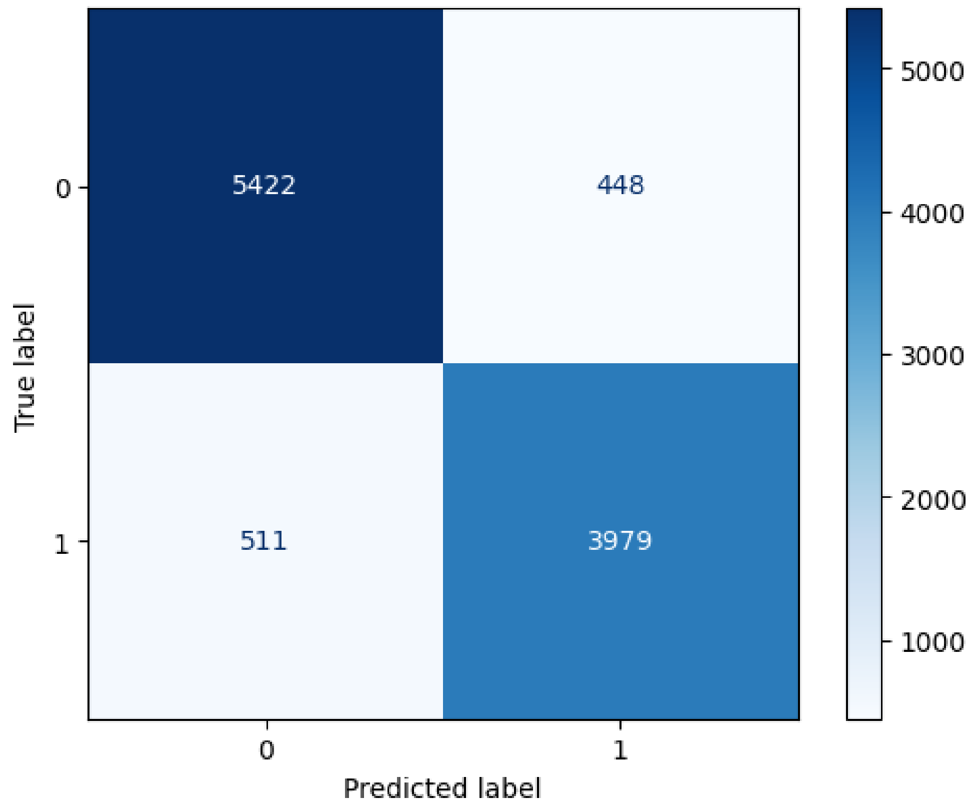

4925
945
1083
3407
0
1
True label
0
1
Predicted label
4500
4000
3500
3000
2500
2000
1500
1000


4991
879
795
3695
0
1
0
1
True label
Predicted label
4500
4000
3500
3000
2500
2000
1500
1000



5349
521
706
3784
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


4925
945
1083
3407
0
1
True label
0
1
Predicted label
4500
4000
3500
3000
2500
2000
1500
1000



[290]:
```
df = pd.DataFrame(Values,columns=['Train Accuracy','Test Accuracy','Test␣
↪F1','Test Recall','Test Precision','AUC'])
df['Models'] = ['Logistic','Logistic With Feature','Logistic Scaling','Logistic␣
↪With Normalize','Logistic With PCA','Logistic With PCA and Scaling',
                'Logistic With PCA and Normalize','Logistic With Feature and␣
↪Poly and Scaling']
df.set_index('Models', inplace=True)
df
```

[290]:
```
                                          Train Accuracy  Test Accuracy  \
Models
Logistic                                        0.784821       0.781274
Logistic With Feature                           0.836551       0.839768
Logistic Scaling                                0.874702       0.881467
Logistic With Normalize                         0.802089       0.804247
Logistic With PCA                               0.834342       0.838417
Logistic With PCA and Scaling                   0.874692       0.881564
Logistic With PCA and Normalize                 0.802079       0.804247
Logistic With Feature and Poly and Scaling      0.906086       0.907432

                                           Test F1  Test Recall  \
```

```
Models
Logistic                                       0.749945    0.756793
Logistic With Feature                          0.813901    0.808463
Logistic Scaling                               0.860391    0.842762
Logistic With Normalize                        0.770640    0.758797
Logistic With PCA                              0.815313    0.822940
Logistic With PCA and Scaling                  0.860489    0.842762
Logistic With PCA and Normalize                0.770640    0.758797
Logistic With Feature and Poly and Scaling     0.892453    0.886192

                                           Test Precision       AUC
Models
Logistic                                         0.743220  0.778396
Logistic With Feature                            0.819413  0.836089
Logistic Scaling                                 0.878774  0.876917
Logistic With Normalize                          0.782858  0.798905
Logistic With PCA                                0.807827  0.836598
Logistic With PCA and Scaling                    0.878978  0.877003
Logistic With PCA and Normalize                  0.782858  0.798905
Logistic With Feature and Poly and Scaling       0.898803  0.904936
```

[291]:
```python
models_draw(df)
```

SVC

[292]:
```python
Search(SVC(kernel= 'rbf',max_iter=1000,C=1.0,gamma='auto'),{'C':[1,.
↪5,2,3,5,10,15,20]},X_train,y_train)
```

[292]:
```
SVC(C=0.5, gamma='auto', max_iter=1000)
```

[293]:
```python
cross_validation(SVC(kernel= 'rbf',max_iter=1000,C=.
↪5,gamma='auto'),X_train,y_train)
```

```
Train Score Value :  [0.48466891 0.49088983 0.5973427  0.59557296 0.59124792]
Mean 0.5519444641883386
Test Score Value :  [0.47085322 0.47557248 0.58261383 0.58320373 0.5734742 ]
Mean 0.5371434919740825
```

[294]:
```python
Values = Models(SVC(kernel= 'rbf',max_iter=1000,C=.
↪5,gamma='auto'),X_train,y_train,X_test,y_test)
```

```
Apply Model With Normal Data :

Model Train Score is :  0.48230259347448357
Model Test Score is :  0.47355212355212356
F1 Score is :  0.6185480486781367
Recall Score is :  0.9848552338530067
Precision Score is :  0.45085644371941275
AUC Value  :  0.5336541927357026
```

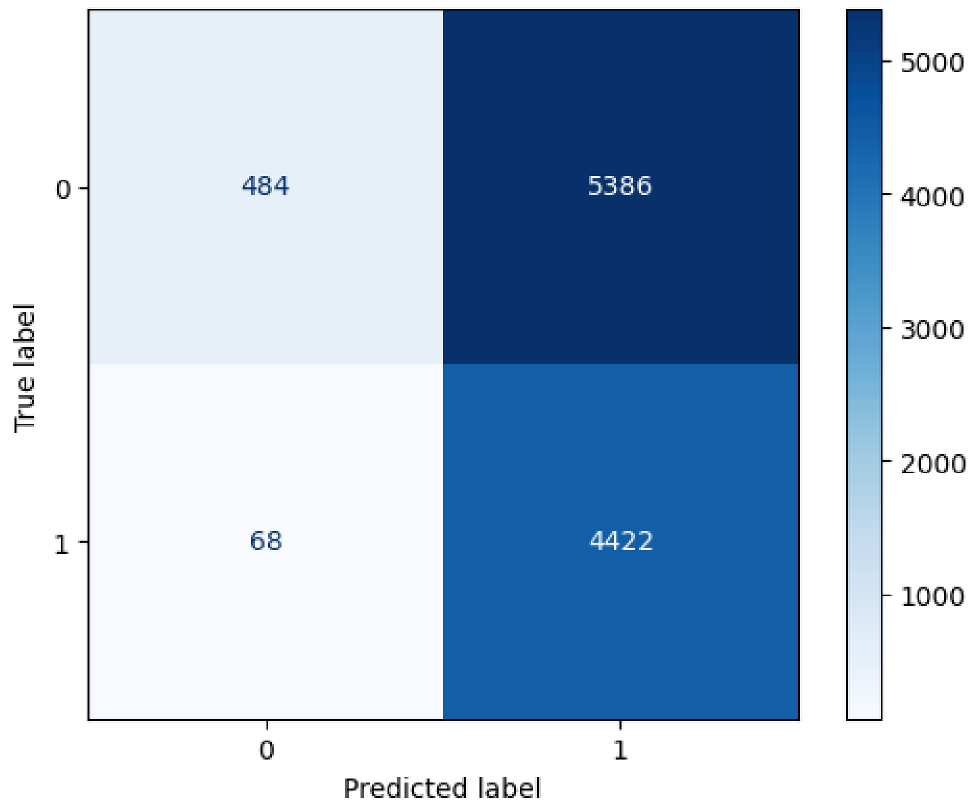
```
Classification Report is :                precision    recall  f1-score
support

           0       0.88      0.08      0.15      5870
           1       0.45      0.98      0.62      4490

    accuracy                           0.47     10360
   macro avg       0.66      0.53      0.38     10360
weighted avg       0.69      0.47      0.35     10360


Confusion Matrix is :
 [[ 484 5386]
 [  68 4422]]


 Apply Model With Feature Selection :

Model Train Score is :  0.48079026964412125
Model Test Score is :  0.4811776061776062
F1 Score is :  0.6188754165780331
Recall Score is :  0.9719376391982183
Precision Score is :  0.4539685842088838
AUC Value  :  0.5388649013708298

Classification Report is :                precision    recall  f1-score
support

           0       0.83      0.11      0.19      5870
           1       0.45      0.97      0.62      4490

    accuracy                           0.48     10360
   macro avg       0.64      0.54      0.40     10360
weighted avg       0.67      0.48      0.37     10360


Confusion Matrix is :
 [[ 621 5249]
 [ 126 4364]]


 Apply Model With Normal Data With Scaling :

Model Train Score is :  0.5699851985327241
Model Test Score is :  0.5658301158301158
F1 Score is :  0.6471049741095246
```

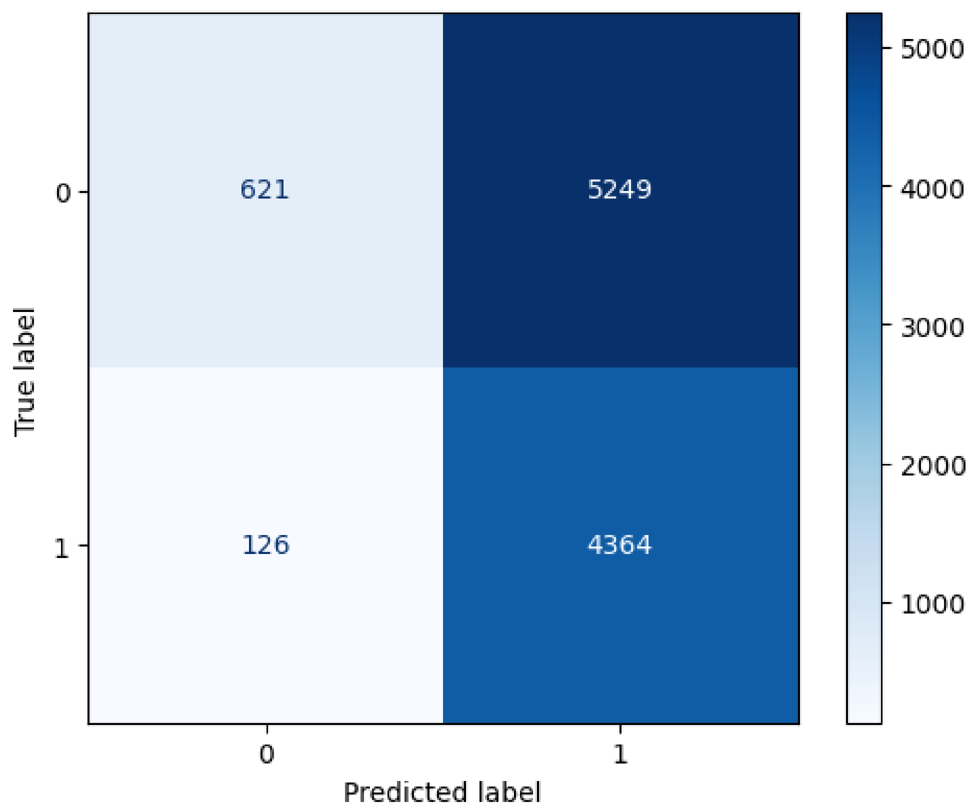
```
Recall Score is :  0.9184855233853007
Precision Score is :  0.499515503875969
AUC Value  :  0.607283647552957

Classification Report is :                precision    recall  f1-score
support

           0       0.83      0.30      0.44      5870
           1       0.50      0.92      0.65      4490

    accuracy                           0.57     10360
   macro avg       0.66      0.61      0.54     10360
weighted avg       0.68      0.57      0.53     10360


Confusion Matrix is :
 [[1738 4132]
 [ 366 4124]]


 Apply Model With Normal Data With Normalize :

Model Train Score is :  0.43376879679087027
Model Test Score is :  0.4335907335907336
F1 Score is :  0.6047420180520006
Recall Score is :  0.9997772828507795
Precision Score is :  0.43346852066434916
AUC Value  :  0.5001441780523063

Classification Report is :                precision    recall  f1-score
support

           0       0.75      0.00      0.00      5870
           1       0.43      1.00      0.60      4490

    accuracy                           0.43     10360
   macro avg       0.59      0.50      0.30     10360
weighted avg       0.61      0.43      0.26     10360


Confusion Matrix is :
 [[   3 5867]
 [   1 4489]]


 Apply Model With Normal Data With PCA :
```

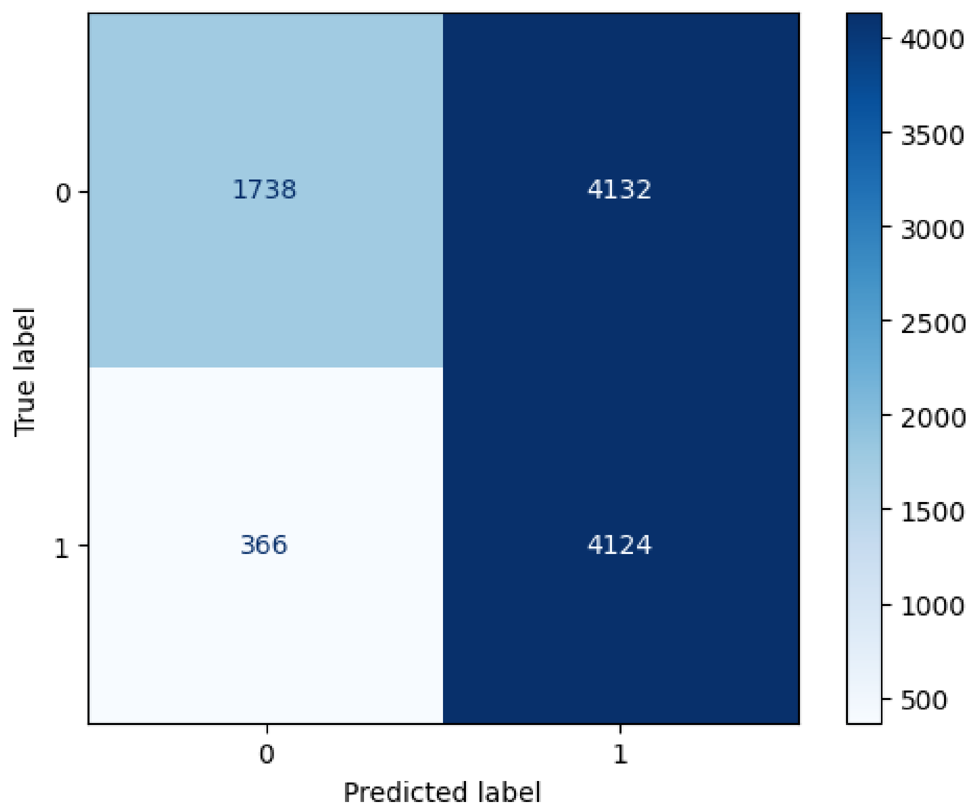
```
Model Train Score is :  0.48230259347448357
Model Test Score is :  0.47355212355212356
F1 Score is :  0.6185480486781367
Recall Score is :  0.9848552338530067
Precision Score is :  0.45085644371941275
AUC Value  :  0.5336541927357026

Classification Report is :                precision    recall  f1-score
support

           0       0.88      0.08      0.15      5870
           1       0.45      0.98      0.62      4490

    accuracy                           0.47     10360
   macro avg       0.66      0.53      0.38     10360
weighted avg       0.69      0.47      0.35     10360


Confusion Matrix is :
 [[ 484 5386]
 [  68 4422]]


 Apply Model With Normal Data With PCA and Scaling :

Model Train Score is :  0.5699851985327241
Model Test Score is :  0.5658301158301158
F1 Score is :  0.6471049741095246
Recall Score is :  0.9184855233853007
Precision Score is :  0.499515503875969
AUC Value  :  0.607283647552957

Classification Report is :                precision    recall  f1-score
support

           0       0.83      0.30      0.44      5870
           1       0.50      0.92      0.65      4490

    accuracy                           0.57     10360
   macro avg       0.66      0.61      0.54     10360
weighted avg       0.68      0.57      0.53     10360


Confusion Matrix is :
 [[1738 4132]
 [ 366 4124]]
```

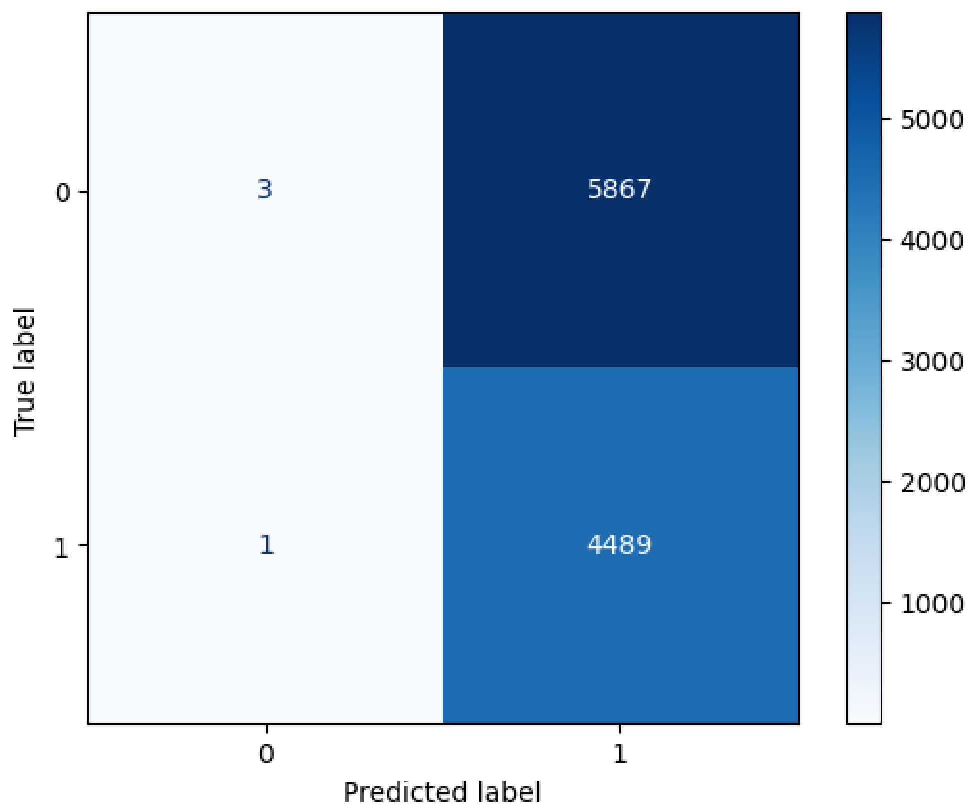
```
 Apply Model With Normal Data With PCA and Normalize :

Model Train Score is :  0.43376879679087027
Model Test Score is :  0.4335907335907336
F1 Score is :  0.6047420180520006
Recall Score is :  0.9997772828507795
Precision Score is :  0.43346852066434916
AUC Value  :  0.5001441780523063

Classification Report is :               precision    recall  f1-score
support

           0       0.75      0.00      0.00      5870
           1       0.43      1.00      0.60      4490

    accuracy                           0.43     10360
   macro avg       0.59      0.50      0.30     10360
weighted avg       0.61      0.43      0.26     10360


Confusion Matrix is :
 [[   3 5867]
 [   1 4489]]


 Apply Model With Normal Data With Feature Selection and Poly and Scaling :

Model Train Score is :  0.5944183452388614
Model Test Score is :  0.5943050193050193
F1 Score is :  0.6544438049823235
Recall Score is :  0.8864142538975501
Precision Score is :  0.518701941874104
AUC Value  :  0.6286415392145331

Classification Report is :               precision    recall  f1-score
support

           0       0.81      0.37      0.51      5870
           1       0.52      0.89      0.65      4490

    accuracy                           0.59     10360
   macro avg       0.66      0.63      0.58     10360
weighted avg       0.68      0.59      0.57     10360


Confusion Matrix is :
```

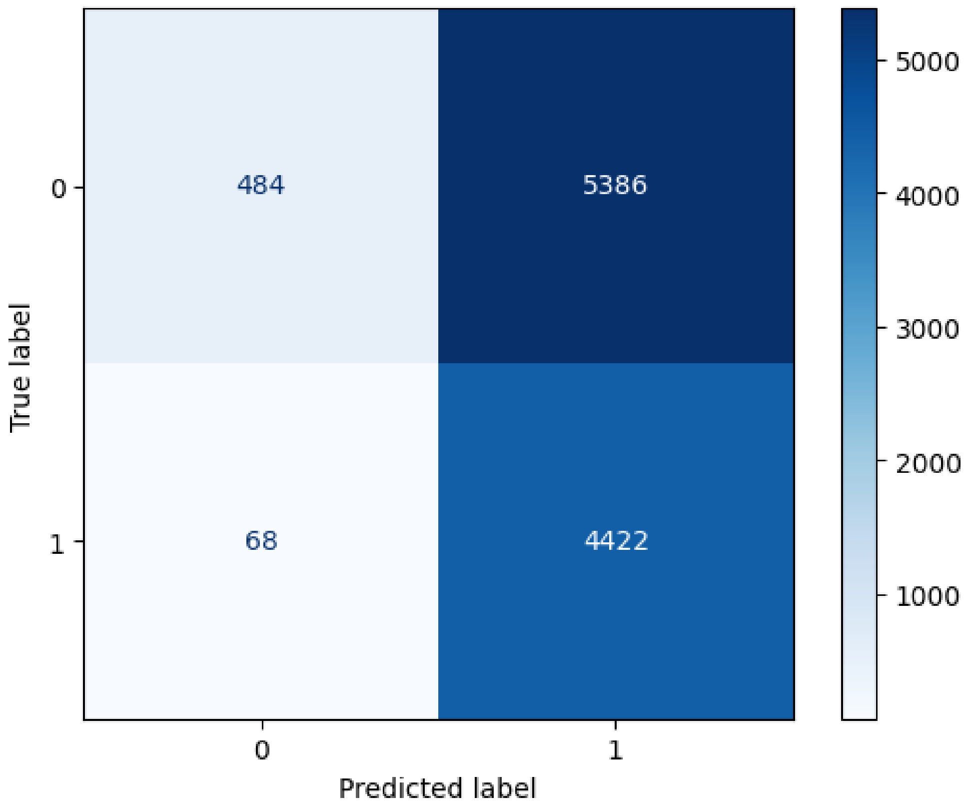
```
[[2177 3693]
 [ 510 3980]]
```

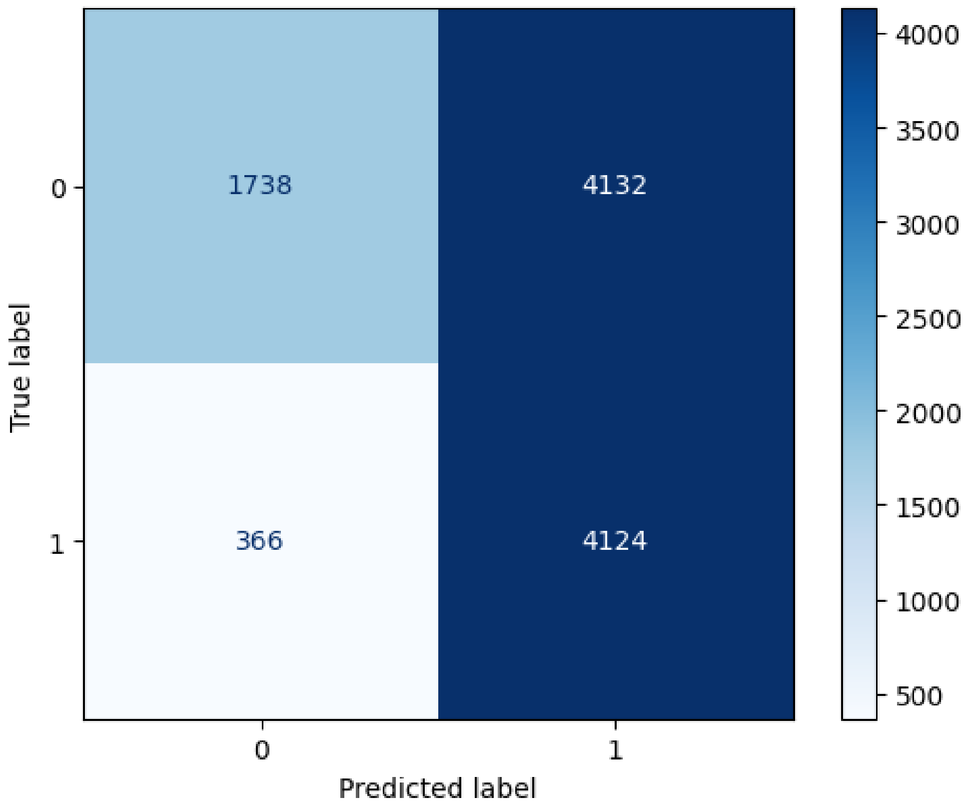


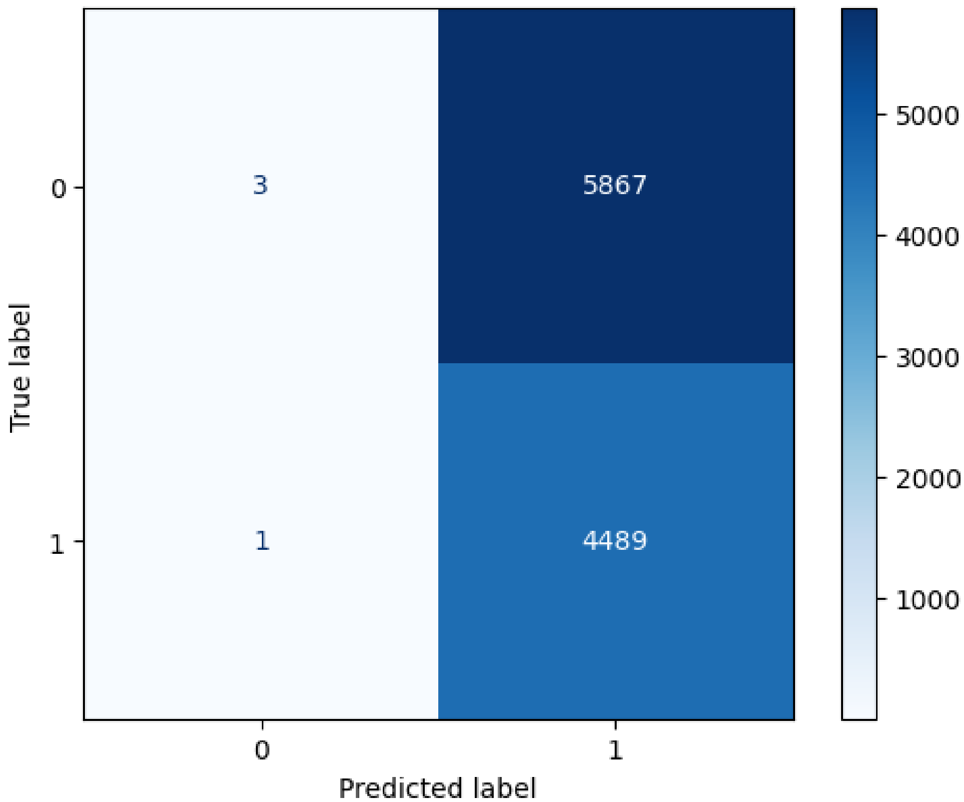

621
5249
126
4364
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000

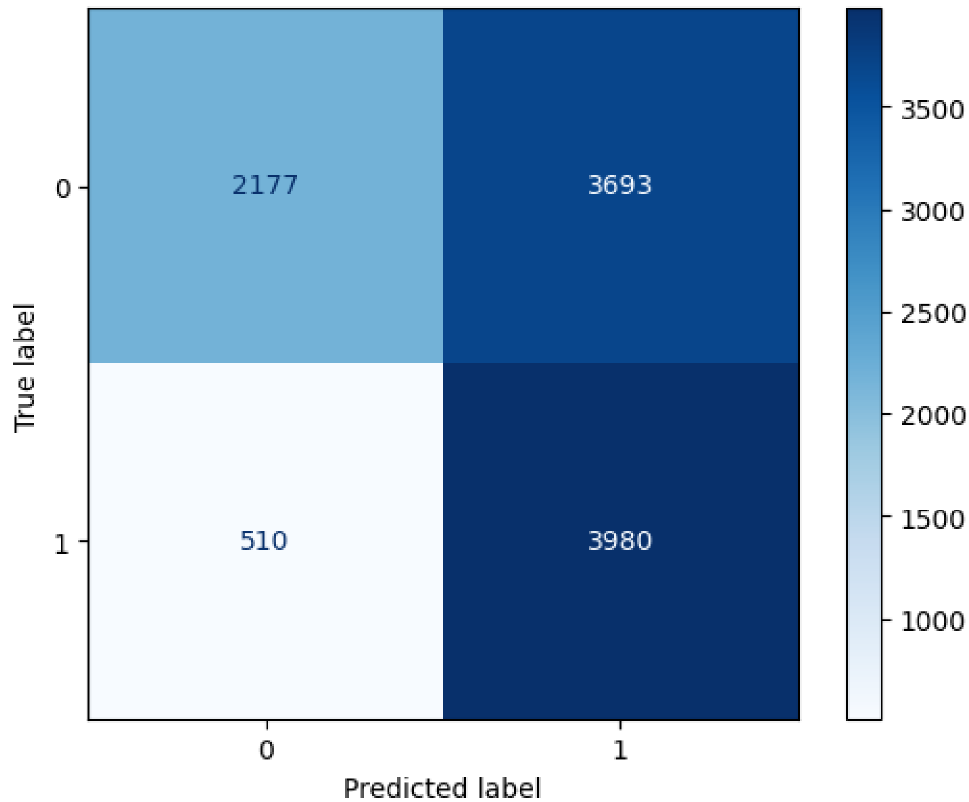

1738
4132
366
4124
0
1
True label
0
1
Predicted label
4000
3500
3000
2500
2000
1500
1000
500


3
5867
1
4489
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


484
5386
68
4422
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


1738
4132
366
4124
0
1
True label
0
1
Predicted label
4000
3500
3000
2500
2000
1500
1000
500


3
5867
1
4489
0
1
True label
Predicted label
5000
4000
3000
2000
1000



[295]:
```python
df = pd.DataFrame(Values,columns=['Train Accuracy','Test Accuracy','Test F1','Test Recall','Test Precision','AUC'])
df['Models'] = ['SVC','SVC With Feature','SVC Scaling','SVC With Normalize','SVC With PCA','SVC With PCA and Scaling',
                'SVC With PCA and Normalize','SVC With Feature and Poly and Scaling']
df.set_index('Models', inplace=True)
df
```

[295]:
```
                                       Train Accuracy  Test Accuracy  \
Models
SVC                                          0.482303       0.473552
SVC With Feature                             0.480790       0.481178
SVC Scaling                                  0.569985       0.565830
SVC With Normalize                           0.433769       0.433591
SVC With PCA                                 0.482303       0.473552
SVC With PCA and Scaling                     0.569985       0.565830
SVC With PCA and Normalize                   0.433769       0.433591
SVC With Feature and Poly and Scaling        0.594418       0.594305

                                        Test F1  Test Recall  Test Precision  \
```

```
Models
SVC                                  0.618548    0.984855    0.450856
SVC With Feature                     0.618875    0.971938    0.453969
SVC Scaling                          0.647105    0.918486    0.499516
SVC With Normalize                   0.604742    0.999777    0.433469
SVC With PCA                         0.618548    0.984855    0.450856
SVC With PCA and Scaling             0.647105    0.918486    0.499516
SVC With PCA and Normalize           0.604742    0.999777    0.433469
SVC With Feature and Poly and Scaling 0.654444   0.886414    0.518702

                                          AUC
Models
SVC                                  0.533654
SVC With Feature                     0.538865
SVC Scaling                          0.607284
SVC With Normalize                   0.500144
SVC With PCA                         0.533654
SVC With PCA and Scaling             0.607284
SVC With PCA and Normalize           0.500144
SVC With Feature and Poly and Scaling 0.628642
```

[296]:
```
models_draw(df)
```

KNeighborsClassifier

[297]:
```
Search(KNeighborsClassifier(n_neighbors=3),{'n_neighbors':
↪[3,5,7,9,11]},X_train,y_train)
```

[297]:
```
KNeighborsClassifier()
```

[298]:
```
cross_validation(KNeighborsClassifier(n_neighbors=11),X_train,y_train)
```

```
Train Score Value :  [0.79496427 0.7961441  0.79478998 0.7953933  0.79692444]
Mean 0.7956432168489462
Test Score Value :  [0.75309701 0.74928943 0.75277525 0.75164906 0.74627266]
Mean 0.7506166812104791
```

[299]:
```
Values =␣
↪Models(KNeighborsClassifier(n_neighbors=11),X_train,y_train,X_test,y_test)
```

```
Apply Model With Normal Data :

Model Train Score is :  0.802121543642877
Model Test Score is :  0.7637065637065638
F1 Score is :  0.7111845210004719
Recall Score is :  0.6712694877505568
Precision Score is :  0.7561465127947817
AUC Value  :  0.7528408767543244
```

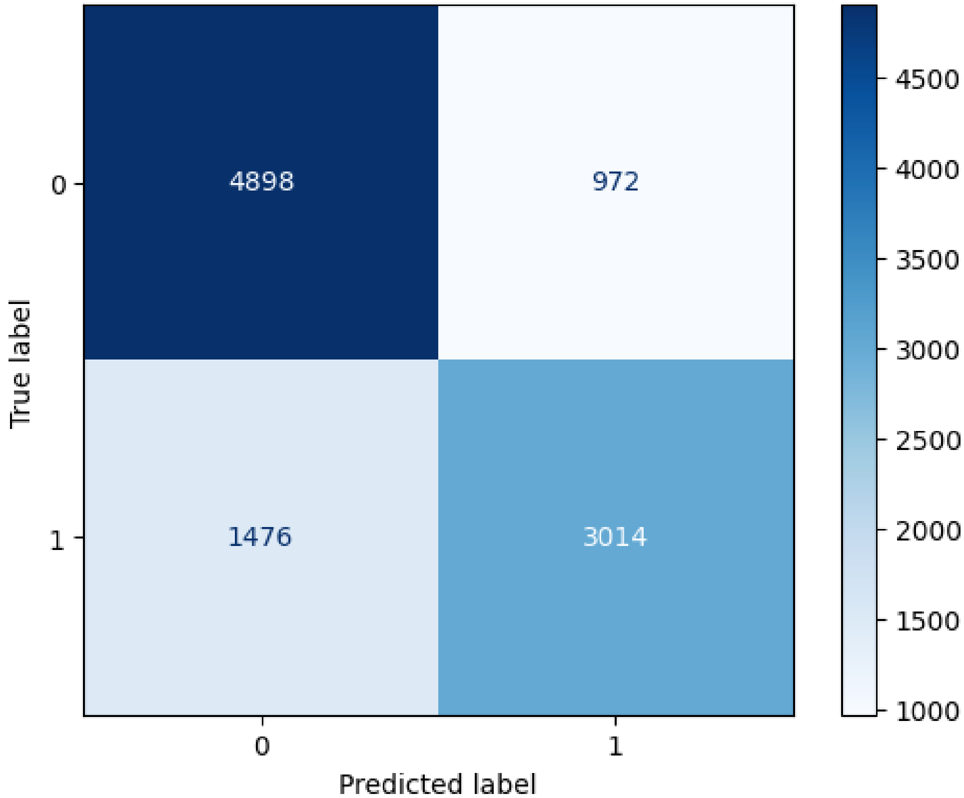
```
Classification Report is :                precision    recall  f1-score
support

           0       0.77      0.83      0.80      5870
           1       0.76      0.67      0.71      4490

    accuracy                           0.76     10360
   macro avg       0.76      0.75      0.76     10360
weighted avg       0.76      0.76      0.76     10360


Confusion Matrix is :
 [[4898  972]
 [1476 3014]]


 Apply Model With Feature Selection :

Model Train Score is :  0.9247377566123947
Model Test Score is :  0.928088803088803
F1 Score is :  0.9154081980242987
Recall Score is :  0.897772828507795
Precision Score is :  0.9337502895529303
AUC Value  :  0.9245252558211888

Classification Report is :                precision    recall  f1-score
support

           0       0.92      0.95      0.94      5870
           1       0.93      0.90      0.92      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.92      0.93     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
 [[5584  286]
 [ 459 4031]]


 Apply Model With Normal Data With Scaling :

Model Train Score is :  0.9355814402471202
Model Test Score is :  0.9275096525096526
F1 Score is :  0.9126642632864287
```

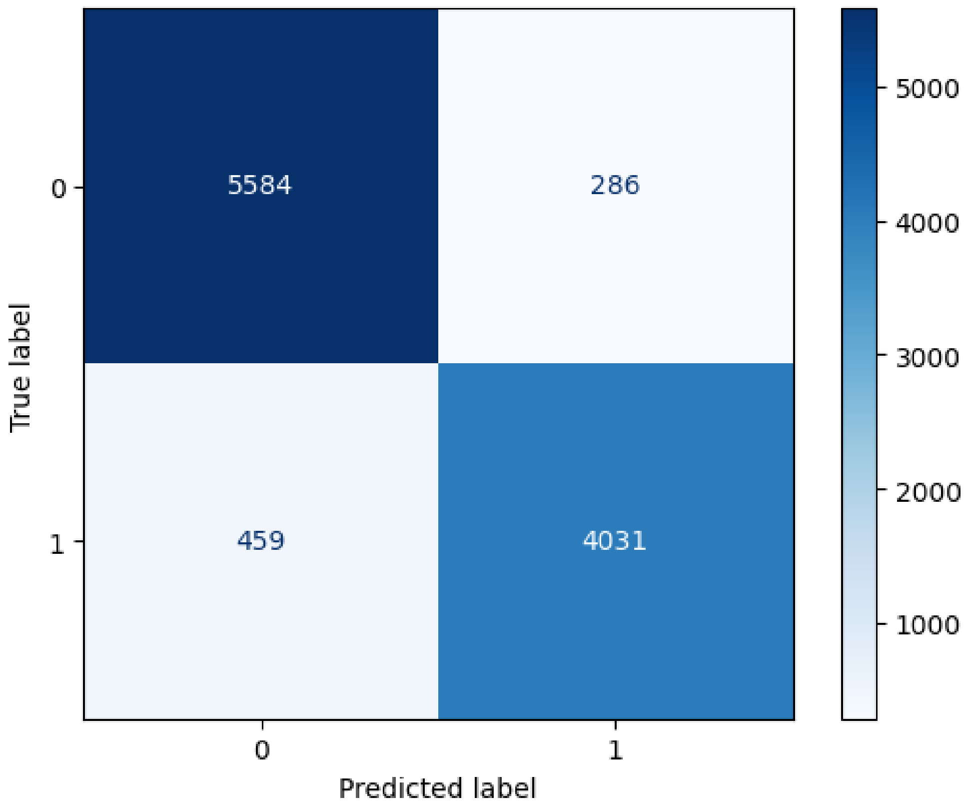
```
Recall Score is :  0.8739420935412027
Precision Score is :  0.9549768800194695
AUC Value  :  0.9212129547774157

Classification Report is :                precision    recall  f1-score
support

           0       0.91      0.97      0.94      5870
           1       0.95      0.87      0.91      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.92      0.93     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
 [[5685  185]
 [ 566 3924]]


 Apply Model With Normal Data With Normalize :

Model Train Score is :  0.8419031683720531
Model Test Score is :  0.8142857142857143
F1 Score is :  0.7913684667100411
Recall Score is :  0.8126948775055679
Precision Score is :  0.7711327134404058
AUC Value  :  0.8140987164359185

Classification Report is :                precision    recall  f1-score
support

           0       0.85      0.82      0.83      5870
           1       0.77      0.81      0.79      4490

    accuracy                           0.81     10360
   macro avg       0.81      0.81      0.81     10360
weighted avg       0.82      0.81      0.81     10360


Confusion Matrix is :
 [[4787 1083]
 [ 841 3649]]


 Apply Model With Normal Data With PCA :
```

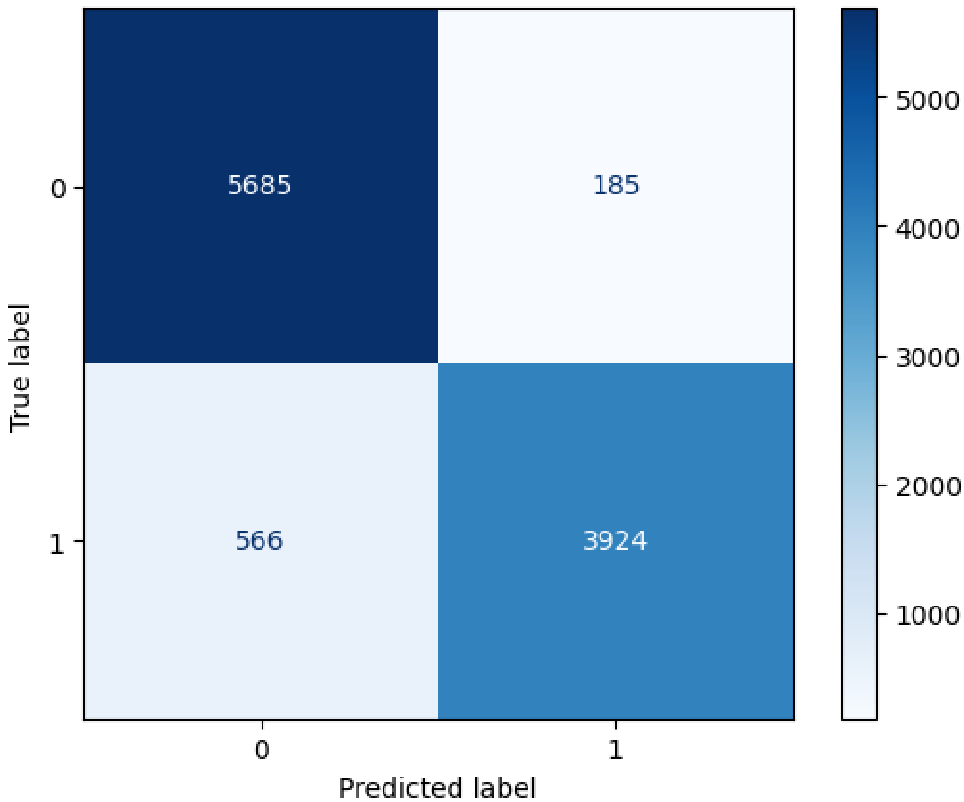
```
Model Train Score is :  0.8019713838299333
Model Test Score is :  0.7637065637065638
F1 Score is :  0.7111845210004719
Recall Score is :  0.6712694877505568
Precision Score is :  0.7561465127947817
AUC Value  :  0.7528408767543244

Classification Report is :                precision    recall  f1-score
support

           0       0.77      0.83      0.80      5870
           1       0.76      0.67      0.71      4490

    accuracy                           0.76     10360
   macro avg       0.76      0.75      0.76     10360
weighted avg       0.76      0.76      0.76     10360


Confusion Matrix is :
 [[4898  972]
 [1476 3014]]


 Apply Model With Normal Data With PCA and Scaling :

Model Train Score is :  0.9355814402471202
Model Test Score is :  0.9275096525096526
F1 Score is :  0.9126642632864287
Recall Score is :  0.8739420935412027
Precision Score is :  0.9549768800194695
AUC Value  :  0.9212129547774157

Classification Report is :                precision    recall  f1-score
support

           0       0.91      0.97      0.94      5870
           1       0.95      0.87      0.91      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.92      0.93     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
 [[5685  185]
 [ 566 3924]]
```

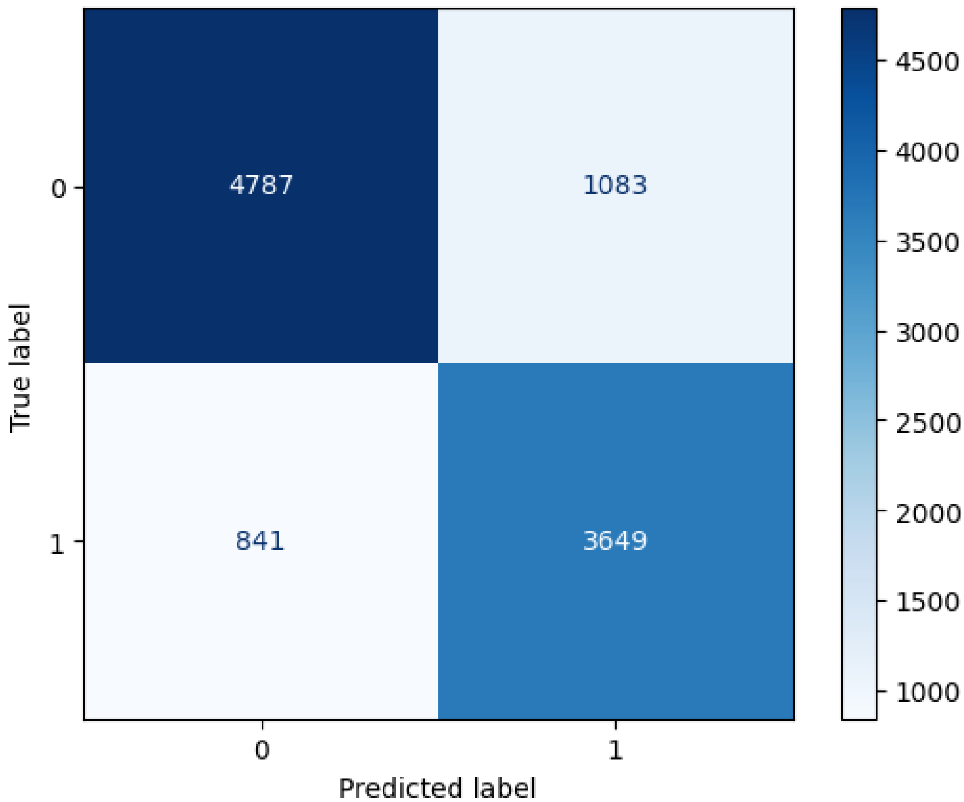
```
 Apply Model With Normal Data With PCA and Normalize :

Model Train Score is :  0.8419031683720531
Model Test Score is :  0.8142857142857143
F1 Score is :  0.7913684667100411
Recall Score is :  0.8126948775055679
Precision Score is :  0.7711327134404058
AUC Value  :  0.8140987164359185

Classification Report is :                precision    recall  f1-score
support

           0       0.85      0.82      0.83      5870
           1       0.77      0.81      0.79      4490

    accuracy                           0.81     10360
   macro avg       0.81      0.81      0.81     10360
weighted avg       0.82      0.81      0.81     10360


Confusion Matrix is :
 [[4787 1083]
 [ 841 3649]]


 Apply Model With Normal Data With Feature Selection and Poly and Scaling :

Model Train Score is :  0.9235686552116181
Model Test Score is :  0.9263513513513514
F1 Score is :  0.9131671787868443
Recall Score is :  0.8935412026726058
Precision Score is :  0.9336746567372586
AUC Value  :  0.922494621779233

Classification Report is :                precision    recall  f1-score
support

           0       0.92      0.95      0.94      5870
           1       0.93      0.89      0.91      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.92      0.92     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
```

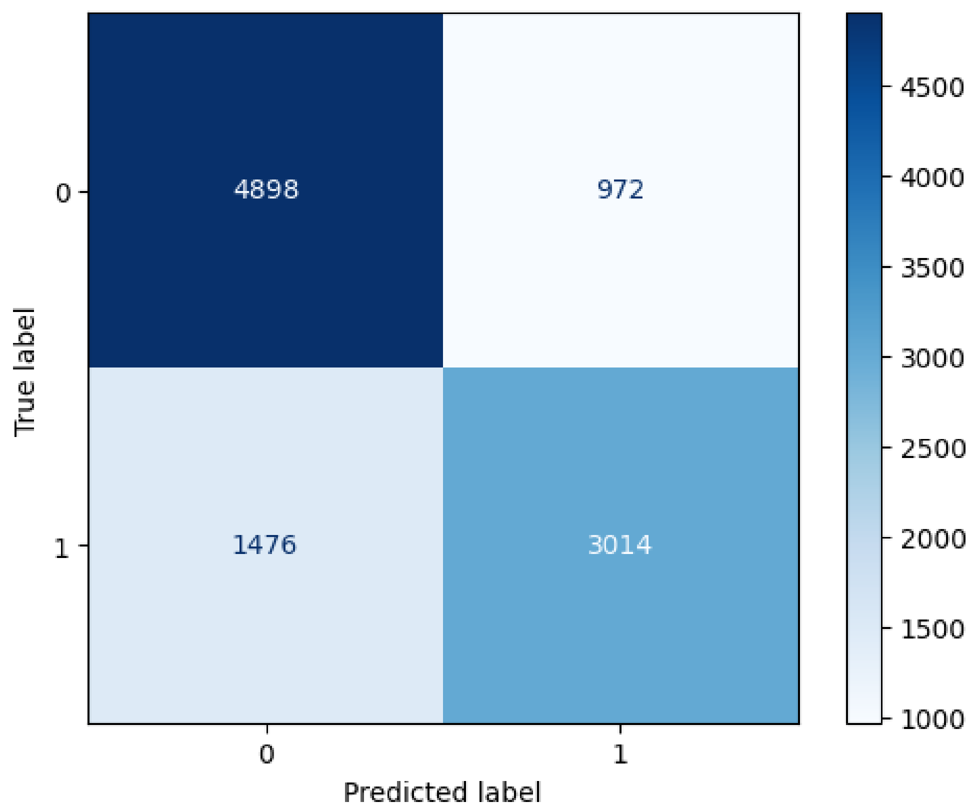
```
[[5585  285]
 [ 478 4012]]
```

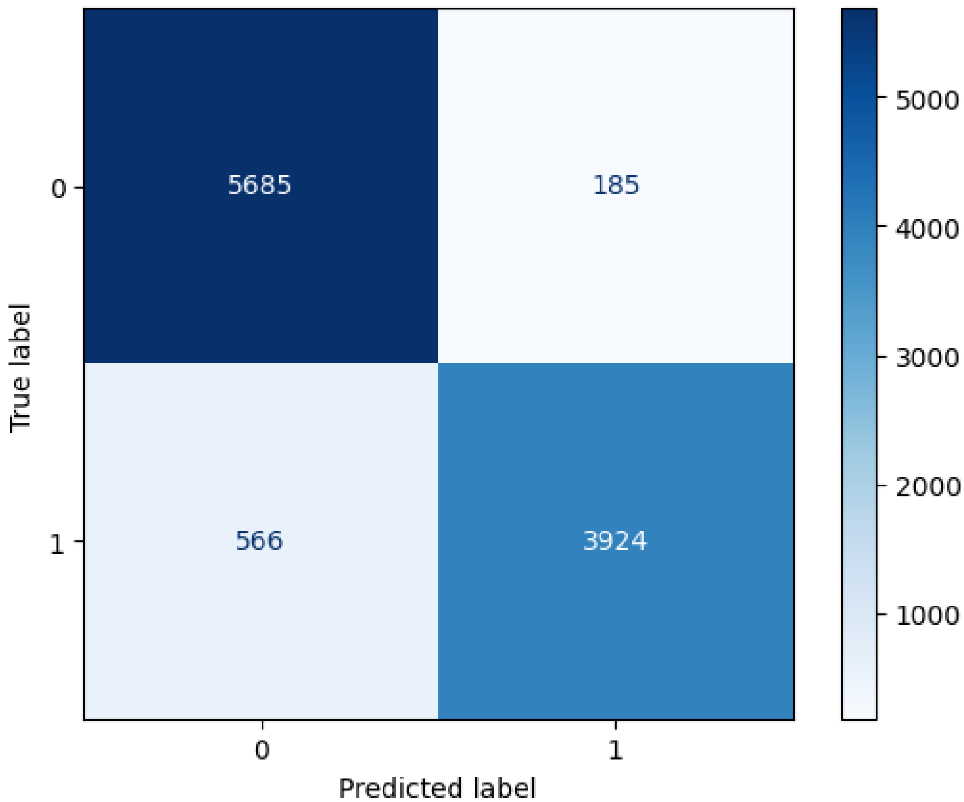


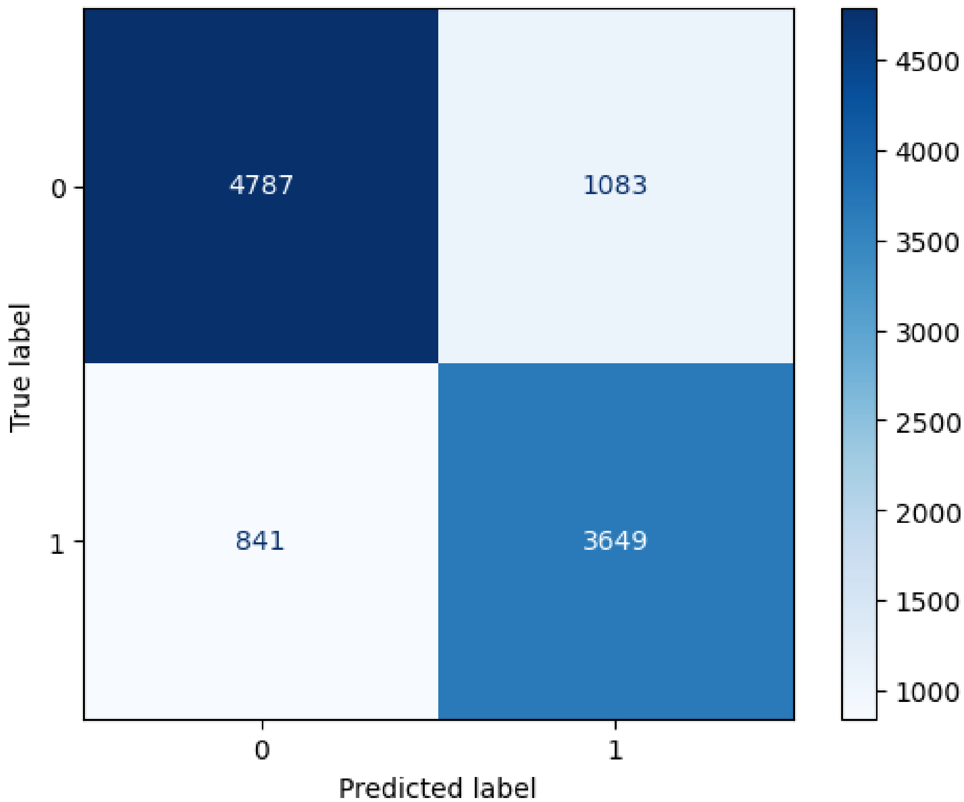

5584
286
459
4031
True label
Predicted label
0
1
0
1
5000
4000
3000
2000
1000

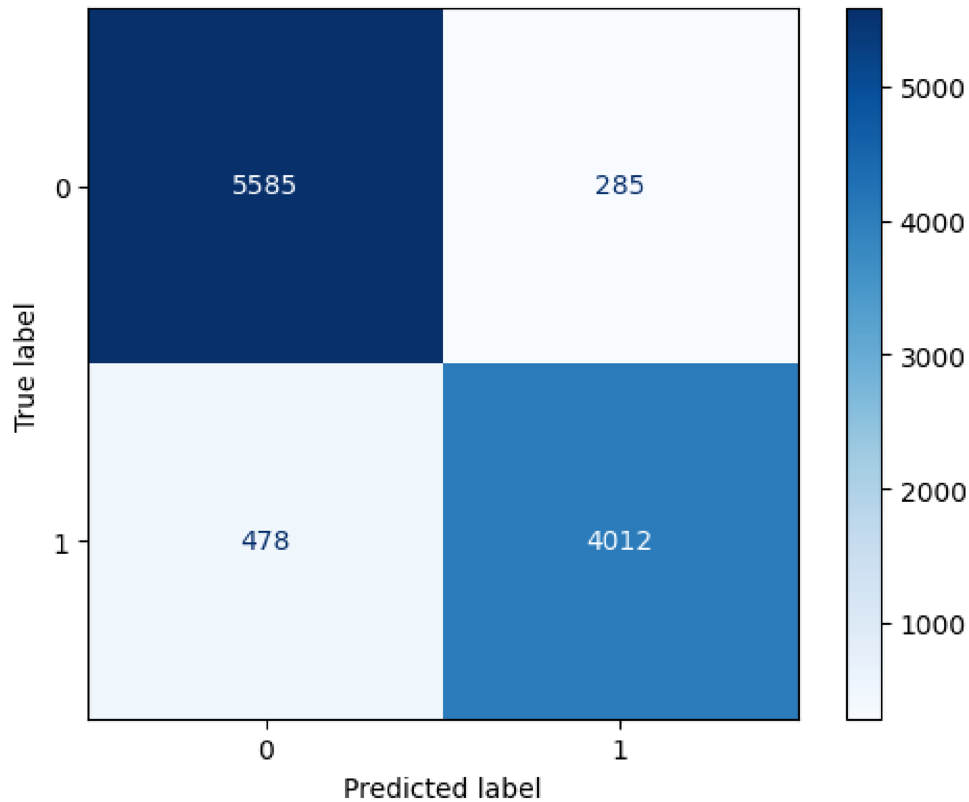

5685
185
566
3924
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


4787
1083
841
3649
0
1
True label
0
1
Predicted label
4500
4000
3500
3000
2500
2000
1500
1000


4898
972
1476
3014
0
1
True label
0
1
Predicted label
4500
4000
3500
3000
2500
2000
1500
1000


5685
185
566
3924
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


4787
1083
841
3649
True label
0
1
Predicted label
0
1
4500
4000
3500
3000
2500
2000
1500
1000



[300]:
```
df = pd.DataFrame(Values,columns=['Train Accuracy','Test Accuracy','Test␣
 ↪F1','Test Recall','Test Precision','AUC'])
df['Models'] = ['KNN','KNN With Feature','KNN Scaling','KNN With␣
 ↪Normalize','KNN With PCA','KNN With PCA and Scaling',
                'KNN With PCA and Normalize','KNN With Feature and Poly and␣
 ↪Scaling']
df.set_index('Models', inplace=True)
df
```

[300]:
```
                                       Train Accuracy  Test Accuracy  \
Models
KNN                                          0.802122       0.763707
KNN With Feature                             0.924738       0.928089
KNN Scaling                                  0.935581       0.927510
KNN With Normalize                           0.841903       0.814286
KNN With PCA                                 0.801971       0.763707
KNN With PCA and Scaling                     0.935581       0.927510
KNN With PCA and Normalize                   0.841903       0.814286
KNN With Feature and Poly and Scaling        0.923569       0.926351

                                        Test F1  Test Recall  Test Precision  \
```

```
Models
KNN                                  0.711185     0.671269        0.756147
KNN With Feature                     0.915408     0.897773        0.933750
KNN Scaling                          0.912664     0.873942        0.954977
KNN With Normalize                   0.791368     0.812695        0.771133
KNN With PCA                         0.711185     0.671269        0.756147
KNN With PCA and Scaling             0.912664     0.873942        0.954977
KNN With PCA and Normalize           0.791368     0.812695        0.771133
KNN With Feature and Poly and Scaling 0.913167     0.893541        0.933675

                                          AUC
Models
KNN                                  0.752841
KNN With Feature                     0.924525
KNN Scaling                          0.921213
KNN With Normalize                   0.814099
KNN With PCA                         0.752841
KNN With PCA and Scaling             0.921213
KNN With PCA and Normalize           0.814099
KNN With Feature and Poly and Scaling 0.922495
```

[301]:
```
models_draw(df)
```

```
GaussianNB
```

[302]:
```
cross_validation(GaussianNB(),X_train,y_train)
```

```
Train Score Value :   [0.8672825   0.86738976 0.86698754 0.86663896 0.8675122 ]
Mean 0.8671621931108631
Test Score Value :   [0.86678822 0.86700274 0.86807529 0.86845069 0.8656012 ]
Mean 0.8671836284785899
```

[303]:
```
Values = Models(GaussianNB(),X_train,y_train,X_test,y_test)
```

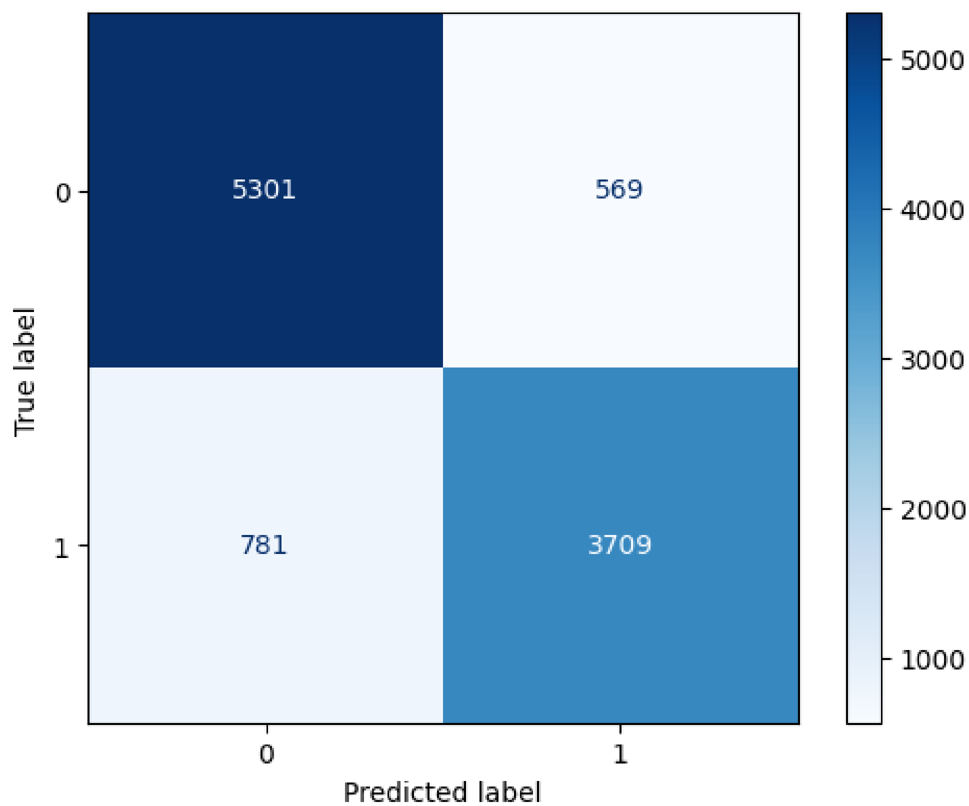
```
Apply Model With Normal Data :

Model Train Score is :   0.8671729197503056
Model Test Score is :   0.8696911196911197
F1 Score is :   0.8460310218978102
Recall Score is :   0.8260579064587973
Precision Score is :   0.8669939223936419
AUC Value  :   0.8645621729908978


Classification Report is :                precision    recall  f1-score
support

           0       0.87      0.90      0.89      5870
           1       0.87      0.83      0.85      4490
```

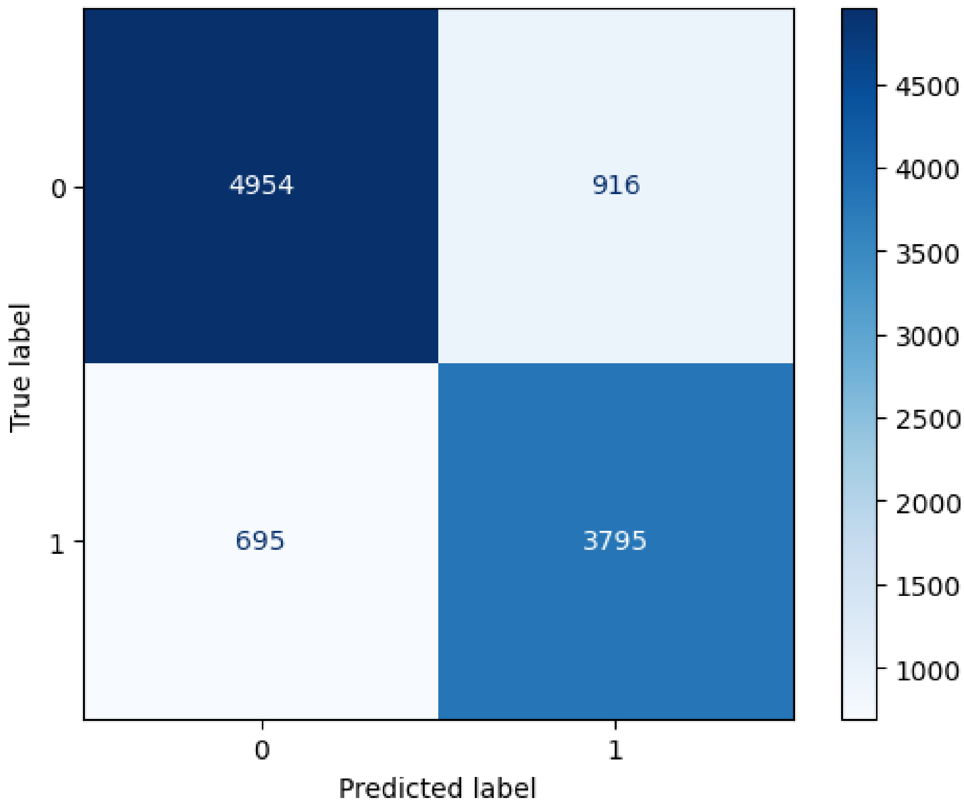
```
   accuracy                           0.87     10360
  macro avg       0.87      0.86      0.87     10360
weighted avg       0.87      0.87      0.87     10360


Confusion Matrix is :
 [[5301  569]
 [ 781 3709]]


 Apply Model With Feature Selection :

Model Train Score is :  0.8408413239805221
Model Test Score is :  0.8444980694980695
F1 Score is :  0.8249103358330617
Recall Score is :  0.8452115812917594
Precision Score is :  0.8055614519210359
AUC Value  :  0.8445819405607009

Classification Report is :                precision    recall  f1-score
support

           0       0.88      0.84      0.86      5870
           1       0.81      0.85      0.82      4490

    accuracy                           0.84     10360
   macro avg       0.84      0.84      0.84     10360
weighted avg       0.85      0.84      0.84     10360


Confusion Matrix is :
 [[4954  916]
 [ 695 3795]]


 Apply Model With Normal Data With Scaling :

Model Train Score is :  0.8673445309650986
Model Test Score is :  0.8696911196911197
F1 Score is :  0.845960748516659
Recall Score is :  0.8256124721603564
Precision Score is :  0.8673373888628919
AUC Value  :  0.8645098135929551

Classification Report is :                precision    recall  f1-score
support
```

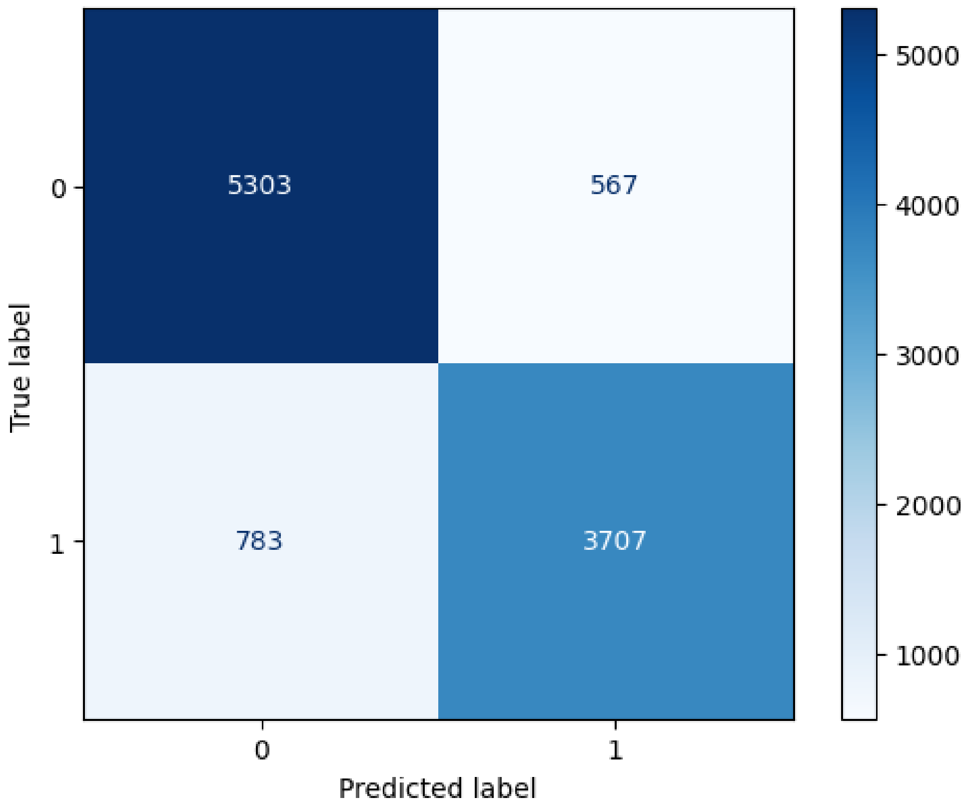
```
           0       0.87      0.90      0.89      5870
           1       0.87      0.83      0.85      4490

    accuracy                           0.87     10360
   macro avg       0.87      0.86      0.87     10360
weighted avg       0.87      0.87      0.87     10360


Confusion Matrix is :
 [[5303  567]
 [ 783 3707]]


 Apply Model With Normal Data With Normalize :

Model Train Score is :  0.6093914237295407
Model Test Score is :  0.6154440154440154
F1 Score is :  0.6603580562659846
Recall Score is :  0.8625835189309576
Precision Score is :  0.5349447513812154
AUC Value  :  0.6444944851894993

Classification Report is :                precision    recall  f1-score
support

           0       0.80      0.43      0.56      5870
           1       0.53      0.86      0.66      4490

    accuracy                           0.62     10360
   macro avg       0.67      0.64      0.61     10360
weighted avg       0.69      0.62      0.60     10360


Confusion Matrix is :
 [[2503 3367]
 [ 617 3873]]


 Apply Model With Normal Data With PCA :

Model Train Score is :  0.8277666945534891
Model Test Score is :  0.8277992277992278
F1 Score is :  0.7935185185185185
Recall Score is :  0.7634743875278397
Precision Score is :  0.8260240963855422
AUC Value  :  0.8202380455526762
```

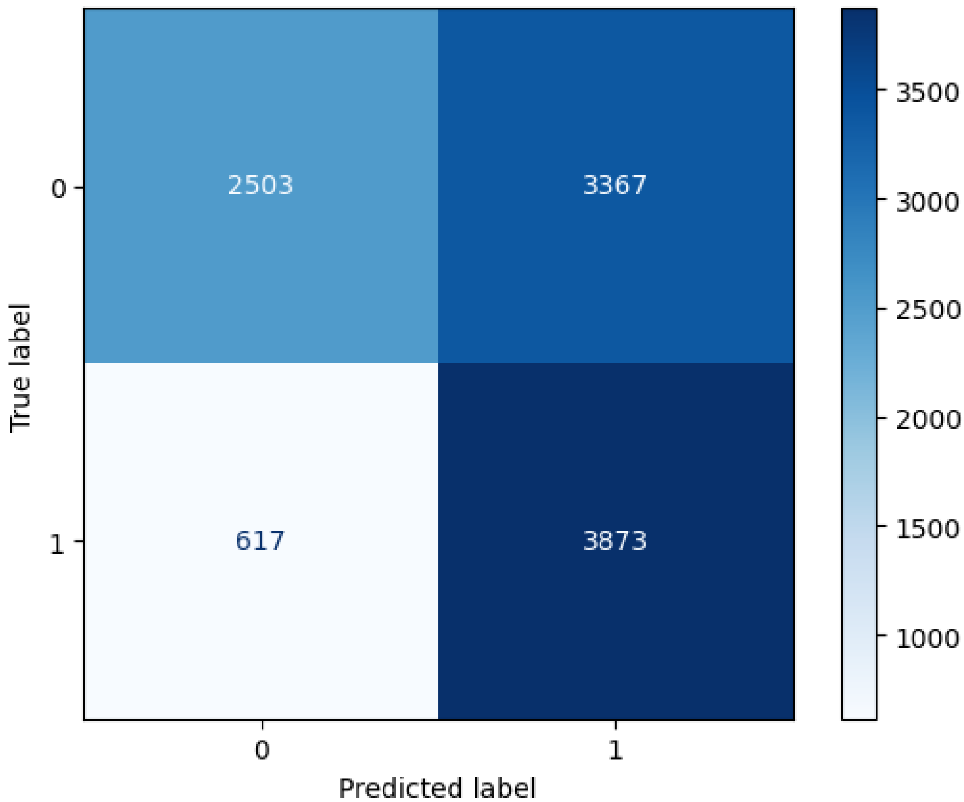
```
Classification Report is :                precision    recall  f1-score
support

           0       0.83      0.88      0.85      5870
           1       0.83      0.76      0.79      4490

    accuracy                           0.83     10360
   macro avg       0.83      0.82      0.82     10360
weighted avg       0.83      0.83      0.83     10360


Confusion Matrix is :
 [[5148  722]
 [1062 3428]]


 Apply Model With Normal Data With PCA and Scaling :

Model Train Score is :  0.844488062294871
Model Test Score is :  0.8442084942084942
F1 Score is :  0.8154162854528819
Recall Score is :  0.7939866369710468
Precision Score is :  0.8380347907851434
AUC Value  :  0.8383050731703616

Classification Report is :                precision    recall  f1-score
support

           0       0.85      0.88      0.87      5870
           1       0.84      0.79      0.82      4490

    accuracy                           0.84     10360
   macro avg       0.84      0.84      0.84     10360
weighted avg       0.84      0.84      0.84     10360


Confusion Matrix is :
 [[5181  689]
 [ 925 3565]]


 Apply Model With Normal Data With PCA and Normalize :

Model Train Score is :  0.5719587275028423
Model Test Score is :  0.5803088803088803
F1 Score is :  0.6423753906892582
```

```
Recall Score is :  0.8697104677060133
Precision Score is :  0.5092592592592593
AUC Value  :  0.6143271248240458

Classification Report is :                precision    recall  f1-score
support

           0       0.78      0.36      0.49      5870
           1       0.51      0.87      0.64      4490

    accuracy                           0.58     10360
   macro avg       0.65      0.61      0.57     10360
weighted avg       0.66      0.58      0.56     10360


Confusion Matrix is :
 [[2107 3763]
 [ 585 3905]]


 Apply Model With Normal Data With Feature Selection and Poly and Scaling :

Model Train Score is :  0.8347491258553746
Model Test Score is :  0.8376447876447877
F1 Score is :  0.8220482437579347
Recall Score is :  0.8652561247216035
Precision Score is :  0.782950423216445
AUC Value  :  0.8408904132977693

Classification Report is :                precision    recall  f1-score
support

           0       0.89      0.82      0.85      5870
           1       0.78      0.87      0.82      4490

    accuracy                           0.84     10360
   macro avg       0.84      0.84      0.84     10360
weighted avg       0.84      0.84      0.84     10360


Confusion Matrix is :
 [[4793 1077]
 [ 605 3885]]
```

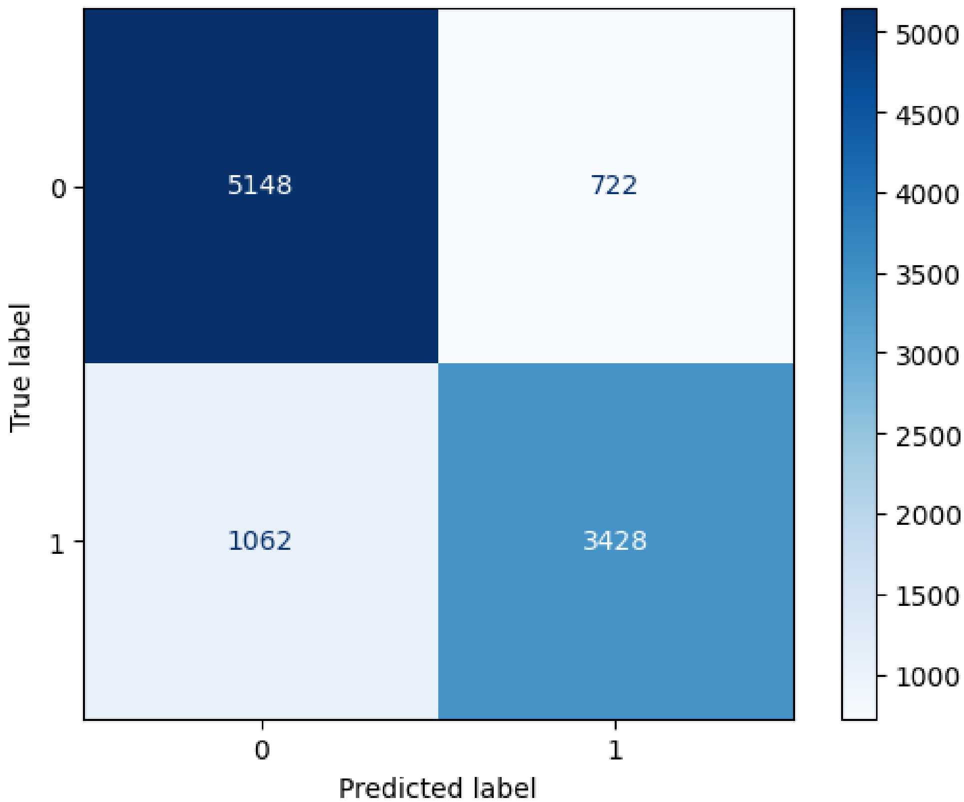

5301
569
781
3709
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000

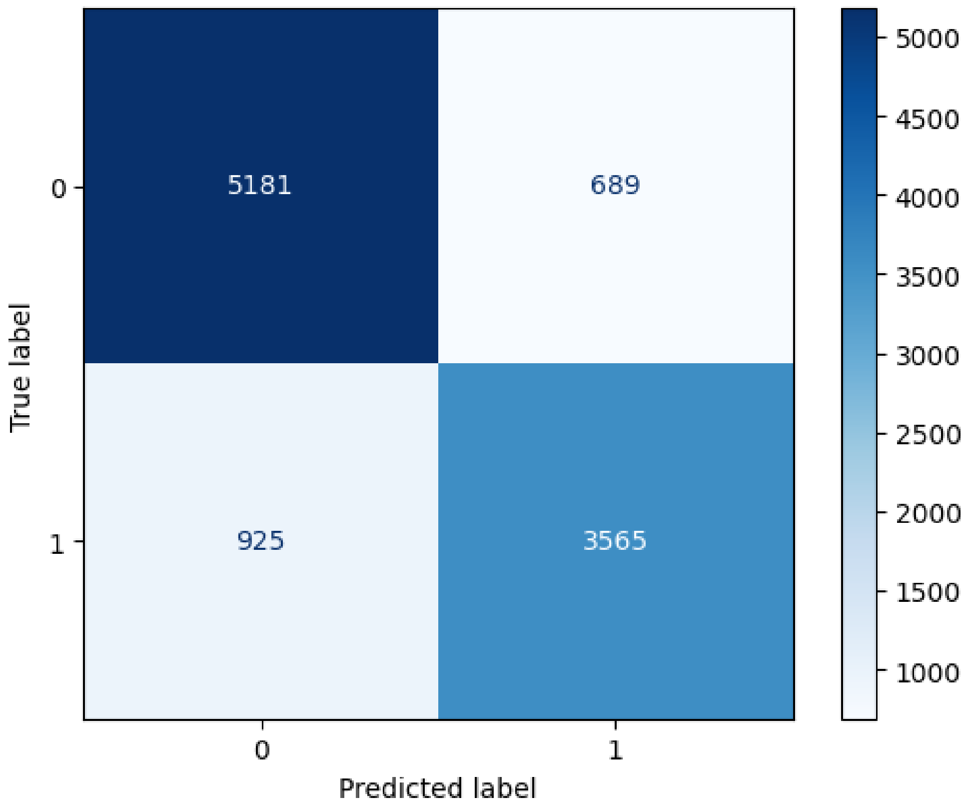

4954
916
695
3795
0
1
True label
0
1
Predicted label
4500
4000
3500
3000
2500
2000
1500
1000

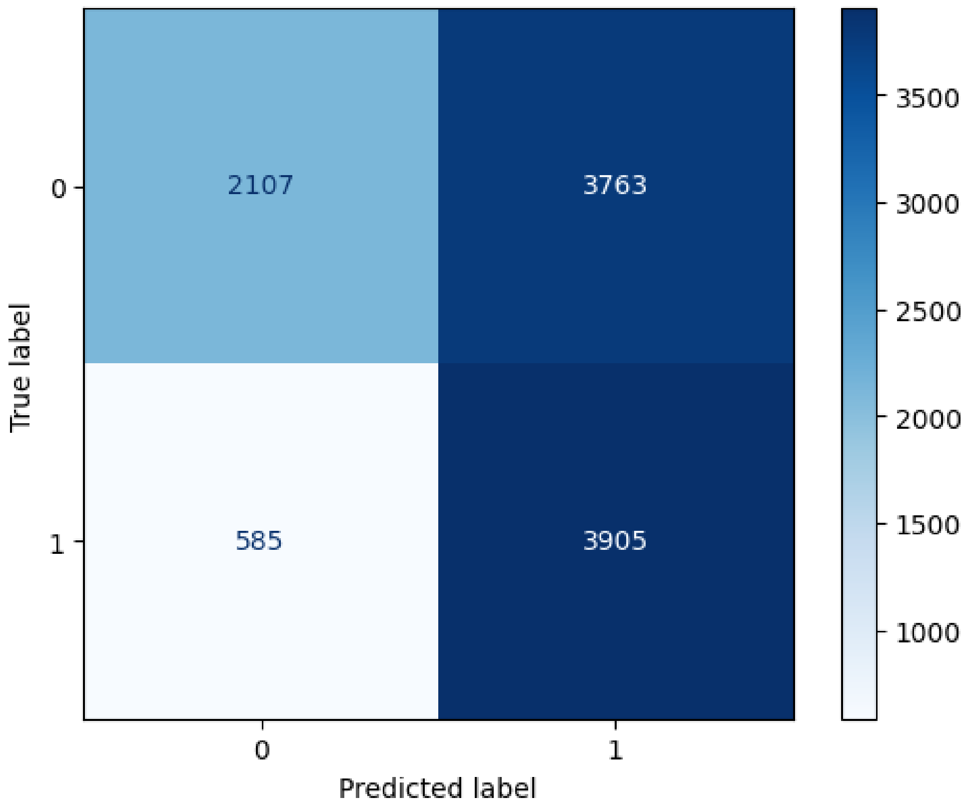

5303
567
783
3707
True label
Predicted label
0
1
0
1
5000
4000
3000
2000
1000



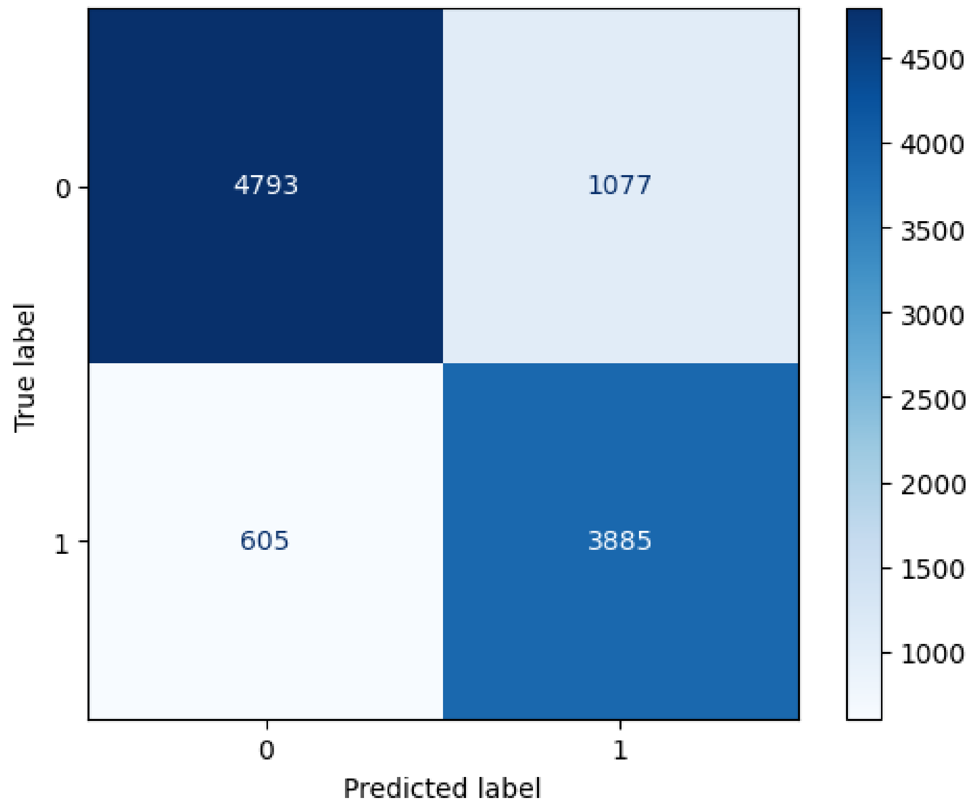
2503
3367
617
3873
0
1
True label
0
1
Predicted label
3500
3000
2500
2000
1500
1000


5148
722
1062
3428
0
1
True label
0
1
Predicted label
5000
4500
4000
3500
3000
2500
2000
1500
1000


5181
689
925
3565
0
1
True label
0
1
Predicted label
5000
4500
4000
3500
3000
2500
2000
1500
1000



2107
3763
585
3905
0
1
True label
0
1
Predicted label
3500
3000
2500
2000
1500
1000



[304]:
```
df = pd.DataFrame(Values,columns=['Train Accuracy','Test Accuracy','Test␣
↪F1','Test Recall','Test Precision','AUC'])
df['Models'] = ['NB','NB With Feature','NB Scaling','KNN With Normalize','NB␣
↪With PCA','NB With PCA and Scaling',
                'NB With PCA and Normalize','NB With Feature and Poly and␣
↪Scaling']
df.set_index('Models', inplace=True)
df
```

[304]:
```
                                     Train Accuracy  Test Accuracy   Test F1  \
Models
NB                                         0.867173       0.869691  0.846031
NB With Feature                            0.840841       0.844498  0.824910
NB Scaling                                 0.867345       0.869691  0.845961
KNN With Normalize                         0.609391       0.615444  0.660358
NB With PCA                                0.827767       0.827799  0.793519
NB With PCA and Scaling                    0.844488       0.844208  0.815416
NB With PCA and Normalize                  0.571959       0.580309  0.642375
NB With Feature and Poly and Scaling       0.834749       0.837645  0.822048

                                     Test Recall  Test Precision       AUC
```

```
Models
NB                                     0.826058        0.866994  0.864562
NB With Feature                        0.845212        0.805561  0.844582
NB Scaling                             0.825612        0.867337  0.864510
KNN With Normalize                     0.862584        0.534945  0.644494
NB With PCA                            0.763474        0.826024  0.820238
NB With PCA and Scaling                0.793987        0.838035  0.838305
NB With PCA and Normalize              0.869710        0.509259  0.614327
NB With Feature and Poly and Scaling   0.865256        0.782950  0.840890
```

[305]:
```
models_draw(df)
```

GradientBoostingClassifier

[306]:
```
Search(GradientBoostingClassifier(max_depth=3),{'max_depth':
 ↪[5,10,15,20,25,30,35,40]},X_train,y_train)
```

[306]:
```
GradientBoostingClassifier(max_depth=10)
```

[307]:
```
cross_validation(GradientBoostingClassifier(max_depth=10),X_train,y_train)
```

```
Train Score Value :  [0.99501254 0.99568289 0.99671525 0.9953209  0.99514667]
Mean 0.995575649518891
Test Score Value :  [0.96213868 0.96187054 0.96256771 0.96224594 0.96428188]
Mean 0.9626209500925995
```

[308]:
```
Values =␣
 ↪Models(GradientBoostingClassifier(max_depth=10),X_train,y_train,X_test,y_test)
```

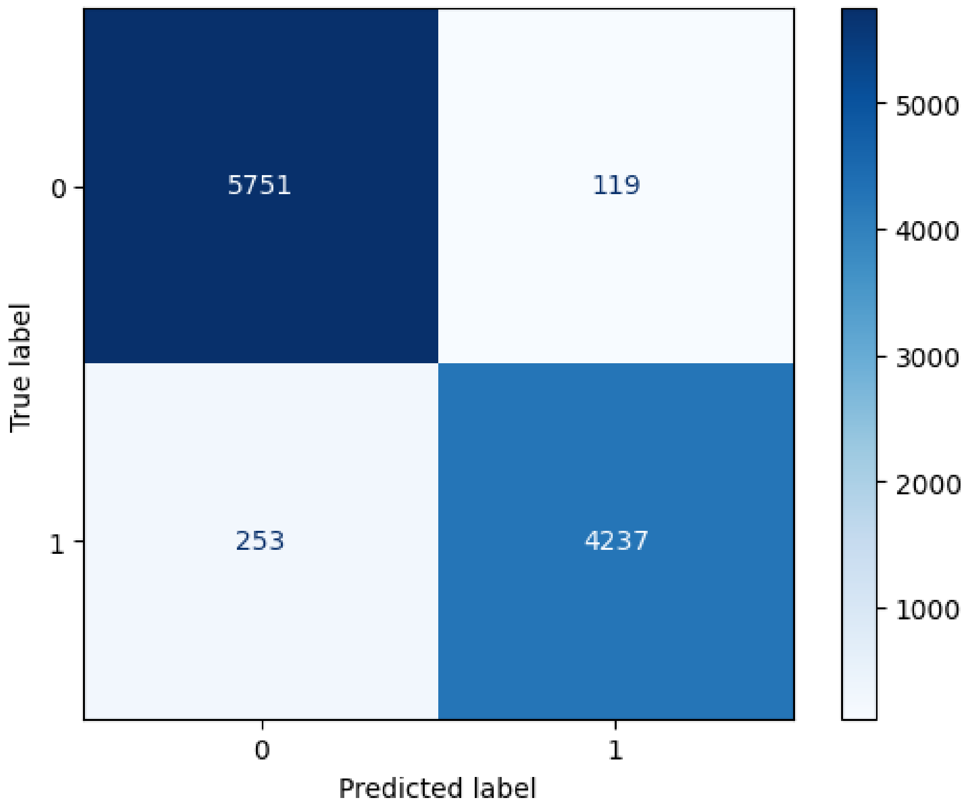
```
Apply Model With Normal Data :

Model Train Score is :  0.992931763090718
Model Test Score is :  0.9640926640926641
F1 Score is :  0.9579470947320823
Recall Score is :  0.9436525612472161
Precision Score is :  0.9726813590449954
AUC Value  :  0.9616899944225858


Classification Report is :                precision    recall  f1-score
support

           0       0.96      0.98      0.97      5870
           1       0.97      0.94      0.96      4490

    accuracy                           0.96     10360
   macro avg       0.97      0.96      0.96     10360
weighted avg       0.96      0.96      0.96     10360
```

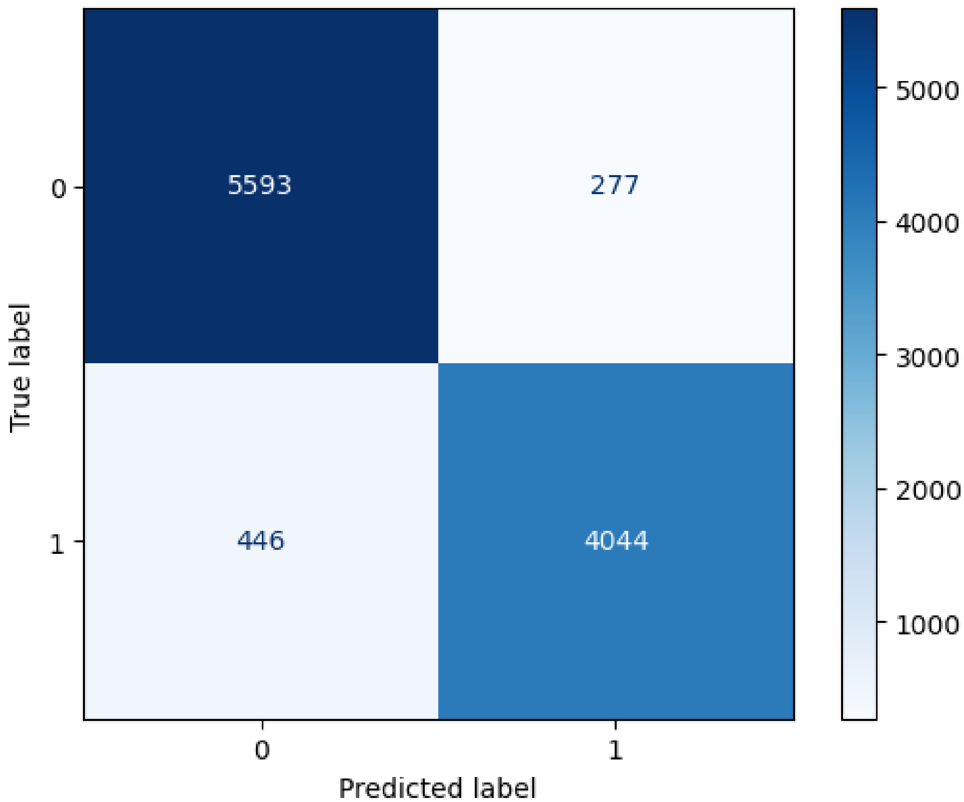
```
Confusion Matrix is :
 [[5751  119]
 [ 253 4237]]


 Apply Model With Feature Selection :

Model Train Score is :  0.9263787888538516
Model Test Score is :  0.9302123552123552
F1 Score is :  0.9179434797412325
Recall Score is :  0.9006681514476614
Precision Score is :  0.935894468872946
AUC Value  :  0.9267395271718716

Classification Report is :               precision    recall  f1-score
support

           0       0.93      0.95      0.94      5870
           1       0.94      0.90      0.92      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.93      0.93     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
 [[5593  277]
 [ 446 4044]]


 Apply Model With Normal Data With Scaling :

Model Train Score is :  0.9925349121565095
Model Test Score is :  0.9640926640926641
F1 Score is :  0.9579661016949153
Recall Score is :  0.944097995545657
Precision Score is :  0.9722477064220183
AUC Value  :  0.9617423538205285

Classification Report is :               precision    recall  f1-score
support

           0       0.96      0.98      0.97      5870
           1       0.97      0.94      0.96      4490

    accuracy                           0.96     10360
```

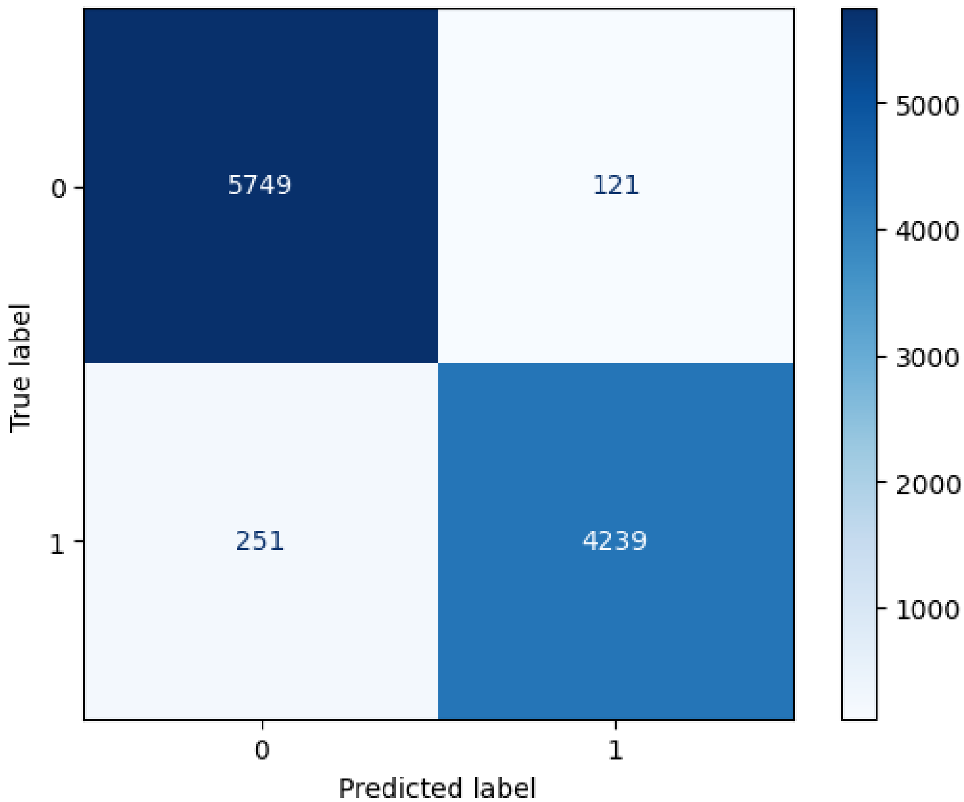
```
   macro avg       0.97      0.96      0.96     10360
weighted avg       0.96      0.96      0.96     10360


Confusion Matrix is :
 [[5749  121]
 [ 251 4239]]


 Apply Model With Normal Data With Normalize :

Model Train Score is :  0.9876118154321385
Model Test Score is :  0.9475868725868726
F1 Score is :  0.9391187352842246
Recall Score is :  0.9327394209354121
Precision Score is :  0.945585911040867
AUC Value  :  0.9458416014387453

Classification Report is :                precision    recall  f1-score
support

           0       0.95      0.96      0.95      5870
           1       0.95      0.93      0.94      4490

    accuracy                           0.95     10360
   macro avg       0.95      0.95      0.95     10360
weighted avg       0.95      0.95      0.95     10360


Confusion Matrix is :
 [[5629  241]
 [ 302 4188]]


 Apply Model With Normal Data With PCA :

Model Train Score is :  0.994862389257138
Model Test Score is :  0.9488416988416989
F1 Score is :  0.9396355353075171
Recall Score is :  0.9187082405345212
Precision Score is :  0.9615384615384616
AUC Value  :  0.9452996057868518

Classification Report is :                precision    recall  f1-score
support

           0       0.94      0.97      0.96      5870
```

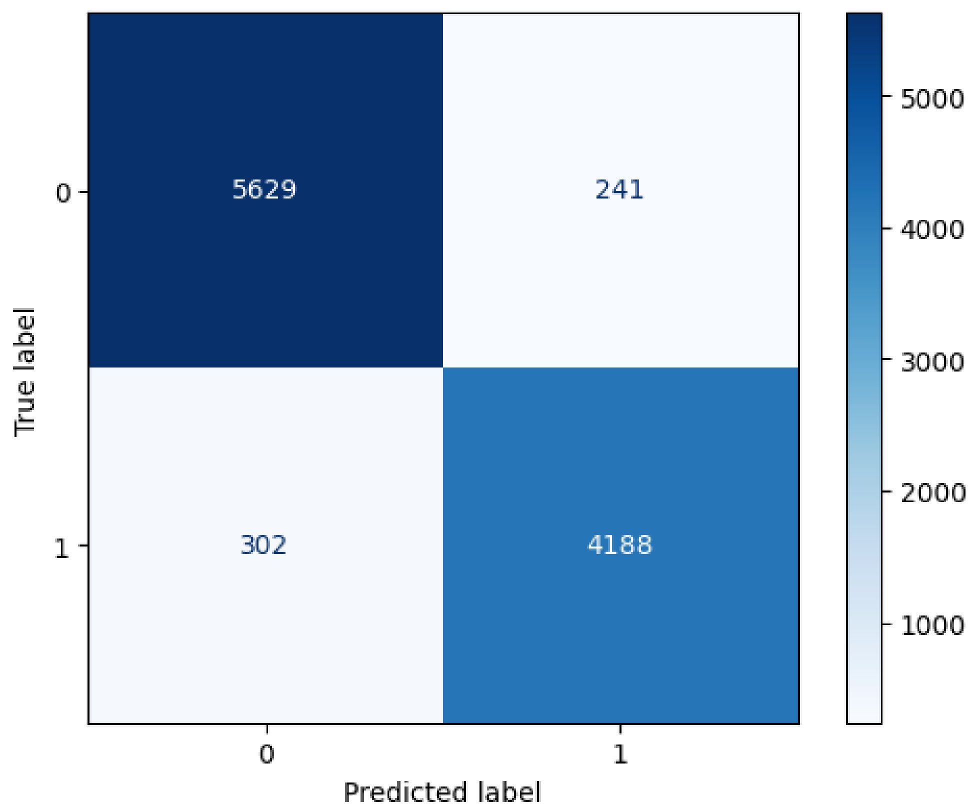
```
           1       0.96      0.92      0.94      4490

    accuracy                           0.95     10360
   macro avg       0.95      0.95      0.95     10360
weighted avg       0.95      0.95      0.95     10360


Confusion Matrix is :
 [[5705  165]
 [ 365 4125]]


 Apply Model With Normal Data With PCA and Scaling :

Model Train Score is :  0.9925992663620568
Model Test Score is :  0.946911196911197
F1 Score is :  0.9375851112119837
Recall Score is :  0.9200445434298441
Precision Score is :  0.9558074965293846
AUC Value  :  0.9437531064679033

Classification Report is :                precision    recall  f1-score
support

           0       0.94      0.97      0.95      5870
           1       0.96      0.92      0.94      4490

    accuracy                           0.95     10360
   macro avg       0.95      0.94      0.95     10360
weighted avg       0.95      0.95      0.95     10360


Confusion Matrix is :
 [[5679  191]
 [ 359 4131]]


 Apply Model With Normal Data With PCA and Normalize :

Model Train Score is :  0.9940043331831735
Model Test Score is :  0.9226833976833977
F1 Score is :  0.9086971389490482
Recall Score is :  0.8877505567928731
Precision Score is :  0.9306560821853841
AUC Value  :  0.9185771523317006

Classification Report is :                precision    recall  f1-score
```

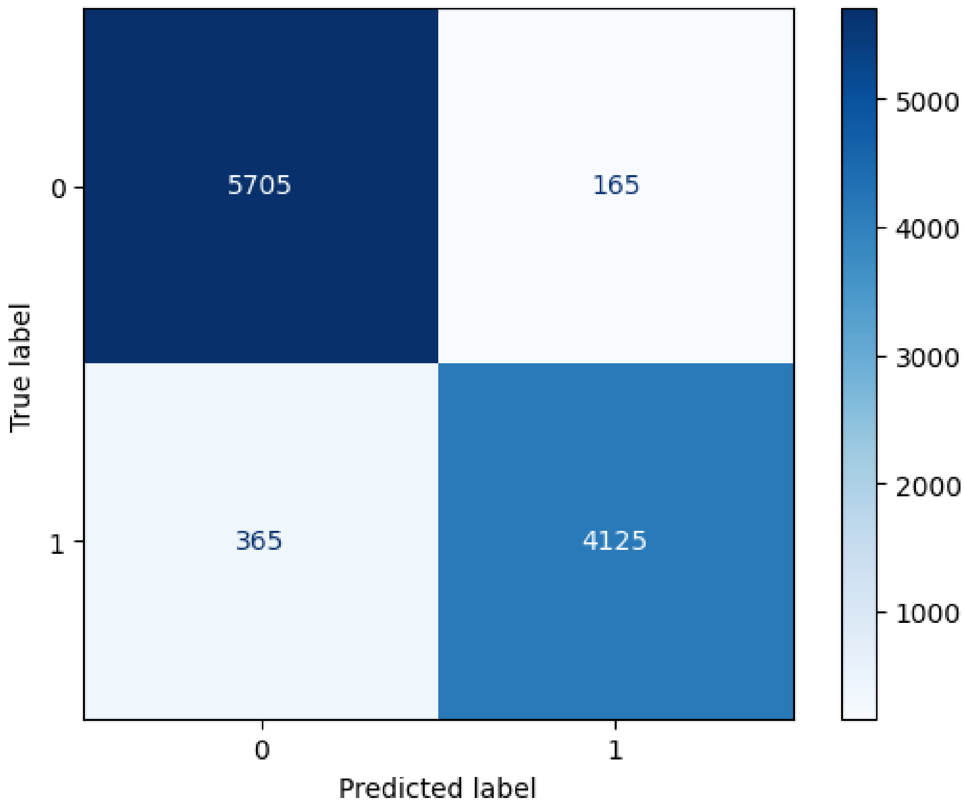
```
support

           0       0.92      0.95      0.93      5870
           1       0.93      0.89      0.91      4490

    accuracy                           0.92     10360
   macro avg       0.92      0.92      0.92     10360
weighted avg       0.92      0.92      0.92     10360


Confusion Matrix is :
 [[5573  297]
 [ 504 3986]]


 Apply Model With Normal Data With Feature Selection and Poly and Scaling :

Model Train Score is :  0.9263787888538516
Model Test Score is :  0.9298262548262548
F1 Score is :  0.9175456504479982
Recall Score is :  0.9008908685968819
Precision Score is :  0.934827825283106
AUC Value  :  0.9264249913682877

Classification Report is :                precision    recall  f1-score
support

           0       0.93      0.95      0.94      5870
           1       0.93      0.90      0.92      4490

    accuracy                           0.93     10360
   macro avg       0.93      0.93      0.93     10360
weighted avg       0.93      0.93      0.93     10360


Confusion Matrix is :
 [[5588  282]
 [ 445 4045]]
```

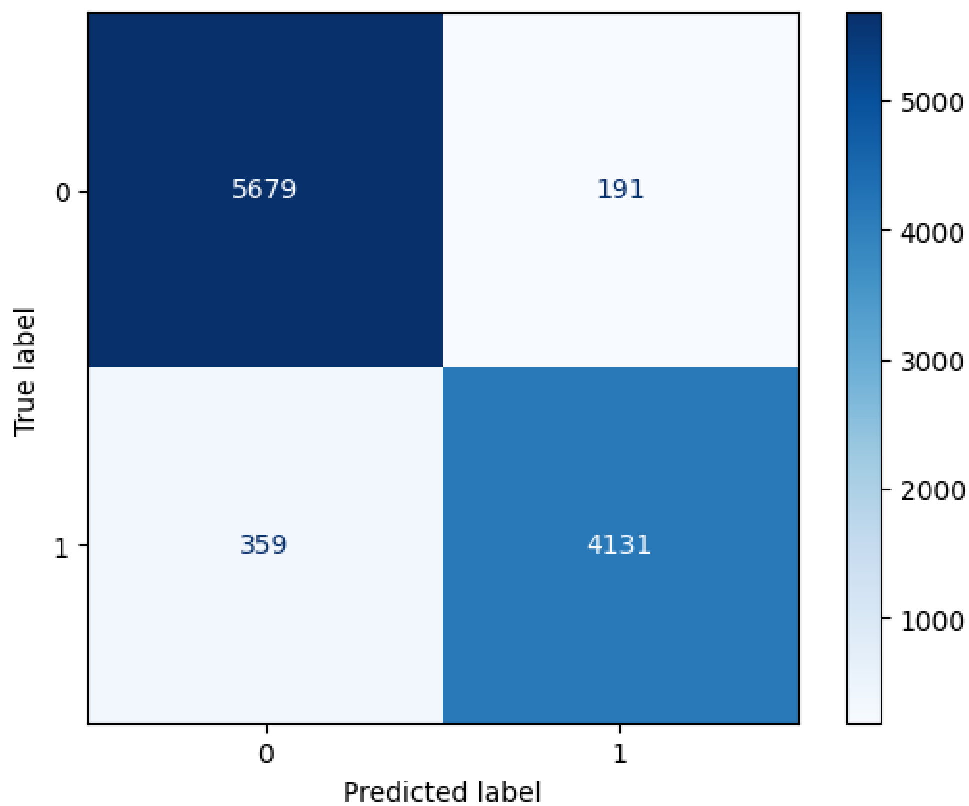

5751
119
253
4237
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000

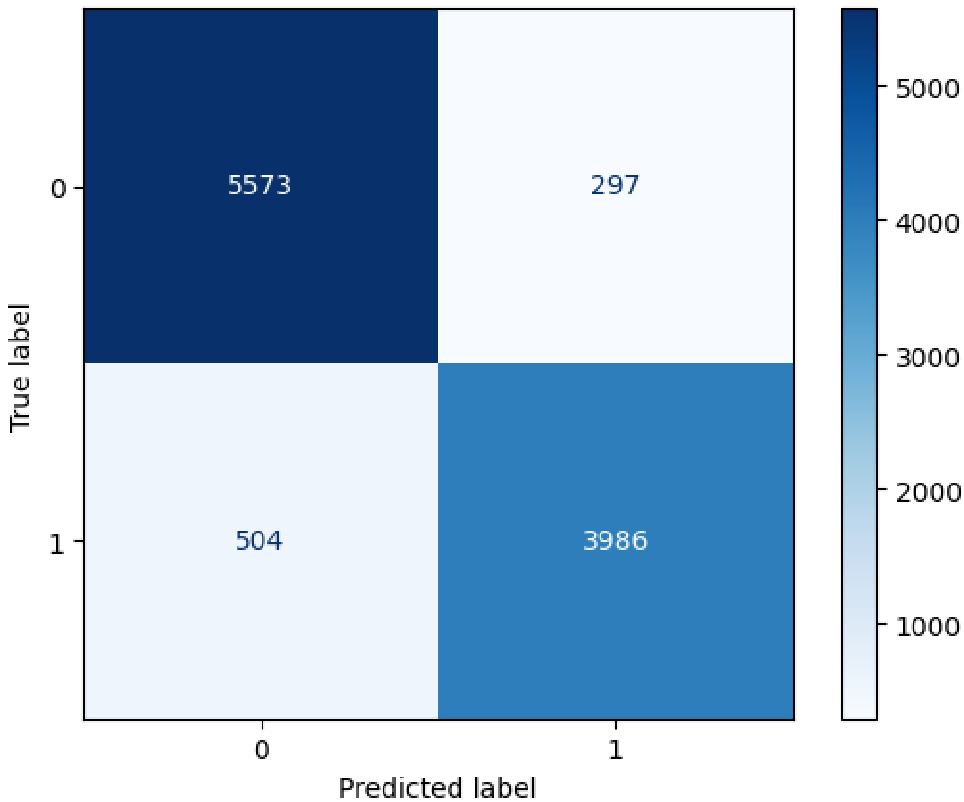

5593
277
446
4044
0
1
0
1
True label
Predicted label
5000
4000
3000
2000
1000

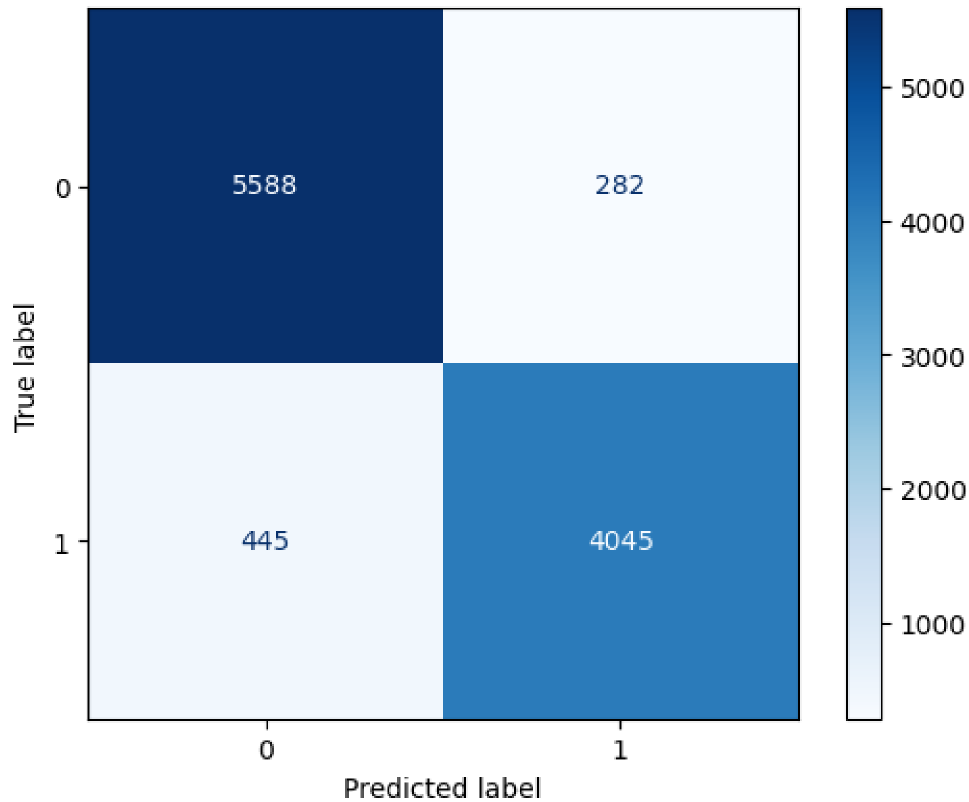

5749
121
251
4239
0
1
True label
Predicted label
5000
4000
3000
2000
1000


5629
241
302
4188
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5705
165
365
4125
0
1
True label
Predicted label
5000
4000
3000
2000
1000


5679
191
359
4131
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000


5573
297
504
3986
0
1
True label
0
1
Predicted label
5000
4000
3000
2000
1000



[309]:
```
df = pd.DataFrame(Values,columns=['Train Accuracy','Test Accuracy','Test␣
↪F1','Test Recall','Test Precision','AUC'])
df['Models'] = ['Gradient','Gradient With Feature','Gradient Scaling','Gradient␣
↪With Normalize','Gradient With PCA','Gradient With PCA and Scaling',
                'Gradient With PCA and Normalize','Gradient With Feature and␣
↪Poly and Scaling']
df.set_index('Models', inplace=True)
df
```

[309]:
```
                                    Train Accuracy  Test Accuracy  \
Models
Gradient                                  0.992932       0.964093
Gradient With Feature                     0.926379       0.930212
Gradient Scaling                          0.992535       0.964093
Gradient With Normalize                   0.987612       0.947587
Gradient With PCA                         0.994862       0.948842
Gradient With PCA and Scaling             0.992599       0.946911
Gradient With PCA and Normalize           0.994004       0.922683
Gradient With Feature and Poly and Scaling 0.926379      0.929826

                                     Test F1  Test Recall  \
```

```
Models
Gradient                                         0.957947     0.943653
Gradient With Feature                            0.917943     0.900668
Gradient Scaling                                 0.957966     0.944098
Gradient With Normalize                          0.939119     0.932739
Gradient With PCA                                0.939636     0.918708
Gradient With PCA and Scaling                    0.937585     0.920045
Gradient With PCA and Normalize                  0.908697     0.887751
Gradient With Feature and Poly and Scaling       0.917546     0.900891

                                                 Test Precision       AUC
Models
Gradient                                               0.972681  0.961690
Gradient With Feature                                  0.935894  0.926740
Gradient Scaling                                       0.972248  0.961742
Gradient With Normalize                                0.945586  0.945842
Gradient With PCA                                      0.961538  0.945300
Gradient With PCA and Scaling                          0.955807  0.943753
Gradient With PCA and Normalize                        0.930656  0.918577
Gradient With Feature and Poly and Scaling             0.934828  0.926425
```

[310]:
```
models_draw(df)
```

** #

DL Models

Tabel of Contents

[311]:
```
X_train_c,y_train_c,X_test_c,y_test_c=Split(X_classification,y_classification)
```

```
X_train shape is  (93234, 22)
X_test shape is  (10360, 22)
y_train shape is  (93234,)
y_test shape is  (10360,)
```

[312]:
```
classification_Input = keras.Input(shape=(X_classification.shape[1],))

dense_layer1 = keras.layers.Dense(128, activation='relu',␣
 ↪name='Dense_Layer1')(classification_Input)
batch = keras.layers.BatchNormalization()(dense_layer1)
drop = keras.layers.Dropout(.2)(batch)
dense_layer2 = keras.layers.Dense(256, activation='relu',␣
 ↪name='Dense_Layer2')(drop)
batch = keras.layers.BatchNormalization()(dense_layer2)
layer_C = keras.layers.Dense(1, activation='sigmoid',␣
 ↪name='Dense_Layer3')(batch)

model = keras.Model(inputs=[classification_Input], outputs=[layer_C])
```

[313]:
```
model.summary()
```

```
Model: "functional_1"
```

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 22)	0
Dense_Layer1 (Dense)	(None, 128)	2,944
batch_normalization (BatchNormalization)	(None, 128)	512
dropout (Dropout)	(None, 128)	0
Dense_Layer2 (Dense)	(None, 256)	33,024
batch_normalization_1 (BatchNormalization)	(None, 256)	1,024
Dense_Layer3 (Dense)	(None, 1)	257

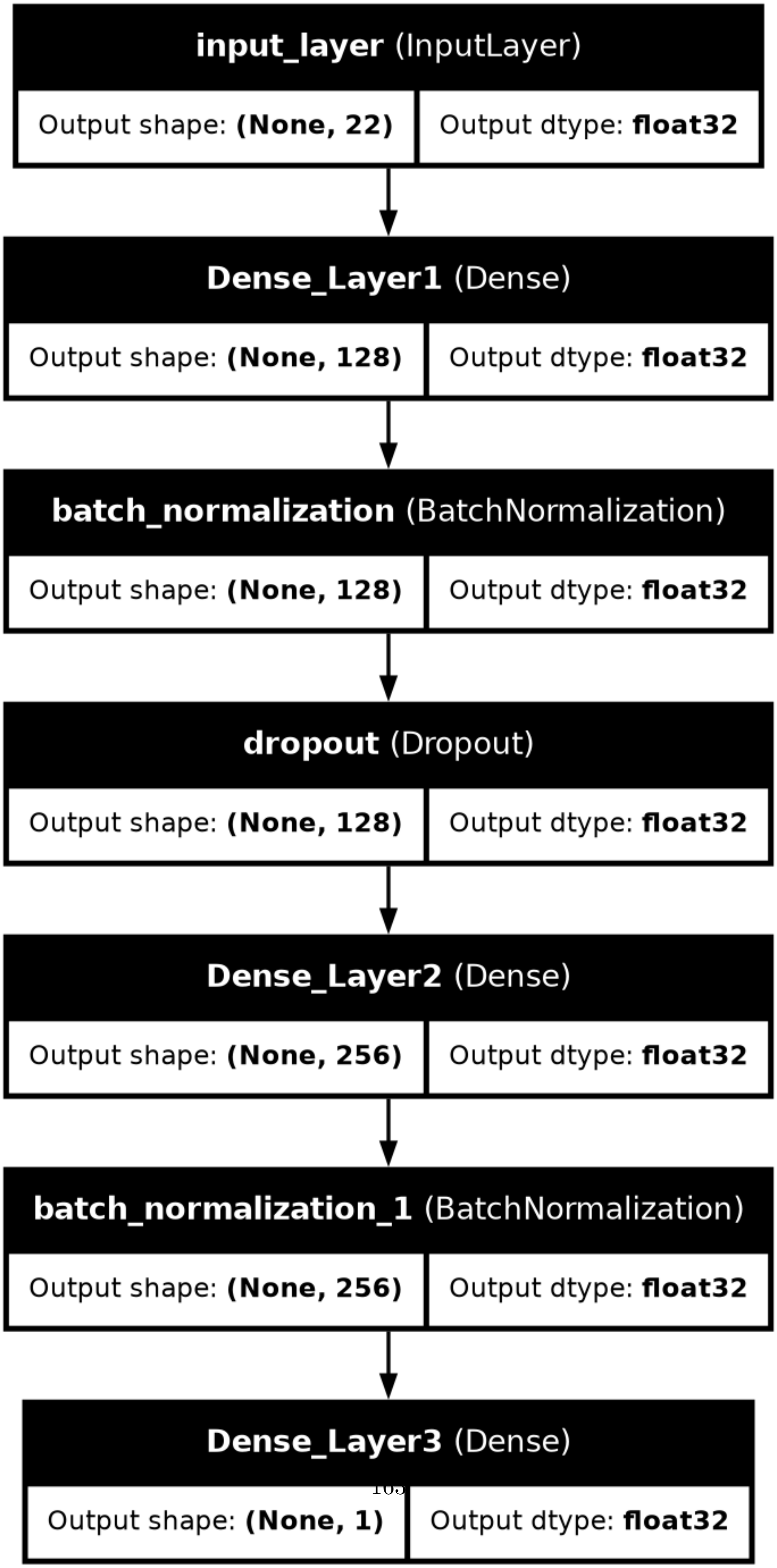
Total params: 37,761 (147.50 KB)

Trainable params: 36,993 (144.50 KB)

Non-trainable params: 768 (3.00 KB)

[314]:
```
keras.utils.plot_model(model, to_file='model.png', show_shapes=True,
    show_layer_names=True,show_dtype=True,dpi=120)
```

[314]:


input_layer (InputLayer)
Output shape: (None, 22)
Output dtype: float32
Dense_Layer1 (Dense)
Output shape: (None, 128)
Output dtype: float32
batch_normalization (BatchNormalization)
Output shape: (None, 128)
Output dtype: float32
dropout (Dropout)
Output shape: (None, 128)
Output dtype: float32
Dense_Layer2 (Dense)
Output shape: (None, 256)
Output dtype: float32
batch_normalization_1 (BatchNormalization)
Output shape: (None, 256)
Output dtype: float32
Dense_Layer3 (Dense)
Output shape: (None, 1)
Output dtype: float32

[315]:
```python
model.compile(optimizer='adam',
              loss={'Dense_Layer3': 'binary_crossentropy'},
              metrics={'Dense_Layer3': 'accuracy'})
checkpoint_cb = keras.callbacks.ModelCheckpoint("my_keras_model.keras",␣
 ↪save_best_only=True)
early_stopping_cb = keras.callbacks.EarlyStopping(patience=10,␣
 ↪restore_best_weights=True)
hist = model.fit(X_train_c,y_train_c,
          epochs=50,
          batch_size=32,validation_split=.1,
          callbacks=[checkpoint_cb, early_stopping_cb])
```

```
Epoch 1/50
2623/2623             10s 3ms/step -
accuracy: 0.7784 - loss: 0.4769 - val_accuracy: 0.8225 - val_loss: 0.4617
Epoch 2/50
2623/2623             10s 3ms/step -
accuracy: 0.8604 - loss: 0.3454 - val_accuracy: 0.8886 - val_loss: 0.2620
Epoch 3/50
2623/2623             8s 3ms/step -
accuracy: 0.8754 - loss: 0.2977 - val_accuracy: 0.8871 - val_loss: 0.2660
Epoch 4/50
2623/2623             8s 3ms/step -
accuracy: 0.8853 - loss: 0.2742 - val_accuracy: 0.8705 - val_loss: 0.3019
Epoch 5/50
2623/2623             10s 3ms/step -
accuracy: 0.8913 - loss: 0.2633 - val_accuracy: 0.9044 - val_loss: 0.2236
Epoch 6/50
2623/2623             7s 3ms/step -
accuracy: 0.8974 - loss: 0.2479 - val_accuracy: 0.9027 - val_loss: 0.2256
Epoch 7/50
2623/2623             8s 3ms/step -
accuracy: 0.8959 - loss: 0.2489 - val_accuracy: 0.9026 - val_loss: 0.2315
Epoch 8/50
2623/2623             8s 3ms/step -
accuracy: 0.9014 - loss: 0.2366 - val_accuracy: 0.9142 - val_loss: 0.2015
Epoch 9/50
2623/2623             8s 3ms/step -
accuracy: 0.8989 - loss: 0.2443 - val_accuracy: 0.9162 - val_loss: 0.2028
Epoch 10/50
2623/2623             10s 3ms/step -
accuracy: 0.9013 - loss: 0.2350 - val_accuracy: 0.9115 - val_loss: 0.2162
Epoch 11/50
2623/2623             7s 3ms/step -
accuracy: 0.9056 - loss: 0.2285 - val_accuracy: 0.9139 - val_loss: 0.2091
```

```
Epoch 12/50
2623/2623            7s 3ms/step -
accuracy: 0.9032 - loss: 0.2301 - val_accuracy: 0.9114 - val_loss: 0.2109
Epoch 13/50
2623/2623            7s 3ms/step -
accuracy: 0.9049 - loss: 0.2305 - val_accuracy: 0.8967 - val_loss: 0.2594
Epoch 14/50
2623/2623            7s 3ms/step -
accuracy: 0.9074 - loss: 0.2227 - val_accuracy: 0.9014 - val_loss: 0.2385
Epoch 15/50
2623/2623            7s 3ms/step -
accuracy: 0.9087 - loss: 0.2208 - val_accuracy: 0.9206 - val_loss: 0.1904
Epoch 16/50
2623/2623            11s 3ms/step -
accuracy: 0.9093 - loss: 0.2173 - val_accuracy: 0.8944 - val_loss: 0.2419
Epoch 17/50
2623/2623            9s 3ms/step -
accuracy: 0.9091 - loss: 0.2189 - val_accuracy: 0.9002 - val_loss: 0.2436
Epoch 18/50
2623/2623            8s 3ms/step -
accuracy: 0.9077 - loss: 0.2224 - val_accuracy: 0.9157 - val_loss: 0.2056
Epoch 19/50
2623/2623            10s 3ms/step -
accuracy: 0.9092 - loss: 0.2202 - val_accuracy: 0.9256 - val_loss: 0.1890
Epoch 20/50
2623/2623            8s 3ms/step -
accuracy: 0.9094 - loss: 0.2194 - val_accuracy: 0.8935 - val_loss: 0.2539
Epoch 21/50
2623/2623            7s 3ms/step -
accuracy: 0.9122 - loss: 0.2136 - val_accuracy: 0.9261 - val_loss: 0.1853
Epoch 22/50
2623/2623            7s 3ms/step -
accuracy: 0.9135 - loss: 0.2115 - val_accuracy: 0.9183 - val_loss: 0.1879
Epoch 23/50
2623/2623            7s 3ms/step -
accuracy: 0.9121 - loss: 0.2125 - val_accuracy: 0.9022 - val_loss: 0.2228
Epoch 24/50
2623/2623            11s 3ms/step -
accuracy: 0.9118 - loss: 0.2129 - val_accuracy: 0.8959 - val_loss: 0.2805
Epoch 25/50
2623/2623            7s 3ms/step -
accuracy: 0.9118 - loss: 0.2141 - val_accuracy: 0.9019 - val_loss: 0.2341
Epoch 26/50
2623/2623            8s 3ms/step -
accuracy: 0.9138 - loss: 0.2082 - val_accuracy: 0.9281 - val_loss: 0.1763
Epoch 27/50
2623/2623            10s 3ms/step -
accuracy: 0.9128 - loss: 0.2071 - val_accuracy: 0.9172 - val_loss: 0.1940
```

```
Epoch 28/50
2623/2623          7s 3ms/step -
accuracy: 0.9155 - loss: 0.2046 - val_accuracy: 0.9280 - val_loss: 0.1954
Epoch 29/50
2623/2623          7s 3ms/step -
accuracy: 0.9169 - loss: 0.2036 - val_accuracy: 0.9168 - val_loss: 0.1904
Epoch 30/50
2623/2623          10s 3ms/step -
accuracy: 0.9186 - loss: 0.1997 - val_accuracy: 0.9159 - val_loss: 0.2117
Epoch 31/50
2623/2623          10s 3ms/step -
accuracy: 0.9174 - loss: 0.2016 - val_accuracy: 0.9172 - val_loss: 0.1979
Epoch 32/50
2623/2623          7s 3ms/step -
accuracy: 0.9154 - loss: 0.2043 - val_accuracy: 0.9037 - val_loss: 0.2355
Epoch 33/50
2623/2623          8s 3ms/step -
accuracy: 0.9134 - loss: 0.2098 - val_accuracy: 0.9166 - val_loss: 0.1971
Epoch 34/50
2623/2623          8s 3ms/step -
accuracy: 0.9188 - loss: 0.2025 - val_accuracy: 0.9340 - val_loss: 0.1625
Epoch 35/50
2623/2623          10s 3ms/step -
accuracy: 0.9178 - loss: 0.1989 - val_accuracy: 0.9317 - val_loss: 0.1685
Epoch 36/50
2623/2623          7s 3ms/step -
accuracy: 0.9198 - loss: 0.1940 - val_accuracy: 0.9299 - val_loss: 0.1723
Epoch 37/50
2623/2623          7s 3ms/step -
accuracy: 0.9199 - loss: 0.1959 - val_accuracy: 0.9258 - val_loss: 0.1775
Epoch 38/50
2623/2623          7s 3ms/step -
accuracy: 0.9167 - loss: 0.1996 - val_accuracy: 0.8923 - val_loss: 0.2516
Epoch 39/50
2623/2623          7s 3ms/step -
accuracy: 0.9180 - loss: 0.2008 - val_accuracy: 0.9089 - val_loss: 0.2061
Epoch 40/50
2623/2623          7s 3ms/step -
accuracy: 0.9200 - loss: 0.1954 - val_accuracy: 0.9325 - val_loss: 0.1697
Epoch 41/50
2623/2623          11s 3ms/step -
accuracy: 0.9197 - loss: 0.1958 - val_accuracy: 0.9290 - val_loss: 0.1761
Epoch 42/50
2623/2623          10s 3ms/step -
accuracy: 0.9204 - loss: 0.1932 - val_accuracy: 0.9323 - val_loss: 0.1609
Epoch 43/50
2623/2623          7s 3ms/step -
accuracy: 0.9201 - loss: 0.1921 - val_accuracy: 0.9175 - val_loss: 0.1959
```

```
Epoch 44/50
2623/2623              7s 3ms/step -
accuracy: 0.9207 - loss: 0.1935 - val_accuracy: 0.9270 - val_loss: 0.1771
Epoch 45/50
2623/2623              7s 3ms/step -
accuracy: 0.9205 - loss: 0.1914 - val_accuracy: 0.9343 - val_loss: 0.1639
Epoch 46/50
2623/2623              10s 3ms/step -
accuracy: 0.9187 - loss: 0.1956 - val_accuracy: 0.9347 - val_loss: 0.1674
Epoch 47/50
2623/2623              7s 3ms/step -
accuracy: 0.9212 - loss: 0.1906 - val_accuracy: 0.9101 - val_loss: 0.1937
Epoch 48/50
2623/2623              8s 3ms/step -
accuracy: 0.9219 - loss: 0.1866 - val_accuracy: 0.9313 - val_loss: 0.1763
Epoch 49/50
2623/2623              10s 3ms/step -
accuracy: 0.9198 - loss: 0.1938 - val_accuracy: 0.9201 - val_loss: 0.1928
Epoch 50/50
2623/2623              7s 3ms/step -
accuracy: 0.9230 - loss: 0.1897 - val_accuracy: 0.9142 - val_loss: 0.1980
```

[316]:
```
model.evaluate(X_test_c,y_test_c)
```

```
324/324              0s 1ms/step -
accuracy: 0.9365 - loss: 0.1533
```

[316]: [0.15476644039154053, 0.9371621608734131]

[317]:
```
hist_=pd.DataFrame(hist.history)
hist_
```

[317]:

	accuracy	loss	val_accuracy	val_loss
0	0.822965	0.411136	0.822501	0.461745
1	0.863604	0.332448	0.888567	0.262040
2	0.877655	0.293214	0.887066	0.265979
3	0.886390	0.270610	0.870549	0.301910
4	0.893052	0.257998	0.904440	0.223648
5	0.897271	0.248568	0.902724	0.225622
6	0.897271	0.246954	0.902617	0.231477
7	0.901359	0.237320	0.914200	0.201527
8	0.902908	0.235208	0.916238	0.202760
9	0.900608	0.236177	0.911519	0.216159
10	0.904326	0.230920	0.913878	0.209148
11	0.905375	0.228760	0.911411	0.210898
12	0.905613	0.228797	0.896718	0.259375
13	0.908092	0.221319	0.901437	0.238501
14	0.909582	0.218661	0.920635	0.190425

15	0.909403	0.217639	0.894359	0.241898
16	0.909665	0.218897	0.900150	0.243574
17	0.909498	0.218369	0.915701	0.205584
18	0.910821	0.215639	0.925568	0.189040
19	0.909272	0.219879	0.893501	0.253871
20	0.912502	0.214056	0.926105	0.185320
21	0.914087	0.209145	0.918275	0.187862
22	0.911655	0.212910	0.902188	0.222782
23	0.913920	0.209229	0.895860	0.280550
24	0.911167	0.214719	0.901866	0.234056
25	0.914623	0.207081	0.928142	0.176302
26	0.913884	0.205959	0.917203	0.193961
27	0.914968	0.204542	0.928035	0.195399
28	0.916696	0.203741	0.916774	0.190414
29	0.917030	0.203011	0.915916	0.211700
30	0.916434	0.202759	0.917203	0.197885
31	0.914766	0.206424	0.903689	0.235539
32	0.915767	0.203002	0.916559	0.197080
33	0.918770	0.199529	0.934041	0.162538
34	0.919151	0.196935	0.931682	0.168535
35	0.919104	0.195625	0.929858	0.172292
36	0.917912	0.199516	0.925783	0.177545
37	0.917709	0.197901	0.892321	0.251578
38	0.918210	0.200009	0.908945	0.206143
39	0.919843	0.196330	0.932540	0.169685
40	0.919509	0.196825	0.929000	0.176124
41	0.920367	0.193129	0.932325	0.160854
42	0.920081	0.192882	0.917525	0.195895
43	0.921463	0.192312	0.926963	0.177149
44	0.920403	0.191538	0.934256	0.163861
45	0.918615	0.196334	0.934685	0.167436
46	0.920307	0.192769	0.910124	0.193737
47	0.920939	0.189904	0.931253	0.176278
48	0.920224	0.191664	0.920099	0.192812
49	0.922727	0.187906	0.914200	0.197990

[318]:
```
def summary_plot():
    fig = make_subplots(rows=1, cols=2, subplot_titles=("Total␣
↪Loss","Classification Accuracy"))
    fig.add_trace(go.Scatter(x=hist_.index, y=hist_['loss'], mode='lines',␣
↪name='Train Loss', line=dict(color='blue')), row=1, col=1)
    fig.add_trace(go.Scatter(x=hist_.index, y=hist_['val_loss'], mode='lines',␣
↪name='Validation Loss', line=dict(color='blue')), row=1, col=1)
    fig.add_trace(go.Scatter(x=hist_.index, y=hist_['accuracy'], mode='lines',␣
↪name='Train Accuracy', line=dict(color='red')), row=1, col=2)
```

```
    fig.add_trace(go.Scatter(x=hist_.index, y=hist_['val_accuracy'],␣
↪mode='lines', name='Validation Accuracy', line=dict(color='red')), row=1,␣
↪col=2)
    fig.update_layout(
        title_text="Training Summary",
        title_x=0.5,
        title_font=dict(size=20),
        font=dict(size=15),
        width=1100,
        height=600,
        template='plotly_dark'
    )
    fig.update_annotations(font=dict(size=20))
    fig.show()
```

[319]:
```
summary_plot()
```

[320]:
```
predictions = model.predict(X_test_c)
```

```
324/324                1s 2ms/step
```

[321]:
```
classification_predictions = np.where(predictions>=.5,1,0)
```

[322]:
```
def Check():
    train = accuracy_score(y_train_c,np.where(model.predict(X_train_c)>=.5,1,0))
    y_pred=classification_predictions
    test = accuracy_score(y_test_c,y_pred)
    print('Model Train Score is : ' , train)
    print('Model Test Score is : ' , test)
    F1Score = f1_score(y_test_c, y_pred)
    print('F1 Score is : ', F1Score)
    RecallScore = recall_score(y_test_c, y_pred)
    print('Recall Score is : ', RecallScore)
    PrecisionScore = precision_score(y_test_c, y_pred)
    print('Precision Score is : ', PrecisionScore)
    fprValue2, tprValue2, thresholdsValue2 = roc_curve(y_test_c,y_pred)
    AUCValue = auc(fprValue2, tprValue2)
    print('AUC Value  : ', AUCValue)
    Area(fprValue2,tprValue2,AUCValue)
    ClassificationReport = classification_report(y_test_c,y_pred)
    print('Classification Report is : ', ClassificationReport)
    CM = confusion_matrix(y_test_c, y_pred)
    print('Confusion Matrix is : \n', CM)
    disp = ConfusionMatrixDisplay(confusion_matrix=CM, display_labels=[0,1])
    disp.plot(cmap='Blues')
```

[323]:
```
Check()
```

```
2914/2914            4s 1ms/step
Model Train Score is :  0.9349057210888732
Model Test Score is :  0.9371621621621622
F1 Score is :  0.9236542746569718
Recall Score is :  0.8770601336302896
Precision Score is :  0.9754768392370572
AUC Value  :  0.9300973581268995

Classification Report is :                precision    recall  f1-score
support

           0       0.91      0.98      0.95      5870
           1       0.98      0.88      0.92      4490

    accuracy                           0.94     10360
   macro avg       0.94      0.93      0.94     10360
weighted avg       0.94      0.94      0.94     10360

Confusion Matrix is :
 [[5771   99]
 [ 552 3938]]
```