# Customer Satisfaction Prediction

## Objective:

The goal of this project is to predict customer satisfaction using historical data. This involves using machine learning algorithms to analyze factors that influence customer satisfaction and build a predictive model.

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## 1. Problem Statement

The task is to do EDA on dataset and build a model to predict customer satisfaction based on the features provided. The challenge is to create a model that can accurately predict the outcome.

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## 2. Data Pre-Processing

### 2.1 Data Inspection and Summary Statistics

- **Load the Dataset:** Import the dataset and review its basic structure, including column names, data types, and a few initial records.
- **Generate Summary Statistics:** Calculate key statistics (mean, median, min, max, standard deviation, etc.) to understand the primary characteristics of each column.
- Changing column names and data types

### 2.2 Data Cleaning and Feature Engineering

- **Missing Values:** Check and handle missing values if present.
- **Duplicate Values:** Check duplicate values and handle if present.

### 2.3 Outlier Treatment

- **Outlier Detection:** Identify outliers in features box plots or Z-scores and apply treatment if necessary.

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## 3. Exploratory Data Analysis (EDA)

### 3.1 Univariate Analysis

- **Numerical Data:** Visualize distributions with histograms and box plots.
- **Categorical Data:** Use bar charts to observe the distribution of the outcome variable.

### 3.2 Bivariate Analysis

- Create scatter plots to observe relationships between numerical features.

- Use box plots to explore how numerical features differ based on the outcome variable.

### 3.3 Multivariate Analysis

- Generate a heatmap of the correlation matrix to identify potential relationships.

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# 4. Model Building

### 4.1 Encoding Categorical Variables:

- Convert the Categorical columns to binary format

### 4.2 Feature Engineering

- This step involves transforming raw data into meaningful features and outcome

### 4.3 Model Training

- Split the dataset into training and testing sets.
- Scalling the data
- Use a Linear Regression to train the model on the training data.
- Model Evaluation
- Visualize the result

### 5. Advanced Modeling:

- Experiment with more complex models like RandomForest to improve predictions.

### Import Required Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

import warnings # ignore warnings

warnings.filterwarnings('ignore')
```

### Load the Dataset

```
```

```
data =
pd.read_csv('C://Users//PC//Downloads//customer_support_tickets.csv')

data.head() # First 5 records

   Ticket ID        Customer Name              Customer Email
Customer Age  \
0          1        Marisa Obrien  carrollallison@example.com
32
1          2         Jessica Rios    clarkeashley@example.com
42
2          3  Christopher Robbins   gonzalestracy@example.com
48
3          4     Christina Dillon    bradleyolson@example.org
27
4          5    Alexander Carroll     bradleymark@example.com
67

  Customer Gender Product Purchased Date of Purchase      Ticket Type
\
0           Other        GoPro Hero       2021-03-22  Technical issue

1          Female       LG Smart TV       2021-05-22  Technical issue

2           Other          Dell XPS       2020-07-14  Technical issue

3          Female  Microsoft Office       2020-11-13  Billing inquiry

4          Female  Autodesk AutoCAD       2020-02-04  Billing inquiry


             Ticket Subject  \
0             Product setup
1  Peripheral compatibility
2           Network problem
3            Account access
4                 Data loss

                                  Ticket Description  \
0  I'm having an issue with the {product_purchase...
1  I'm having an issue with the {product_purchase...
2  I'm facing a problem with my {product_purchase...
3  I'm having an issue with the {product_purchase...
4  I'm having an issue with the {product_purchase...

               Ticket Status
Resolution  \
0  Pending Customer Response
NaN
1  Pending Customer Response
NaN
```

```
2                     Closed   Case maybe show recently my computer
follow.
3                     Closed  Try capital clearly never color toward
story.
4                     Closed                    West decision evidence
bit.

  Ticket Priority Ticket Channel  First Response Time   Time to
Resolution  \
0        Critical   Social media  2023-06-01 12:15:36
NaN
1        Critical           Chat  2023-06-01 16:45:38
NaN
2             Low   Social media  2023-06-01 11:14:38  2023-06-01
18:05:38
3             Low   Social media  2023-06-01 07:29:40  2023-06-01
01:57:40
4             Low          Email  2023-06-01 00:12:42  2023-06-01
19:53:42

   Customer Satisfaction Rating
0                           NaN
1                           NaN
2                           3.0
3                           3.0
4                           1.0
```

```
data.tail() # Last 5 records
```

```
      Ticket ID     Customer Name        Customer Email  Customer Age
\
8464       8465        David Todd     adam28@example.net            22

8465       8466        Lori Davis  russell68@example.com            27

8466       8467   Michelle Kelley   ashley83@example.org            57

8467       8468  Steven Rodriguez    fpowell@example.org            54

8468       8469   Steven Davis MD     lori20@example.net            53


     Customer Gender       Product Purchased Date of Purchase  \
8464          Female                 LG OLED       2021-12-08
8465          Female  Bose SoundLink Speaker       2020-02-22
8466          Female     GoPro Action Camera       2021-08-17
8467            Male             PlayStation       2021-10-16
8468           Other       Philips Hue Lights      2020-06-01
```

```
          Ticket Type       Ticket Subject  \
8464  Product inquiry  Installation support
8465  Technical issue        Refund request
8466  Technical issue        Account access
8467  Product inquiry         Payment issue
8468  Billing inquiry        Hardware issue

                                    Ticket Description Ticket Status
\
8464  My {product_purchased} is making strange noise...          Open

8465  I'm having an issue with the {product_purchase...          Open

8466  I'm having an issue with the {product_purchase...        Closed

8467  I'm having an issue with the {product_purchase...        Closed

8468  There seems to be a hardware problem with my {...          Open


                                 Resolution Ticket Priority Ticket
Channel  \
8464                                    NaN             Low
Phone
8465                                    NaN        Critical
Email
8466  Eight account century nature kitchen.            High   Social
media
8467                  We seat culture plan.          Medium
Email
8468                                    NaN            High
Phone

      First Response Time   Time to Resolution  Customer Satisfaction
Rating
8464                  NaN                  NaN
NaN
8465                  NaN                  NaN
NaN
8466  2023-06-01 09:44:22  2023-06-01 04:31:22
3.0
8467  2023-06-01 18:28:24  2023-06-01 05:32:24
3.0
8468                  NaN                  NaN
NaN
```

## 2 Data Preprocessing

### 2.1 Data Inspection and Summary Statistics

```
data.shape # rews and col.
```

```
(8469, 17)
```

```
data.ndim # dimentionality of data
```

```
2
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8469 entries, 0 to 8468
Data columns (total 17 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Ticket ID                     8469 non-null   int64
 1   Customer Name                 8469 non-null   object
 2   Customer Email                8469 non-null   object
 3   Customer Age                  8469 non-null   int64
 4   Customer Gender               8469 non-null   object
 5   Product Purchased             8469 non-null   object
 6   Date of Purchase              8469 non-null   object
 7   Ticket Type                   8469 non-null   object
 8   Ticket Subject                8469 non-null   object
 9   Ticket Description            8469 non-null   object
 10  Ticket Status                 8469 non-null   object
 11  Resolution                    2769 non-null   object
 12  Ticket Priority               8469 non-null   object
 13  Ticket Channel                8469 non-null   object
 14  First Response Time           5650 non-null   object
 15  Time to Resolution            2769 non-null   object
 16  Customer Satisfaction Rating  2769 non-null   float64
dtypes: float64(1), int64(2), object(14)
memory usage: 1.1+ MB
```

```
data.describe() # Description of data
```

```
         Ticket ID  Customer Age  Customer Satisfaction Rating
count  8469.000000   8469.000000                   2769.000000
mean   4235.000000     44.026804                      2.991333
std    2444.934048     15.296112                      1.407016
```

```
min        1.000000     18.000000                              1.000000
25%     2118.000000     31.000000                              2.000000
50%     4235.000000     44.000000                              3.000000
75%     6352.000000     57.000000                              4.000000
max     8469.000000     70.000000                              5.000000
```

```
data.size # Total no. of elements
```

```
143973
```

## 2.2 Data Cleaning

Renaming columns

```
data.columns
```

```
Index(['Ticket ID', 'Customer Name', 'Customer Email', 'Customer Age',
       'Customer Gender', 'Product Purchased', 'Date of Purchase',
       'Ticket Type', 'Ticket Subject', 'Ticket Description', 'Ticket
Status',
       'Resolution', 'Ticket Priority', 'Ticket Channel',
       'First Response Time', 'Time to Resolution',
       'Customer Satisfaction Rating'],
      dtype='object')
```

```
data.columns = data.columns.str.replace(' ','_').str.lower()
```

```
data.columns
```

```
Index(['ticket_id', 'customer_name', 'customer_email', 'customer_age',
       'customer_gender', 'product_purchased', 'date_of_purchase',
       'ticket_type', 'ticket_subject', 'ticket_description',
'ticket_status',
       'resolution', 'ticket_priority', 'ticket_channel',
       'first_response_time', 'time_to_resolution',
       'customer_satisfaction_rating'],
      dtype='object')
```

Changing datatypes of col.

```
data['date_of_purchase'] = pd.to_datetime(data['date_of_purchase'])
data['first_response_time'] =
pd.to_datetime(data['first_response_time'])
data['time_to_resolution'] =
pd.to_datetime(data['time_to_resolution'])

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8469 entries, 0 to 8468
Data columns (total 17 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   ticket_id                     8469 non-null   int64
 1   customer_name                 8469 non-null   object
 2   customer_email                8469 non-null   object
 3   customer_age                  8469 non-null   int64
 4   customer_gender               8469 non-null   object
 5   product_purchased             8469 non-null   object
 6   date_of_purchase              8469 non-null   datetime64[ns]
 7   ticket_type                   8469 non-null   object
 8   ticket_subject                8469 non-null   object
 9   ticket_description            8469 non-null   object
 10  ticket_status                 8469 non-null   object
 11  resolution                    2769 non-null   object
 12  ticket_priority               8469 non-null   object
 13  ticket_channel                8469 non-null   object
 14  first_response_time           5650 non-null   datetime64[ns]
 15  time_to_resolution            2769 non-null   datetime64[ns]
 16  customer_satisfaction_rating  2769 non-null   float64
dtypes: datetime64[ns](3), float64(1), int64(2), object(11)
memory usage: 1.1+ MB
```

```
# Unique values of columns

print("# unique values in ticket_id:", data['ticket_id'].nunique())
print("# unique values in customer_name:",
data['customer_name'].nunique())
print("# unique values in customer_email:",
data['customer_email'].nunique())
print("# unique values in customer_age:",
data['customer_age'].nunique())
print("# unique values in customer_gender:",
data['customer_gender'].nunique())
print("# unique values in product_purchased:",
data['product_purchased'].nunique())
print("# unique values in date_of_purchase:",
```

```
data['date_of_purchase'].nunique())
print("# unique values in ticket_type:",
data['ticket_type'].nunique())
print("# unique values in ticket_subject:",
data['ticket_subject'].nunique())
print("# unique values in ticket_description:",
data['ticket_description'].nunique())
print("# unique values in resolution:", data['resolution'].nunique())
print("# unique values in ticket_priority:",
data['ticket_priority'].nunique())
print("# unique values in ticket_status:",
data['ticket_status'].nunique())
print("# unique values in ticket_channel:",
data['ticket_channel'].nunique())
print("# unique values in first_response_time:",
data['first_response_time'].nunique())
print("# unique values in time_to_resolution:",
data['time_to_resolution'].nunique())
print("# unique values in customer_satisfaction_rating:",
data['customer_satisfaction_rating'].nunique())
```

```
# unique values in ticket_id: 8469
# unique values in customer_name: 8028
# unique values in customer_email: 8320
# unique values in customer_age: 53
# unique values in customer_gender: 3
# unique values in product_purchased: 42
# unique values in date_of_purchase: 730
# unique values in ticket_type: 5
# unique values in ticket_subject: 16
# unique values in ticket_description: 8077
# unique values in resolution: 2769
# unique values in ticket_priority: 4
# unique values in ticket_status: 3
# unique values in ticket_channel: 4
# unique values in first_response_time: 5470
# unique values in time_to_resolution: 2728
# unique values in customer_satisfaction_rating: 5
```

Missing Values

```
data.isnull().sum()
```

```
ticket_id                              0
customer_name                          0
```

```
customer_email                    0
customer_age                      0
customer_gender                   0
product_purchased                 0
date_of_purchase                  0
ticket_type                       0
ticket_subject                    0
ticket_description                0
ticket_status                     0
resolution                     5700
ticket_priority                   0
ticket_channel                    0
first_response_time            2819
time_to_resolution             5700
customer_satisfaction_rating   5700
dtype: int64
```

```
# Handling null values by replacing as if we remove Nan rows, there
will be only rows with ticket status as Open.

data['resolution'] = data['resolution'].fillna('Not Provided')
data = data.fillna(0)
```

```
data.isnull().sum()
```

```
ticket_id                       0
customer_name                   0
customer_email                  0
customer_age                    0
customer_gender                 0
product_purchased               0
date_of_purchase                0
ticket_type                     0
ticket_subject                  0
ticket_description              0
ticket_status                   0
resolution                      0
ticket_priority                 0
ticket_channel                  0
first_response_time             0
time_to_resolution              0
customer_satisfaction_rating    0
dtype: int64
```

```
data.head()
```

```
   ticket_id        customer_name              customer_email
customer_age  \
0          1        Marisa Obrien  carrollallison@example.com
32
1          2          Jessica Rios    clarkeashley@example.com
42
2          3  Christopher Robbins   gonzalestracy@example.com
48
3          4     Christina Dillon    bradleyolson@example.org
27
4          5    Alexander Carroll     bradleymark@example.com
67

  customer_gender product_purchased date_of_purchase      ticket_type
\
0           Other        GoPro Hero       2021-03-22  Technical issue

1          Female       LG Smart TV       2021-05-22  Technical issue

2           Other          Dell XPS       2020-07-14  Technical issue

3          Female  Microsoft Office       2020-11-13  Billing inquiry

4          Female  Autodesk AutoCAD       2020-02-04  Billing inquiry


             ticket_subject  \
0             Product setup
1  Peripheral compatibility
2           Network problem
3            Account access
4                 Data loss

                                  ticket_description  \
0  I'm having an issue with the {product_purchase...
1  I'm having an issue with the {product_purchase...
2  I'm facing a problem with my {product_purchase...
3  I'm having an issue with the {product_purchase...
4  I'm having an issue with the {product_purchase...

               ticket_status
resolution  \
0  Pending Customer Response                                   Not
Provided
1  Pending Customer Response                                   Not
Provided
2                     Closed   Case maybe show recently my computer
follow.
3                     Closed  Try capital clearly never color toward
story.
4                     Closed                    West decision evidence
```

```
bit.

  ticket_priority ticket_channel  first_response_time
time_to_resolution  \
0        Critical   Social media  2023-06-01 12:15:36
0
1        Critical           Chat  2023-06-01 16:45:38
0
2             Low   Social media  2023-06-01 11:14:38  2023-06-01
18:05:38
3             Low   Social media  2023-06-01 07:29:40  2023-06-01
01:57:40
4             Low          Email  2023-06-01 00:12:42  2023-06-01
19:53:42

   customer_satisfaction_rating
0                           0.0
1                           0.0
2                           3.0
3                           3.0
4                           1.0
```

Duplicate Values

```
data.duplicated().sum()

0
```

There are no duplicate values

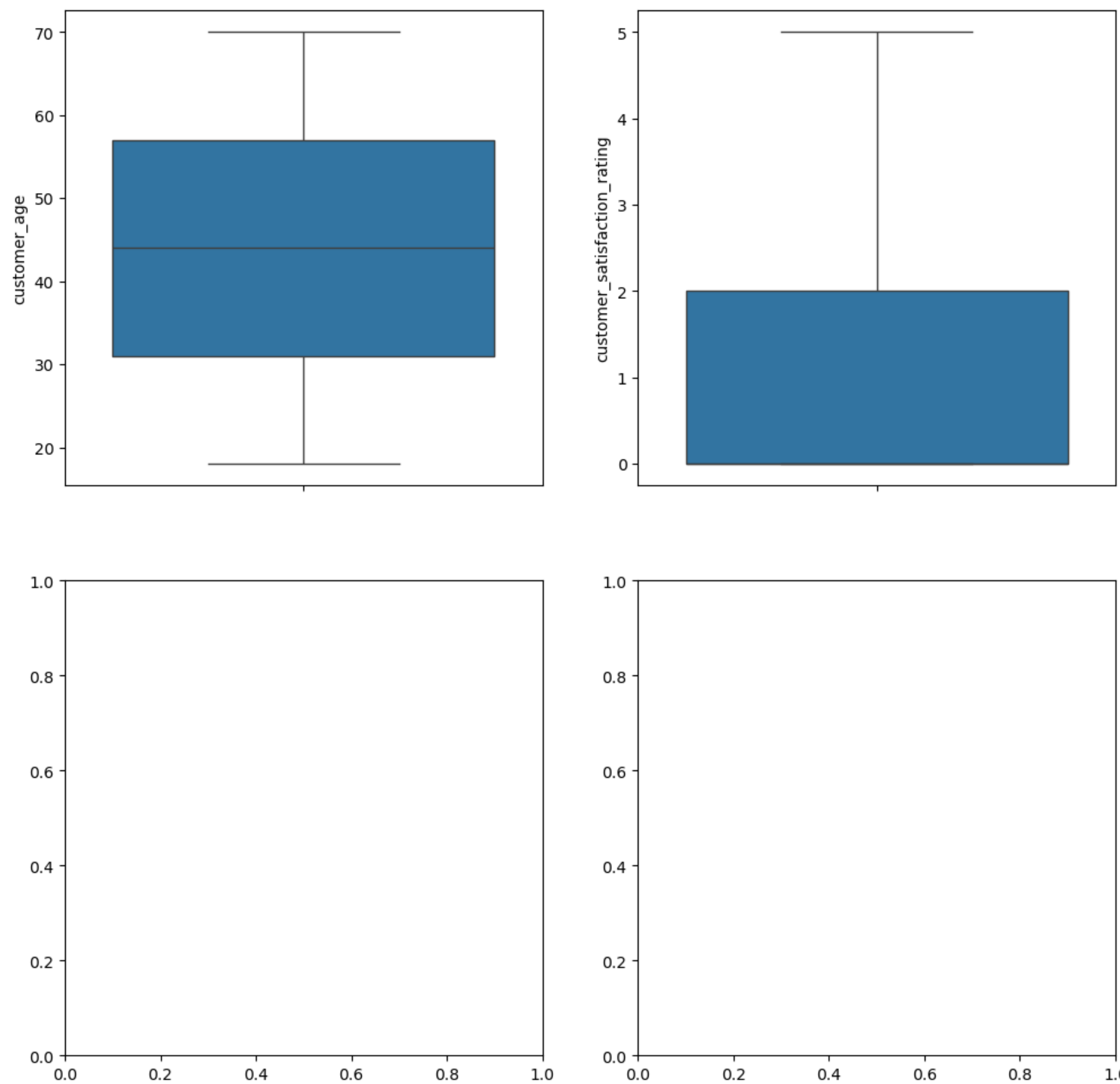
2.3 Outlier Treatment

```
data.dtypes

ticket_id                                               int64
customer_name                                          object
customer_email                                         object
customer_age                                            int64
customer_gender                                        object
product_purchased                                      object
date_of_purchase                               datetime64[ns]
ticket_type                                            object
ticket_subject                                         object
ticket_description                                     object
ticket_status                                          object
```

```
resolution                                              object
ticket_priority                                         object
ticket_channel                                          object
first_response_time                                     object
time_to_resolution                                      object
customer_satisfaction_rating                           float64
dtype: object
```

```
# Checking outlier by using boxplot

fig,axis = plt.subplots(2,2,figsize=(12,12))
sns.boxplot(ax=axis[0][0], data = data['customer_age'])
sns.boxplot(ax=axis[0][1], data =
data['customer_satisfaction_rating'])
```

```
<Axes: ylabel='customer_satisfaction_rating'>
```




There are no outliers in customer age and customer satisfaction

# 3. EDA

## 3.1 Univariate Analysis

Visualize individual variables to understand their distribution (e.g., histograms for numerical data, bar charts for categorical data).

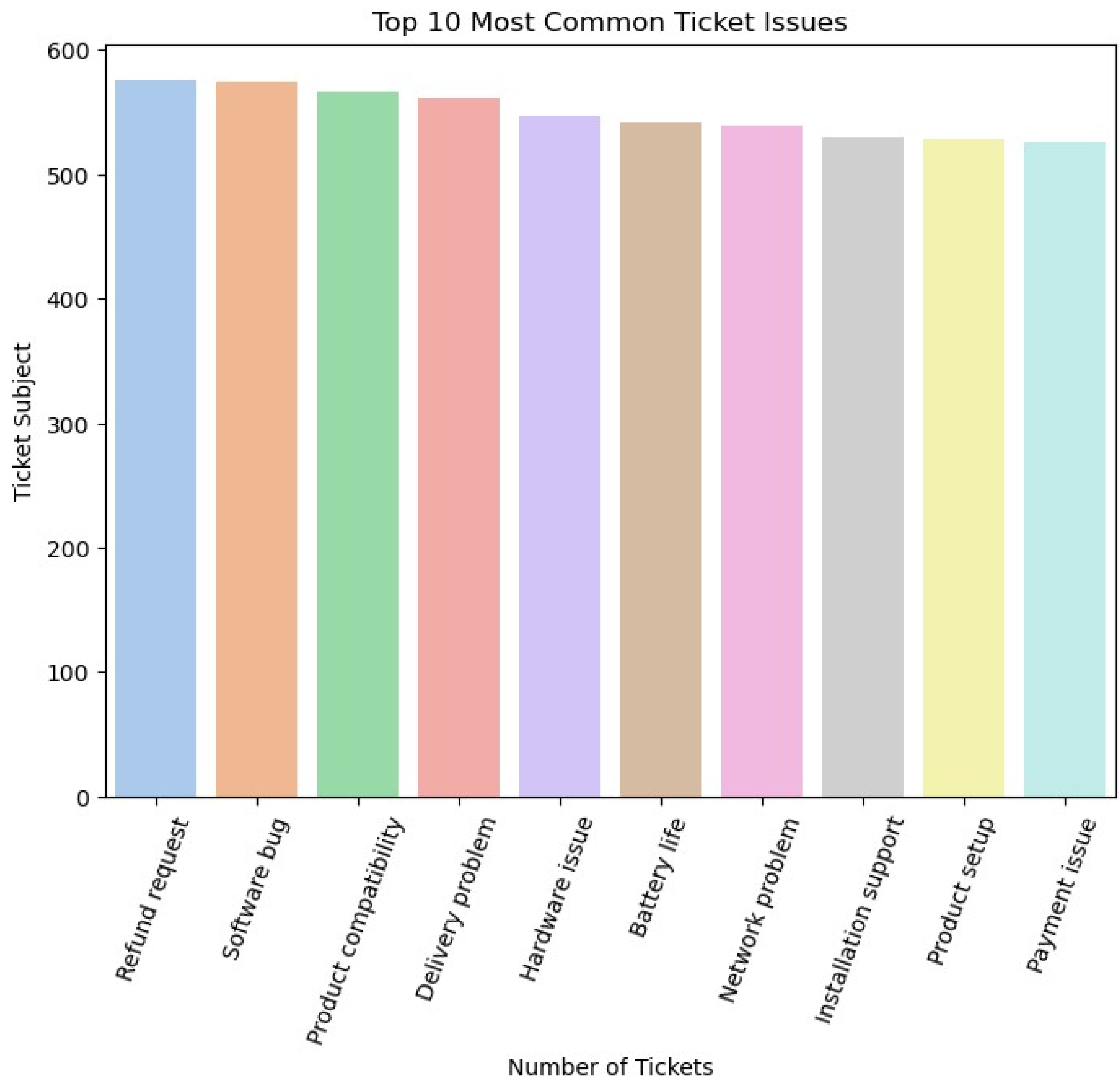
## 3.2 Bivariate and Multivariate Analysis

Explore relationships between variables by visualizing pairs of variables or groups of variables (e.g., scatter plots, heatmaps).

### 3.1 Univariate Analysis

Identify common issue(Top 10 issues)

```
# Identify common issue

top_issue =
data['ticket_subject'].value_counts().head(10).reset_index()
top_issue

          ticket_subject  count
0         Refund request    576
1           Software bug    574
2  Product compatibility    567
3       Delivery problem    561
4         Hardware issue    547
5           Battery life    542
6        Network problem    539
7   Installation support    530
8          Product setup    529
9          Payment issue    526

    plt.figure(figsize=(8, 6))
    sns.barplot(data=top_issue,x ='ticket_subject',y='count',
palette='pastel')
    plt.xticks(rotation=70)
    plt.title('Top 10 Most Common Ticket Issues')
    plt.xlabel('Number of Tickets')
    plt.ylabel('Ticket Subject')
    plt.show()
```

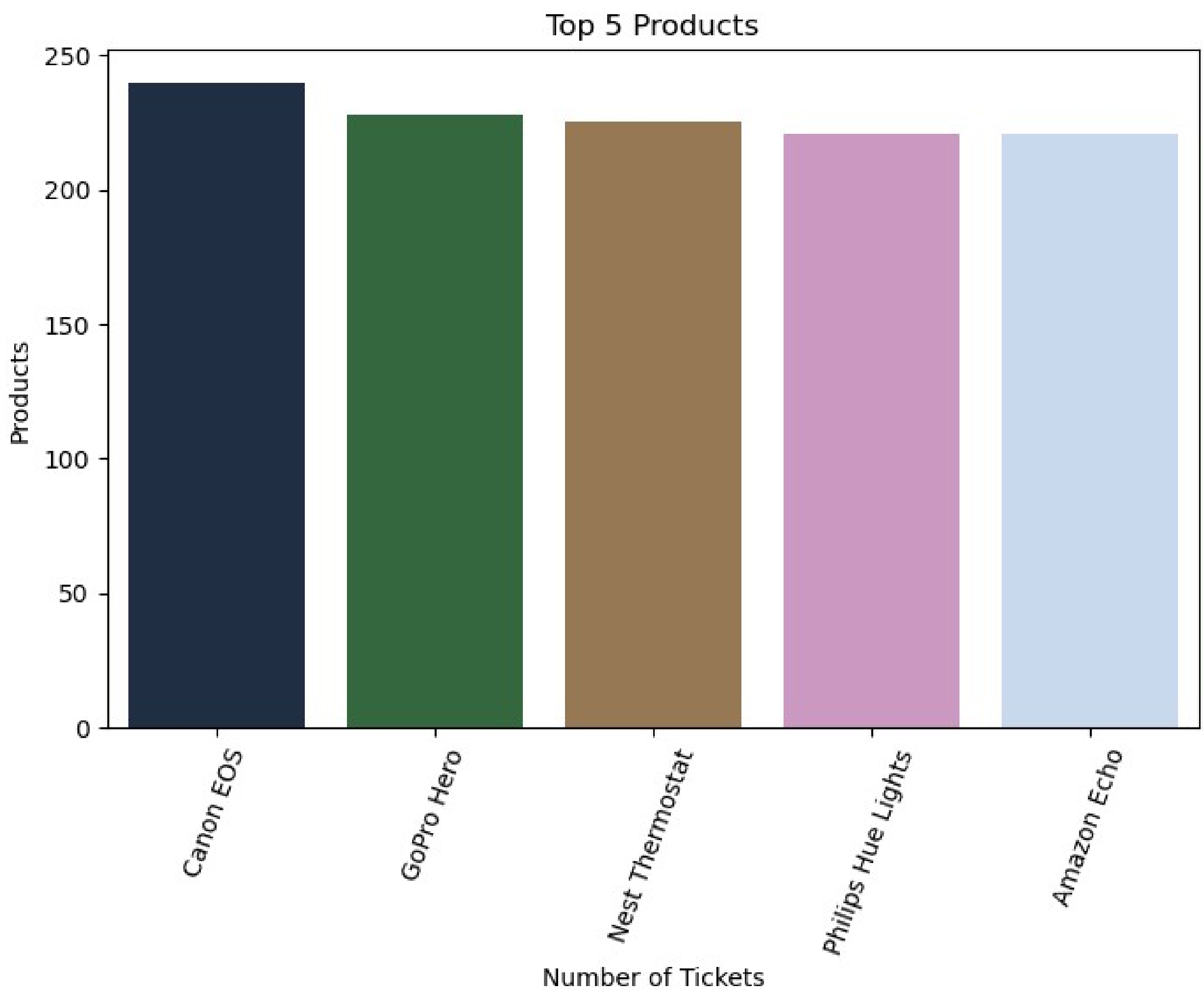



Top 5 products with most tickets

```
top_product =
data['product_purchased'].value_counts().head(5).reset_index()
top_product
```

| | product_purchased | count |
|---|---|---|
| 0 | Canon EOS | 240 |
| 1 | GoPro Hero | 228 |
| 2 | Nest Thermostat | 225 |

```
3  Philips Hue Lights    221
4          Amazon Echo    221

    plt.figure(figsize=(8, 5))
    sns.barplot(data=top_product,x ='product_purchased',y='count',
palette='cubehelix')
    plt.xticks(rotation=70)
    plt.title('Top 5 Products')
    plt.xlabel('Number of Tickets')
    plt.ylabel('Products')
    plt.show()
```



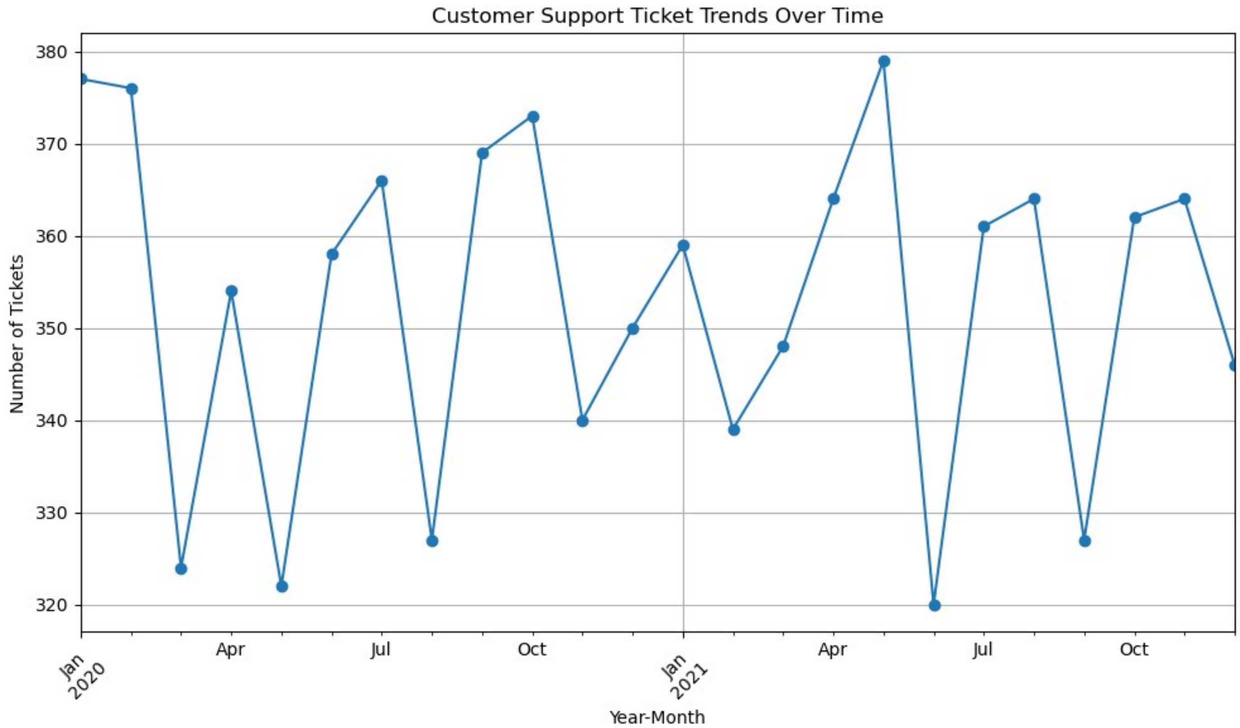

Ticket trend over time

```
data['year_month'] = data['date_of_purchase'].dt.to_period('M')
```

```python
ticket_trends = data.groupby('year_month').size()
ticket_trends
```

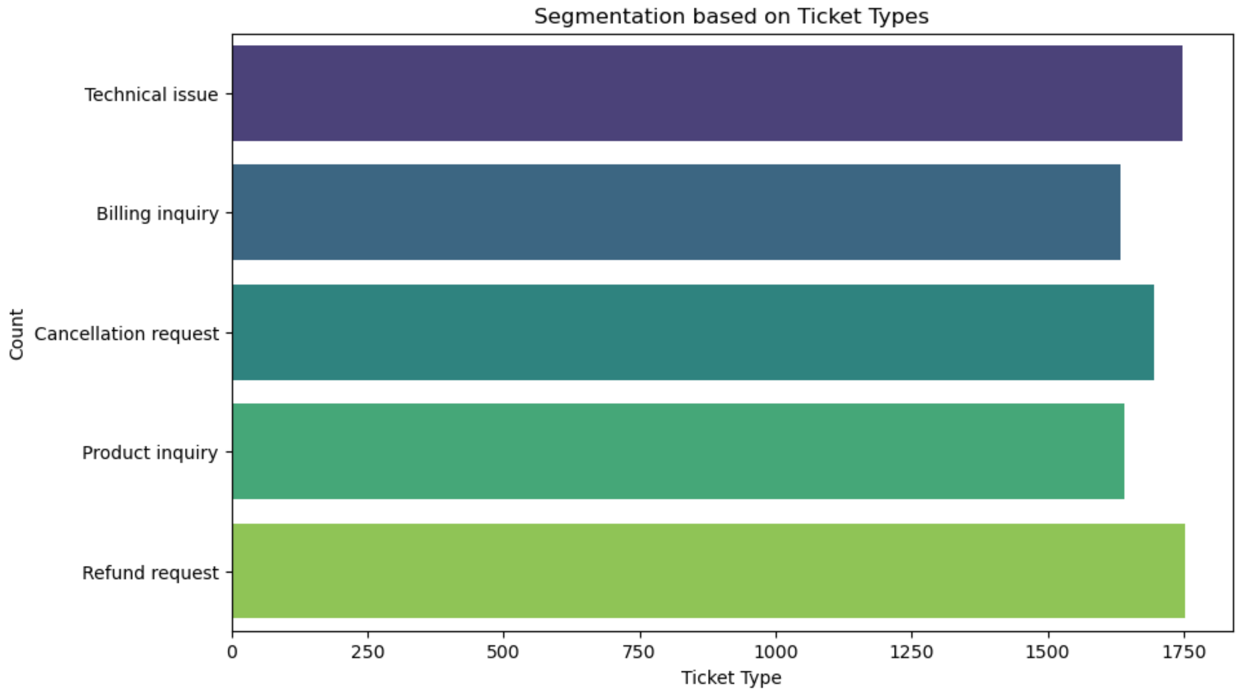
```
year_month
2020-01    377
2020-02    376
2020-03    324
2020-04    354
2020-05    322
2020-06    358
2020-07    366
2020-08    327
2020-09    369
2020-10    373
2020-11    340
2020-12    350
2021-01    359
2021-02    339
2021-03    348
2021-04    364
2021-05    379
2021-06    320
2021-07    361
2021-08    364
2021-09    327
2021-10    362
2021-11    364
2021-12    346
Freq: M, dtype: int64
```

```python
plt.figure(figsize=(10, 6))
ticket_trends.plot(kind='line', marker='o')
plt.title('Customer Support Ticket Trends Over Time')
plt.xlabel('Year-Month')
plt.ylabel('Number of Tickets')
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



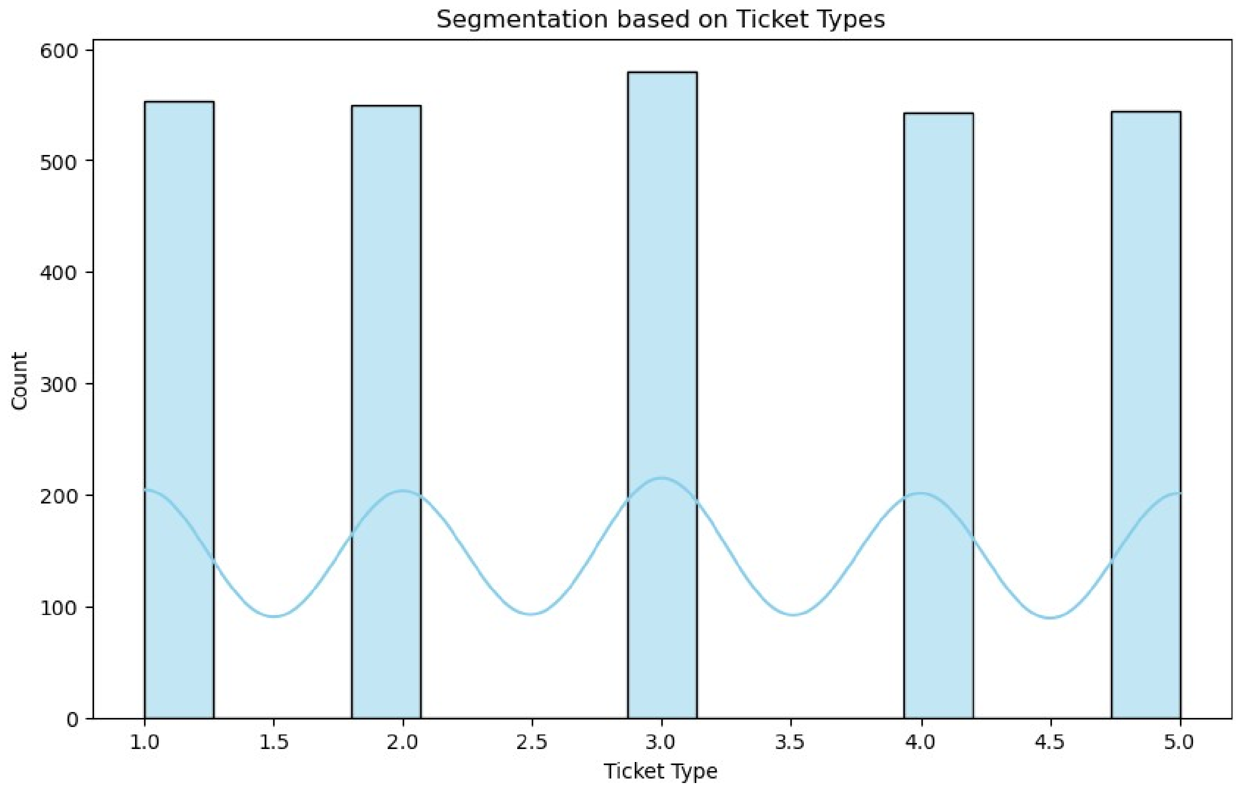

Segmentation based on Ticket type

```
plt.figure(figsize=(10, 6))
sns.countplot(data['ticket_type'], palette='viridis')
plt.title('Segmentation based on Ticket Types')
plt.xlabel('Ticket Type')
plt.ylabel('Count')

plt.show()
```



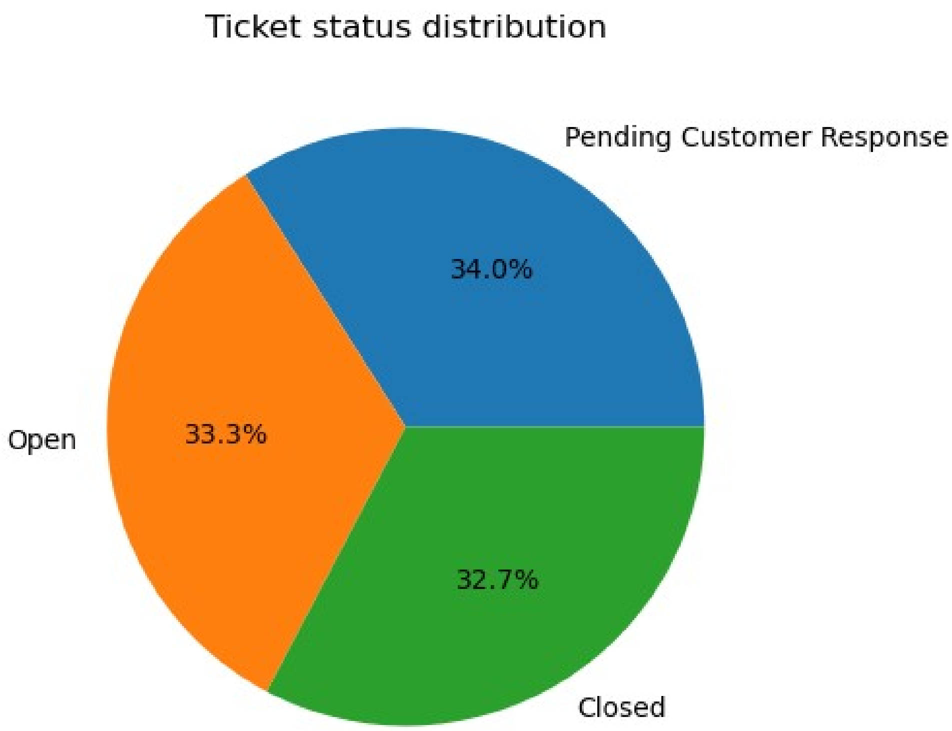

Segmentation based on Customer Statifaction level

```
customer_rating = data[data['customer_satisfaction_rating']!=0]
plt.figure(figsize=(10, 6))
sns.histplot(customer_rating['customer_satisfaction_rating'],
kde=True, color='skyblue')
plt.title('Segmentation based on Ticket Types')
plt.xlabel('Ticket Type')
plt.ylabel('Count')

plt.show()
```



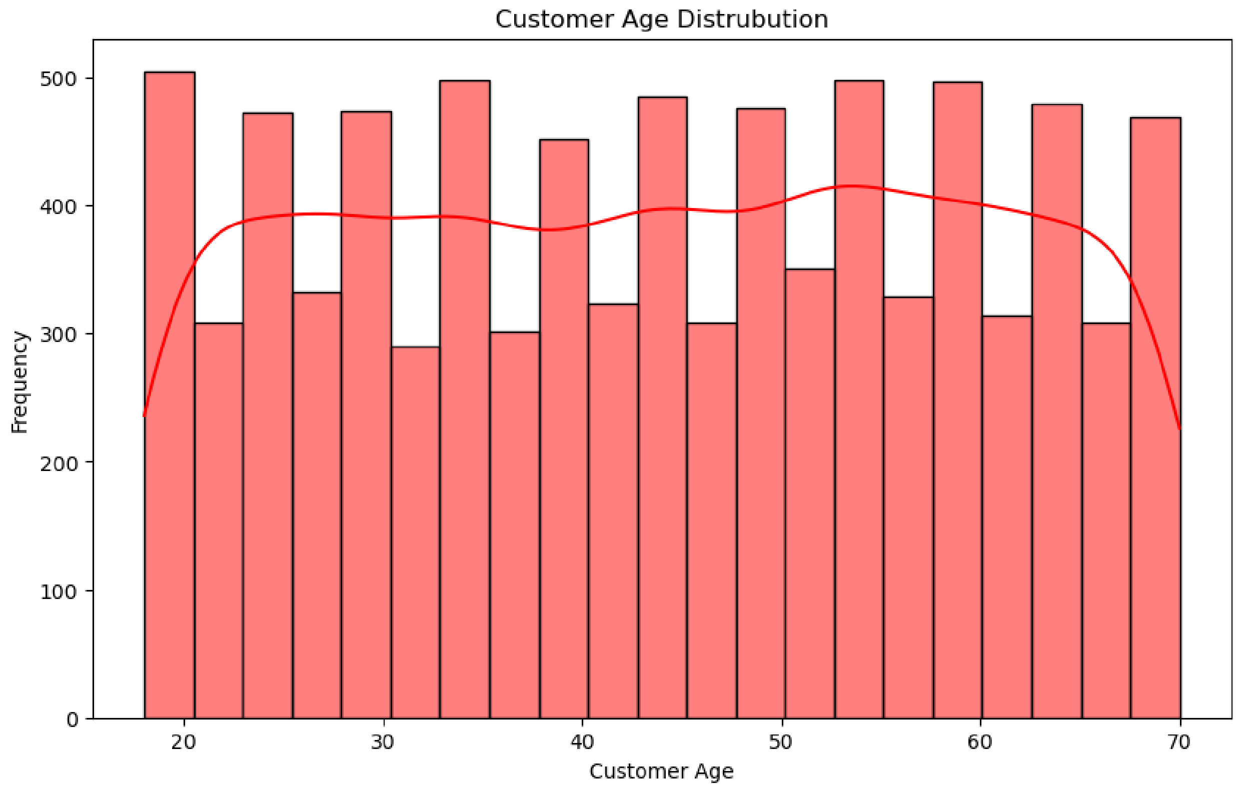

Ticket Status Distribution

```
ticket_status  = data['ticket_status'].value_counts()

plt.figure(figsize=(7,5))
plt.pie(ticket_status,labels=ticket_status.index,autopct='%1.1f%%')
plt.title("Ticket status distribution")

plt.show()
```



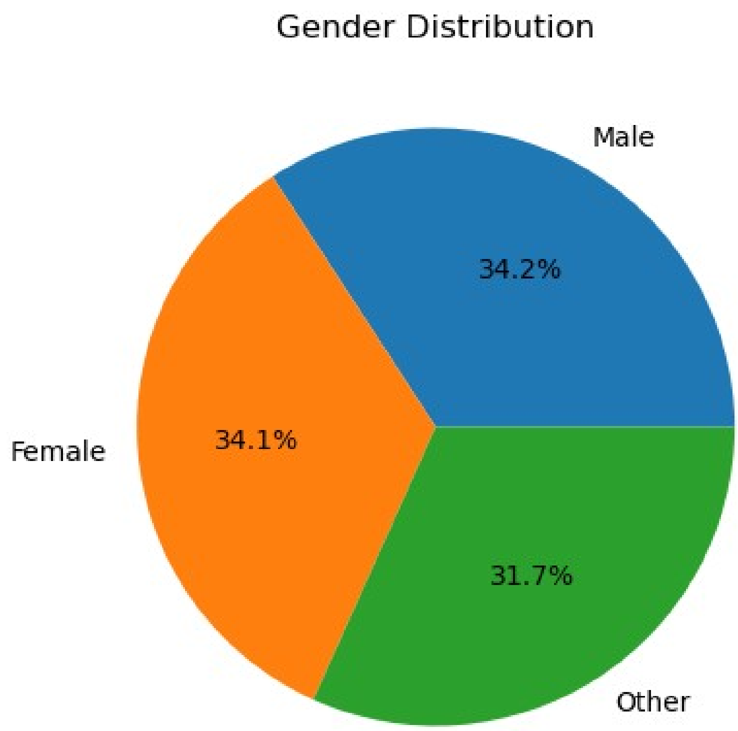

Customer age distribution

```
plt.figure(figsize=(10, 6))
sns.histplot(data['customer_age'],
kde=True, color='red')
plt.title('Customer Age Distrubution')
plt.xlabel('Customer Age')
plt.ylabel('Frequency')

plt.show()
```

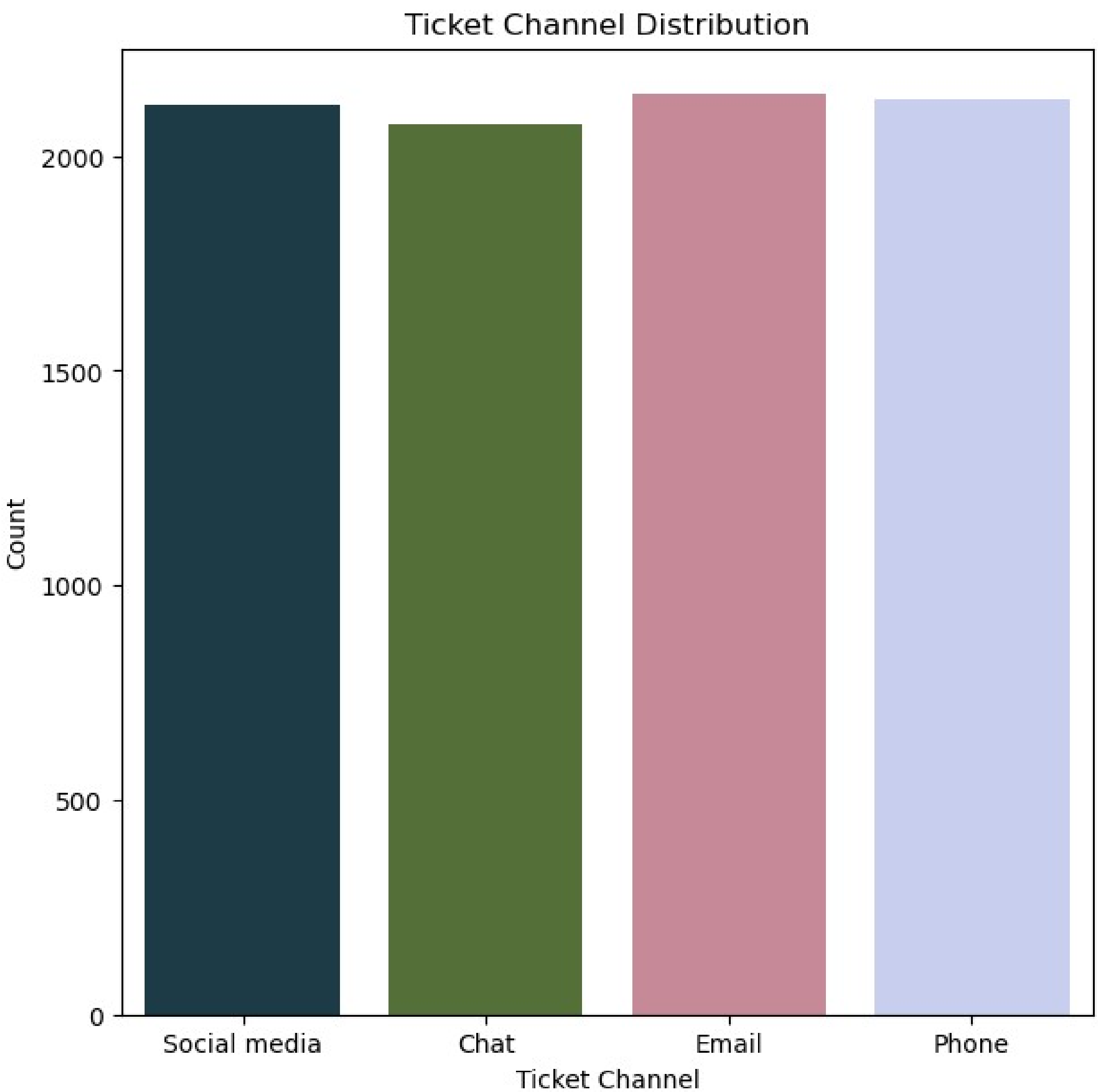



Customer Gender Distribution

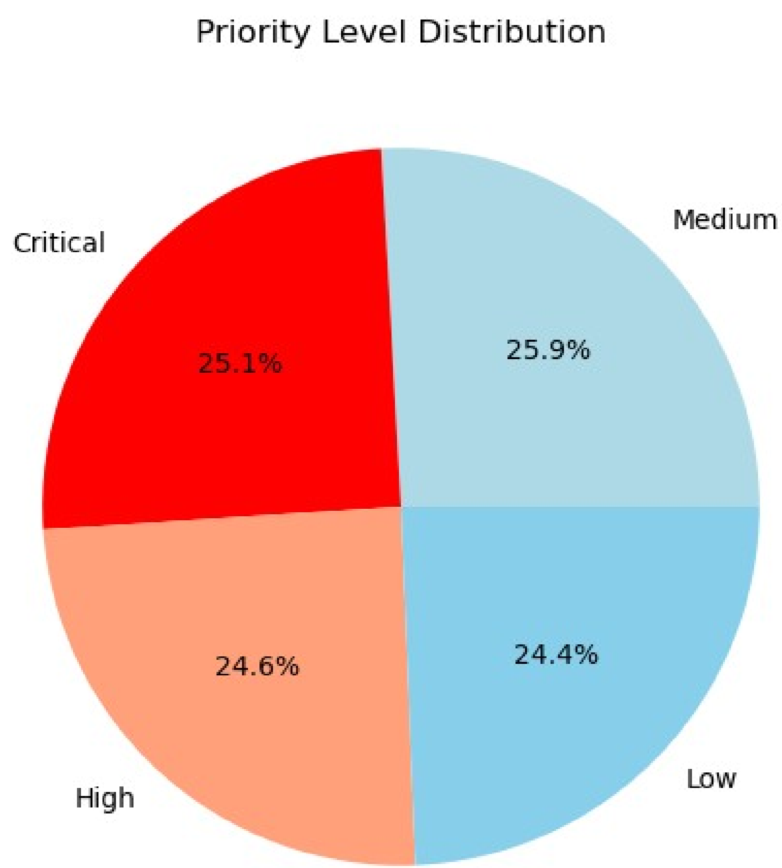
```
gender = data['customer_gender'].value_counts()

plt.figure(figsize=(7,5))
plt.pie(gender,labels=gender.index,autopct='%1.1f%%')
plt.title("Gender Distribution")

plt.show()
```




```
plt.figure(figsize=(7, 7))
sns.countplot(x=data['ticket_channel'],palette='cubehelix')
plt.title('Ticket Channel Distribution')
plt.xlabel('Ticket Channel')
plt.ylabel('Count')
plt.show()
```



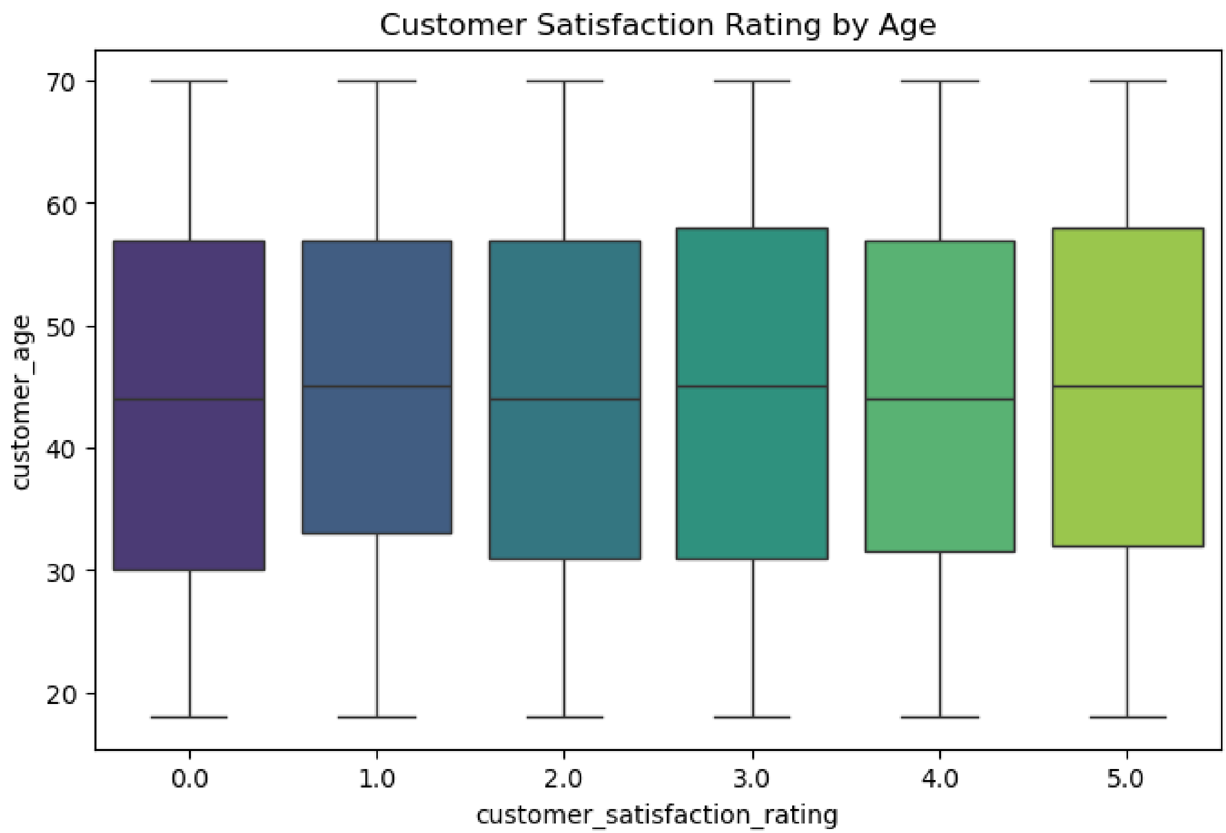

```
# Count ticket priorities
priority = data['ticket_priority'].value_counts()

# Plot
plt.figure(figsize=(8, 6))
plt.pie(priority,labels=priority.index, autopct='%1.1f%%',
colors=['lightblue', 'red', 'lightsalmon', 'skyblue'])
plt.title('Priority Level Distribution')
plt.ylabel('')
plt.show()
```




### 3.2 Bivariate analysis

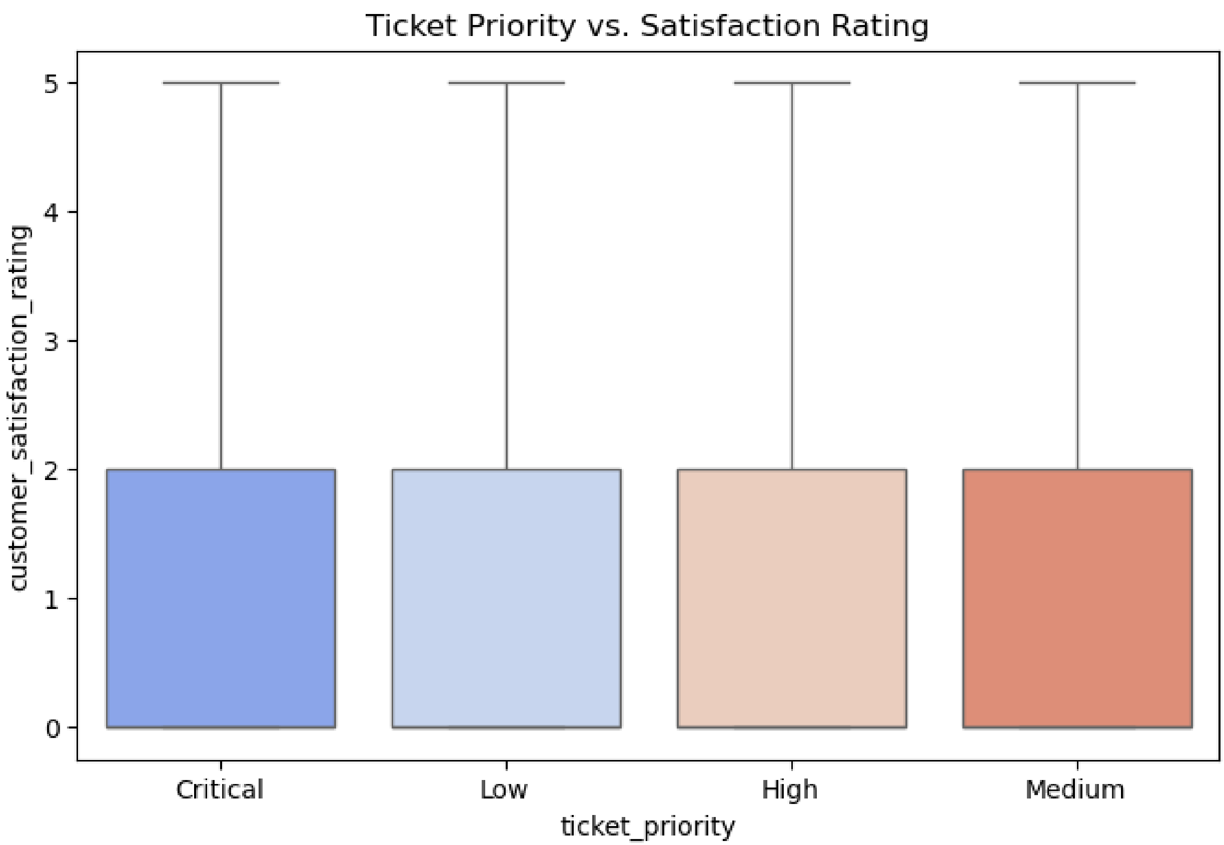
Customer Age vs Statisfaction Rating

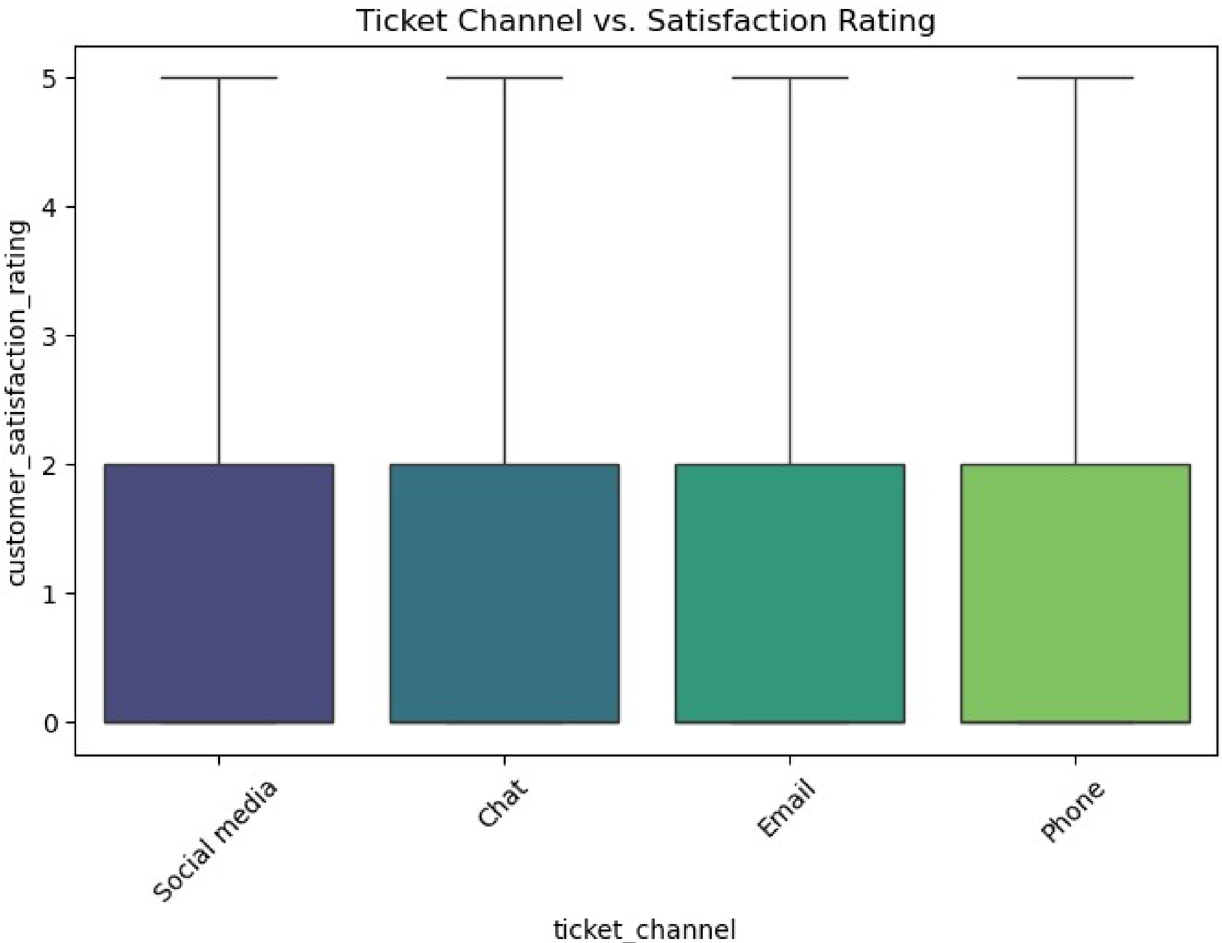
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=data, x='customer_satisfaction_rating',
y='customer_age', palette='viridis')
plt.title('Customer Satisfaction Rating by Age')
plt.show()
```

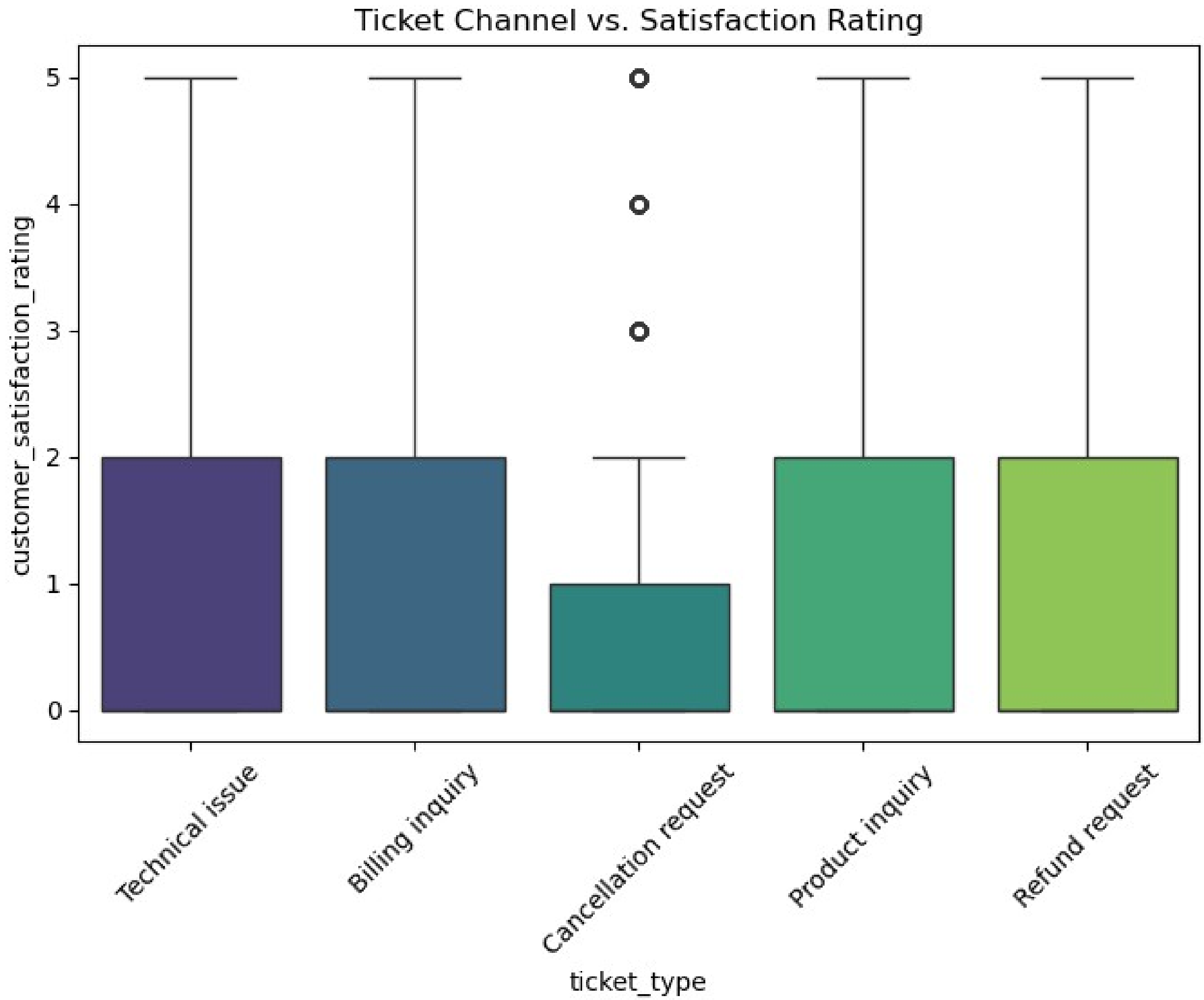


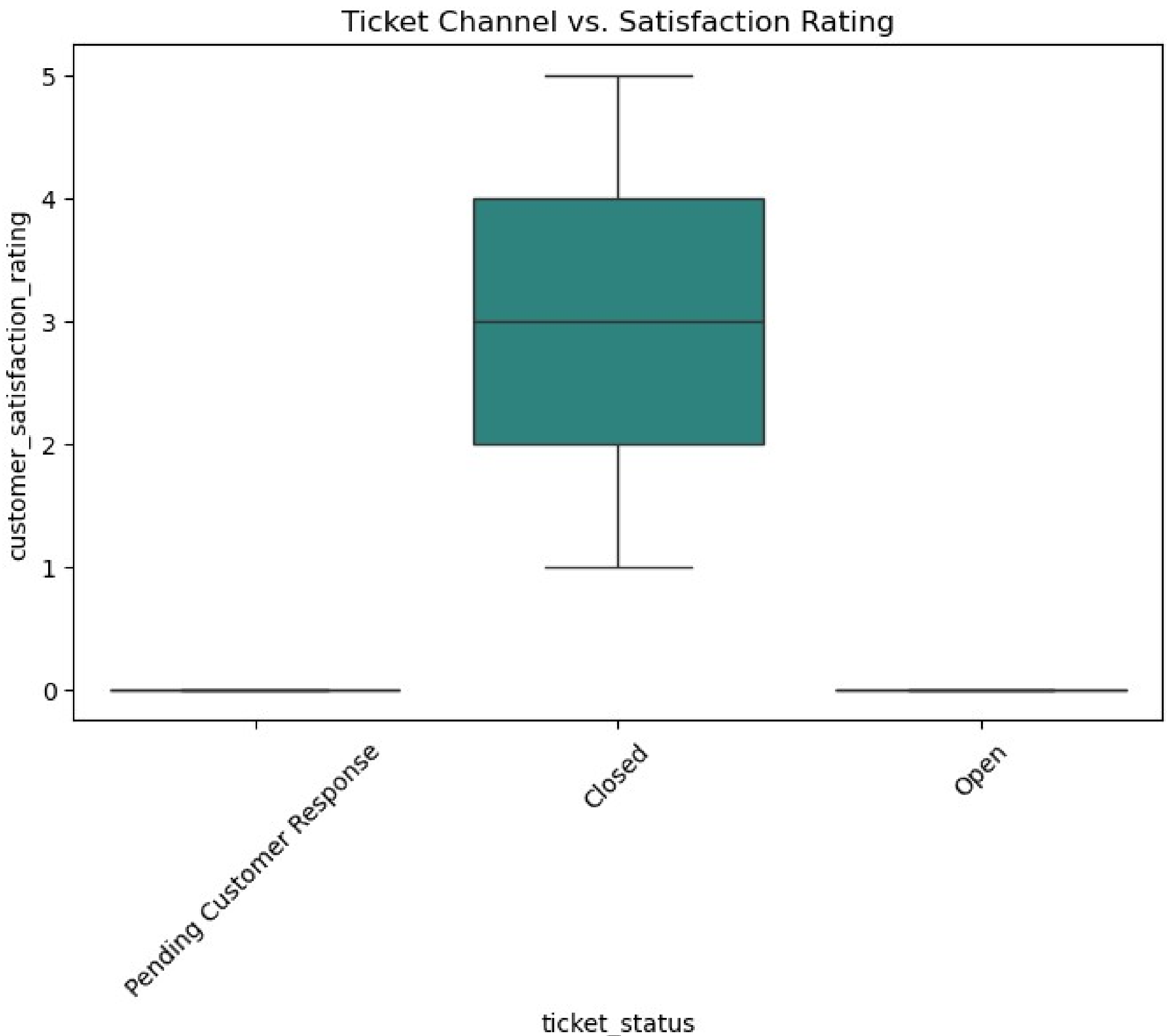

```
plt.figure(figsize=(8, 5))
sns.boxplot(x='ticket_priority', y='customer_satisfaction_rating',
data=data, palette='coolwarm')
plt.title('Ticket Priority vs. Satisfaction Rating')
plt.show()

plt.figure(figsize=(8, 5))
sns.boxplot(x='ticket_channel', y='customer_satisfaction_rating',
data=data, palette='viridis')
plt.title('Ticket Channel vs. Satisfaction Rating')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(8, 5))
sns.boxplot(x='ticket_type', y='customer_satisfaction_rating',
data=data, palette='viridis')
plt.title('Ticket Channel vs. Satisfaction Rating')
plt.xticks(rotation=45)
plt.show()


plt.figure(figsize=(8, 5))
```

```
sns.boxplot(x='ticket_status', y='customer_satisfaction_rating',
data=data, palette='viridis')
plt.title('Ticket Channel vs. Satisfaction Rating')
plt.xticks(rotation=45)
plt.show()
```

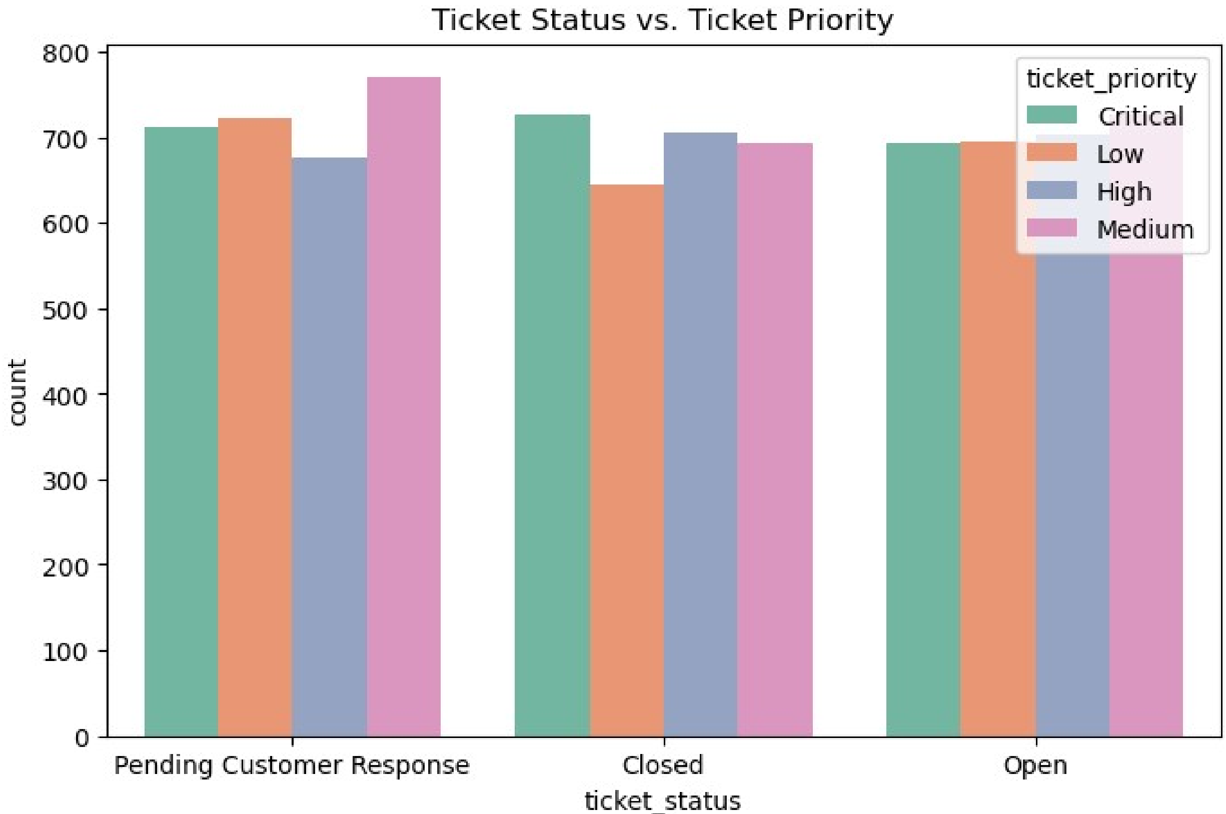



Ticket Channel vs. Satisfaction Rating
customer_satisfaction_rating
0
1
2
3
4
5
Social media
Chat
Email
Phone
ticket_channel

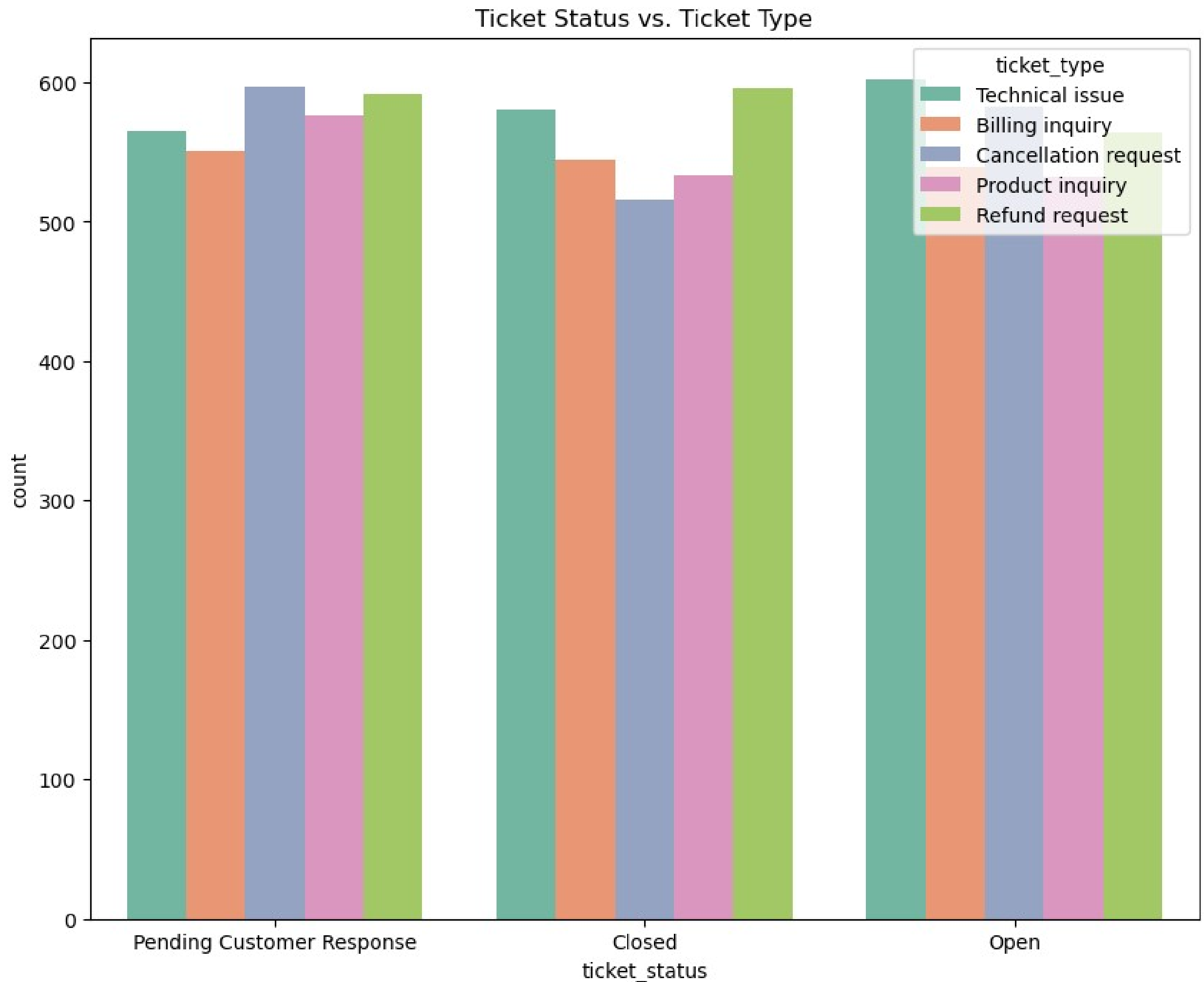

Ticket Channel vs. Satisfaction Rating
customer_satisfaction_rating
0
1
2
3
4
5
Technical issue
Billing inquiry
Cancellation request
Product inquiry
Refund request
ticket_type



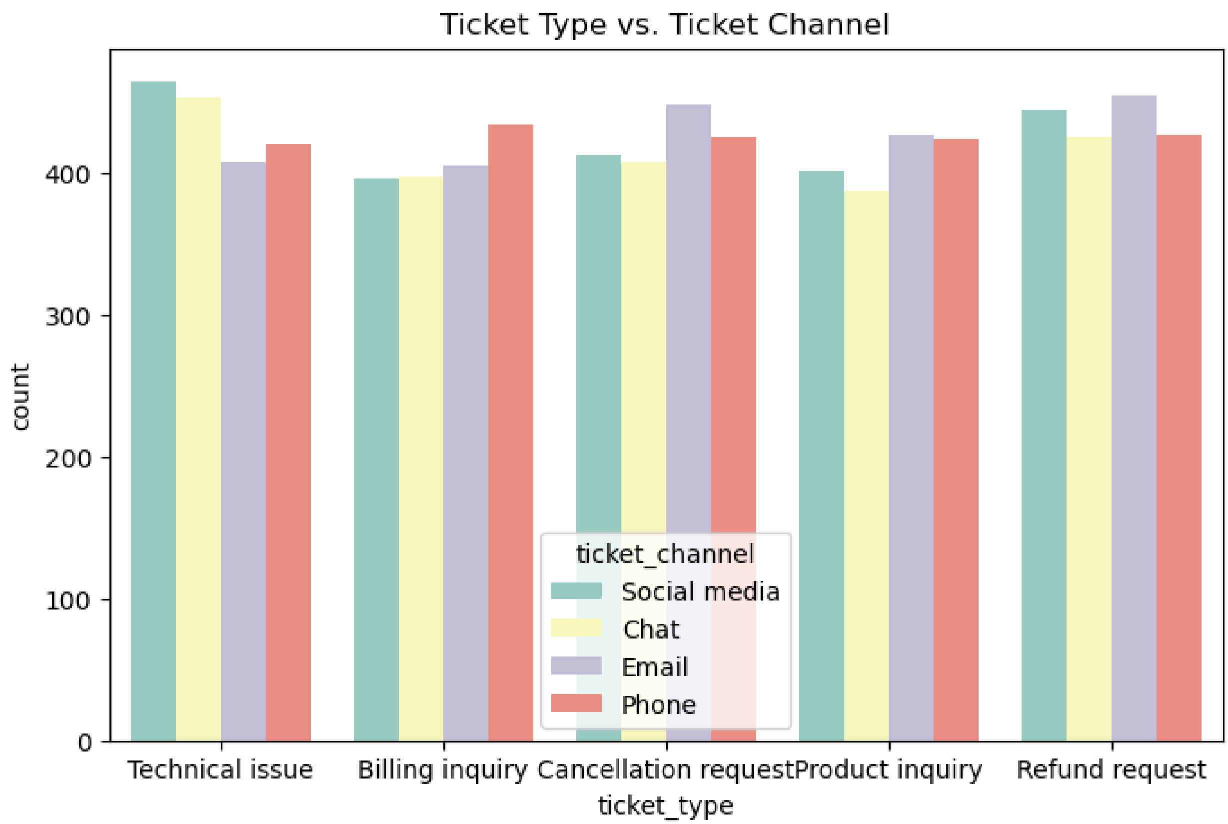

```
# Ticket Status vs Ticket Priority

plt.figure(figsize=(8, 5))
sns.countplot(x='ticket_status', hue='ticket_priority', data=data,
palette='Set2')
plt.title('Ticket Status vs. Ticket Priority')
plt.show()
```



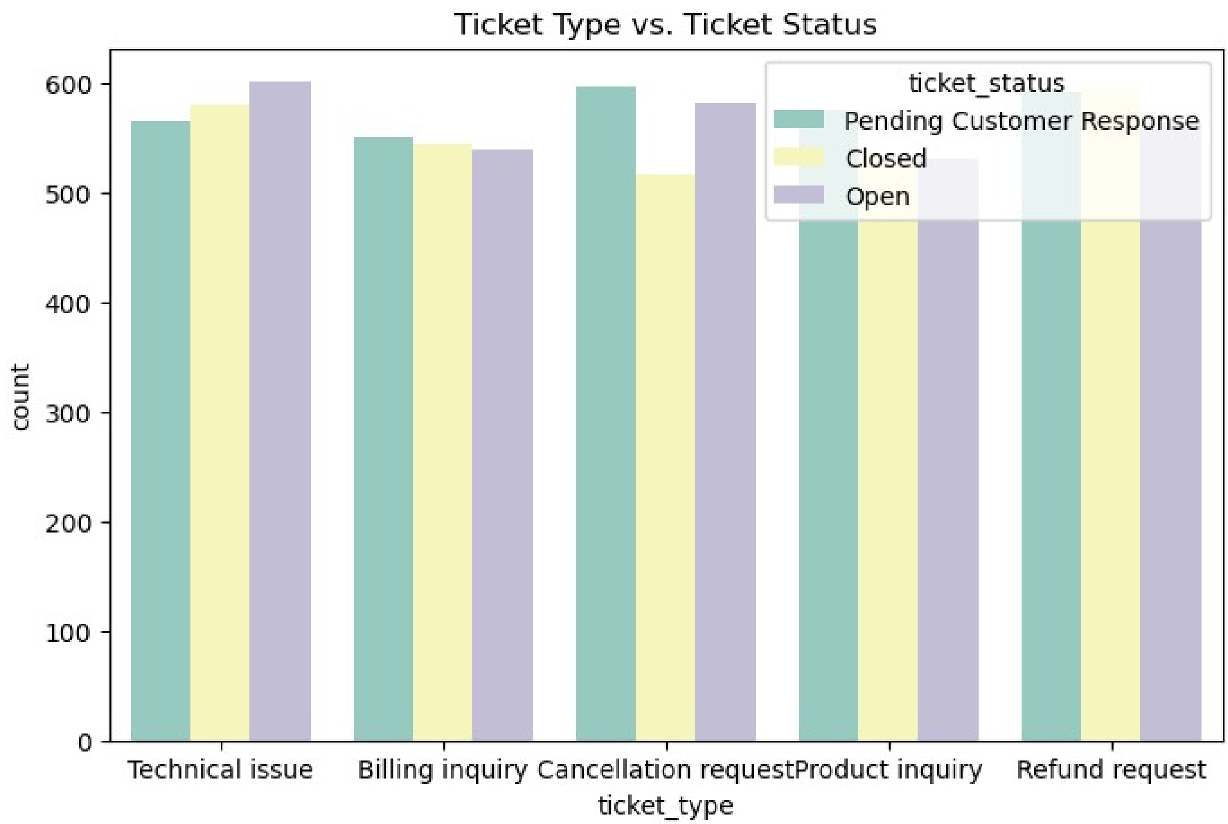

```python
# Ticket status vs ticket type

plt.figure(figsize=(10, 8))
sns.countplot(x='ticket_status', hue='ticket_type', data=data,
palette='Set2')
plt.title('Ticket Status vs. Ticket Type')
plt.show()
```




```
# Ticket type vs ticket channel

plt.figure(figsize=(8, 5))
sns.countplot(x='ticket_type', hue='ticket_channel', data=data,
palette='Set3')
plt.title('Ticket Type vs. Ticket Channel')
plt.show()
```




```
# Ticket type vs ticket status

plt.figure(figsize=(8, 5))
sns.countplot(x='ticket_type', hue='ticket_status', data=data,
palette='Set3')
plt.title('Ticket Type vs. Ticket Status')
plt.show()
```




```
# For EDA Nan values were replaced with 0. Replacing 0 again with NAN
so that they can be dropped and can do model building

data= data.replace({0:np.nan})
data['resolution'] = data['resolution'].replace({'Not
Provided':np.nan})

data.isnull().sum()

ticket_id                    0
customer_name                0
customer_email               0
customer_age                 0
customer_gender              0
product_purchased            0
date_of_purchase             0
ticket_type                  0
ticket_subject               0
ticket_description           0
ticket_status                0
resolution                5700
```

```
ticket_priority                     0
ticket_channel                      0
first_response_time              2819
time_to_resolution               5700
customer_satisfaction_rating     5700
year_month                          0
dtype: int64
```

```
data = data.dropna()
```

```
data.isnull().sum()
```

```
ticket_id                       0
customer_name                   0
customer_email                  0
customer_age                    0
customer_gender                 0
product_purchased               0
date_of_purchase                0
ticket_type                     0
ticket_subject                  0
ticket_description              0
ticket_status                   0
resolution                      0
ticket_priority                 0
ticket_channel                  0
first_response_time             0
time_to_resolution              0
customer_satisfaction_rating    0
year_month                      0
dtype: int64
```

# 4. Model Building

## 4.1 Encoding Categorical columns

```
#### Feature Engineering and Encoding

label = LabelEncoder()

columns_to_encode = [
    'customer_age',
    'customer_gender',
    'product_purchased',
    'ticket_type',
    'ticket_subject',
    'ticket_priority',
```

```
    'ticket_channel',
    'ticket_status'
]

for col in columns_to_encode:
    data[col] = label.fit_transform(data[col])
```

5.2 Feature Engineering

```
X =
data.drop(columns=['ticket_id','customer_name','customer_email','date_
of_purchase','first_response_time','time_to_resolution','customer_sati
sfaction_rating','year_month','ticket_description','resolution'])
y = data['customer_satisfaction_rating']



# Split the data into training and testing

X_train,X_test, y_train, y_test = train_test_split(X, y ,
test_size=0.2, random_state=42)
```

5.3 Model Training

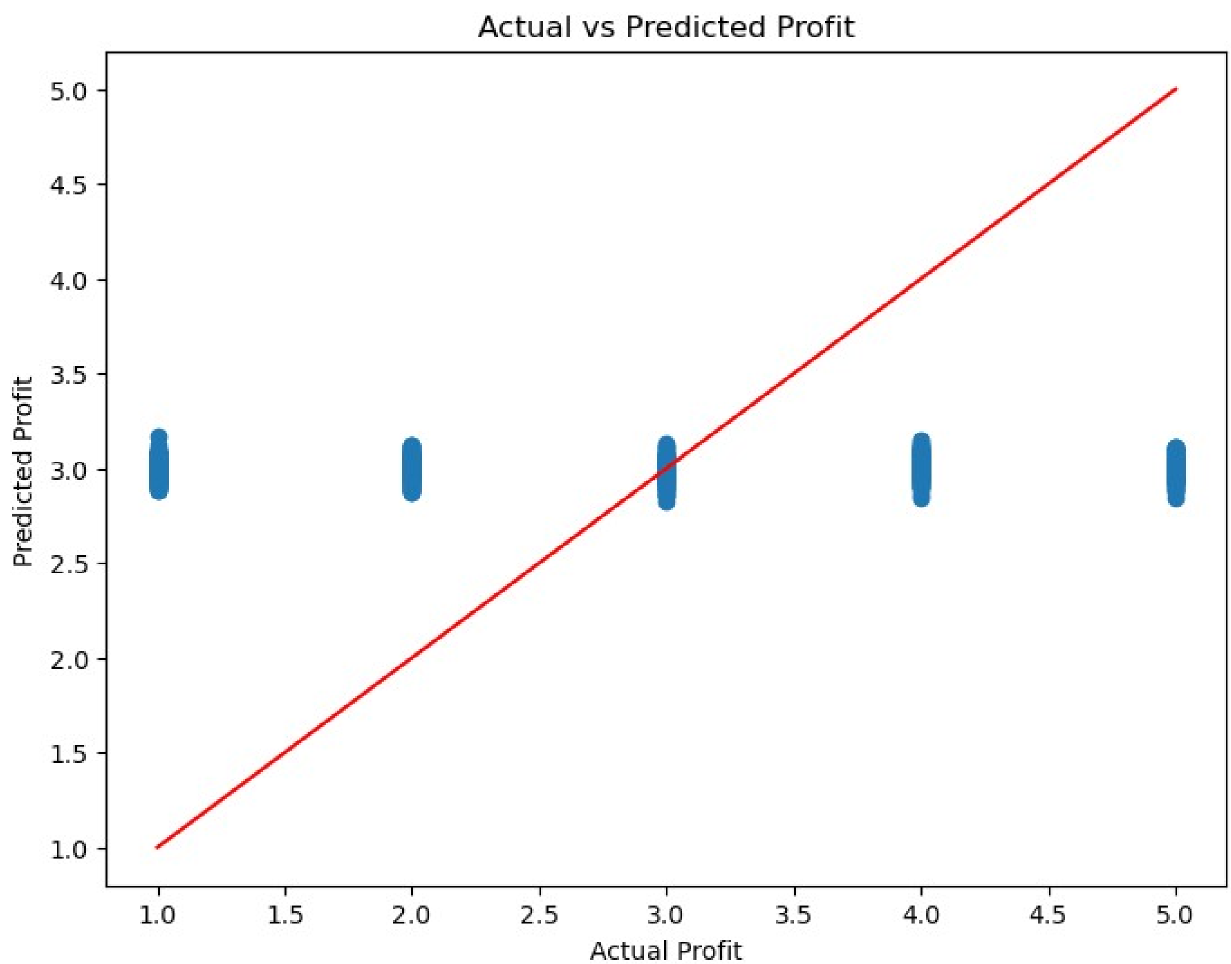
```
# Using Linear Regression to predict customer satisfaction

model = LinearRegression()

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

# Make Prediction
y_pred = model.predict(X_test)
```

Model Evaluation

```
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f" Root Mean Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
 Root Mean Squared Error: 1.4044048137893521
R-squared: 8.976393601789479e-05
```

```
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred)
plt.plot([min(y_test), max(y_test)], [min(y_test),
max(y_test)], color='red')
plt.title('Actual vs Predicted Profit')
plt.xlabel('Actual Profit')
plt.ylabel('Predicted Profit')
plt.show()
```




## 5. Advance Model

```
# Random Forest

model = RandomForestClassifier(n_estimators=50, random_state=42)

model.fit(X_train,y_train)

y_pred_random = model.predict(X_test)
```

```python
mse_random = mean_squared_error(y_test, y_pred_random)
rmse_random = np.sqrt(mse)
r2_random = r2_score(y_test, y_pred_random)

print(f" Root Mean Squared Error: {rmse_random}")
print(f"R-squared: {r2_random}")
```

```
 Root Mean Squared Error: 1.4044048137893521
R-squared: -0.8091446826153241
```