CUSTOMER SATISFACTION PREDICTION – ML & DATA ANALYSIS PROJECT

DONE BY,

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INTRODUCTION

In today's competitive market, customer satisfaction plays a crucial role in determining a company's success. Understanding and predicting customer satisfaction can help businesses improve their products, services, and overall customer experience. This project leverages data science and machine learning techniques to analyse support ticket data and predict customer satisfaction levels.

The dataset used contains various attributes such as customer demographics, product details, ticket types, issue descriptions, and resolution times. By performing thorough exploratory data analysis (EDA) and building predictive models, we aim to identify the key drivers of customer satisfaction. This not only helps in anticipating customer concerns but also aids in making data-driven decisions to enhance service quality.

ABOUT THE DATASET

The dataset used in this project is a Customer Support Ticket Dataset that contains support records for various tech products. It includes detailed information about customer interactions with support teams, covering issues like hardware failures, software bugs, account access problems, and more.

📋 Dataset Features:

- Ticket ID – Unique identifier for each support ticket
- Customer Name & Email – Anonymized personal identifiers
- Customer Age & Gender – Demographic details

- Product Purchased & Date of Purchase – Information about the product
- Ticket Type – Type of issue (e.g., technical, billing, inquiry)
- Ticket Subject & Description – Overview of the customer's concern
- Ticket Status – Open, closed, or pending response
- Resolution – Final solution provided
- Ticket Priority – Severity level (Low to Critical)
- Ticket Channel – How the ticket was raised (Email, Phone, Chat, etc.)
- First Response Time & Resolution Time – Time-based metrics
- Customer Satisfaction Rating – Rating given by the customer (1 to 5 scale)

The dataset offers rich and diverse features suitable for data analysis, customer segmentation, issue trend detection, and machine learning modelling. It helps simulate real-world customer service scenarios, making it ideal for predictive analytics and business insight generation.

DATA PREPROCESSING

Step 1: Import Libraries and Load the Dataset

Let us import the libraries and then load them into the project, use appropriate commands to load it into the project

```python
import pandas as pd
import numpy as np

df = pd.read_csv(r"C:\Users\sreea\Downloads\customer_support_tickets.csv")

df.head()
```

	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
0	1	Marisa Obrien	carrollallison@example.com	32	Other	GoPro Hero	2021-03-22	Technical issue	Product setup	I'm having an issue with the {product_purchase...	Pending Customer Response	NaN	Critical
1	2	Jessica Rios	clarkeashley@example.com	42	Female	LG Smart TV	2021-05-22	Technical issue	Peripheral compatibility	I'm having an issue with the {product_purchase...	Pending Customer Response	NaN	Critical
2	3	Christopher Robbins	gonzalestracy@example.com	48	Other	Dell XPS	2020-07-14	Technical issue	Network problem	I'm facing a problem with my {product_purchase...	Closed	Case maybe show recently my computer follow.	Low
3	4	Christina Dillon	bradleyolson@example.org	27	Female	Microsoft Office	2020-11-13	Billing inquiry	Account access	I'm having an issue with the {product_purchase...	Closed	Try capital clearly never color toward story.	Low
4	5	Alexander Carroll	bradleymark@example.com	67	Female	Autodesk AutoCAD	2020-02-04	Billing inquiry	Data loss	I'm having an issue with the {product_purchase...	Closed	West decision evidence bit.	Low

Step 2: Check Dataset Info and Null Values

```python
df.info()

df.isnull().sum()
```

```
<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
```

```
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
```

Step 3: Drop Unnecessary Columns

Since we're predicting Customer Satisfaction Rating, and columns like name or email are not useful, let's drop them.

```
print(df.columns.tolist())
df.drop(['Ticket ID', 'Customer Name', 'Customer Email', 'Ticket Subject', 'Ticket Description', 'Resolution'],
        axis=1, inplace=True, errors='ignore')
```

```
['Customer Age', 'Customer Gender', 'Product Purchased', 'Date of Purchase', 'Ticket Type', 'Ticket Status', 'Ticket Priority', 'Ticket Channel', 'First Response Tim
e', 'Time to Resolution', 'Customer Satisfaction Rating']
```

Step 4: Handle Missing Values

We'll remove rows with missing target values (Customer Satisfaction Rating) and other important fields.

```
df = df.dropna(subset=['Customer Satisfaction Rating'])

df = df.dropna()
```

Step 5: Encode Categorical Variables

We'll use LabelEncoder for columns like Gender, Product Purchased, Ticket Type, etc.

```
from sklearn.preprocessing import LabelEncoder

label_cols = ['Customer Gender', 'Product Purchased', 'Ticket Type', 'Ticket Status',
              'Ticket Priority', 'Ticket Channel']

label_encoders = {}
for col in label_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
```

Step 6: Convert Date Columns

Convert the date columns to datetime for further feature engineering.

```
df['Date of Purchase'] = pd.to_datetime(df['Date of Purchase'])
df['First Response Time'] = pd.to_datetime(df['First Response Time'])
df['Time to Resolution'] = pd.to_datetime(df['Time to Resolution'])

df['Purchase Year'] = df['Date of Purchase'].dt.year
df['Purchase Month'] = df['Date of Purchase'].dt.month
```

Step 7: Final Check

```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2769 entries, 2 to 8467
Data columns (total 13 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Customer Age                  2769 non-null   int64
 1   Customer Gender               2769 non-null   int32
 2   Product Purchased             2769 non-null   int32
 3   Date of Purchase              2769 non-null   datetime64[ns]
 4   Ticket Type                   2769 non-null   int32
 5   Ticket Status                 2769 non-null   int32
 6   Ticket Priority               2769 non-null   int32
 7   Ticket Channel                2769 non-null   int32
 8   First Response Time           2769 non-null   datetime64[ns]
 9   Time to Resolution            2769 non-null   datetime64[ns]
 10  Customer Satisfaction Rating  2769 non-null   float64
 11  Purchase Year                 2769 non-null   int32
 12  Purchase Month                2769 non-null   int32
dtypes: datetime64[ns](3), float64(1), int32(8), int64(1)
memory usage: 216.3 KB
```

	Customer Age	Customer Gender	Product Purchased	Date of Purchase	Ticket Type	Ticket Status	Ticket Priority	Ticket Channel	First Response Time	Time to Resolution	Customer Satisfaction Rating	
count	2769.000000	2769.000000	2769.000000	2769	2769.000000	2769.0	2769.000000	2769.000000	2769	2769	2769.000000	27
mean	44.333694	0.958469	20.468761	2020-12-28 16:55:38.678223104	2.054893	0.0	1.471650	1.500181	2023-06-01 11:20:49.245575936	2023-06-01 11:17:21.509931520	2.991333	20
min	18.000000	0.000000	0.000000	2020-01-01 00:00:00	0.000000	0.0	0.000000	0.000000	2023-05-31 21:55:39	2023-05-31 21:53:30	1.000000	20
25%	31.000000	0.000000	9.000000	2020-06-29 00:00:00	1.000000	0.0	0.000000	1.000000	2023-06-01 05:19:36	2023-06-01 05:34:43	2.000000	20
50%	45.000000	1.000000	20.000000	2020-12-26 00:00:00	2.000000	0.0	1.000000	1.000000	2023-06-01 11:22:02	2023-06-01 11:17:48	3.000000	20
75%	57.000000	2.000000	31.000000	2021-07-01 00:00:00	3.000000	0.0	3.000000	2.000000	2023-06-01 17:27:08	2023-06-01 17:07:32	4.000000	20
max	70.000000	2.000000	41.000000	2021-12-30 00:00:00	4.000000	0.0	3.000000	3.000000	2023-06-02 00:54:21	2023-06-02 00:55:33	5.000000	20
std	15.195495	0.817136	12.266807	NaN	1.422321	0.0	1.129291	1.109641	NaN	NaN	1.407016	

EXPLORATORY DATA ANALYSIS(EDA)

Step 1: Basic Overview of the Dataset

```
import pandas as pd
import numpy as np
df = pd.read_csv(r"C:\Users\sreea\Downloads\customer_support_tickets.csv")
print("Dataset shape:", df.shape)

print(df.describe())

print(df.info())
print(df.isnull().sum())
```

```
Dataset shape: (8469, 17)
          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
<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
None
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
```

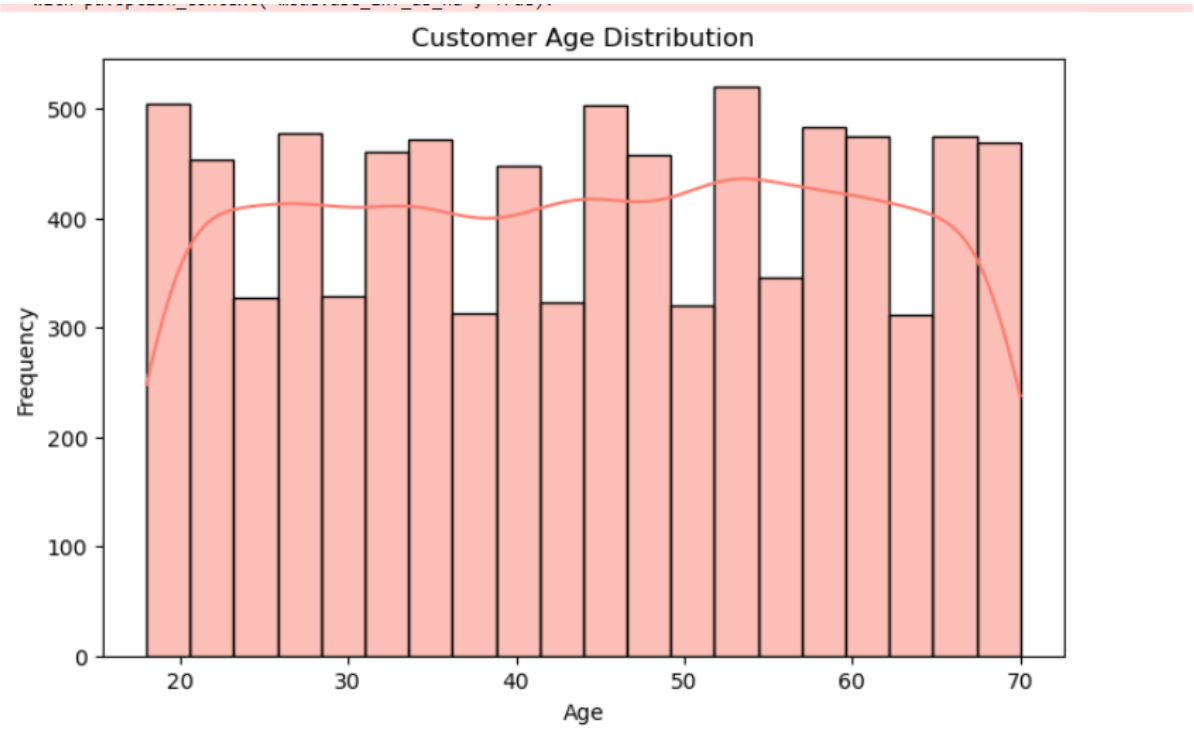
Step 2: Target Variable Distribution (Customer Satisfaction Rating)

```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8,5))
sns.countplot(x='Customer Satisfaction Rating', data=df, palette='viridis')
plt.title("Customer Satisfaction Rating Distribution")
plt.xlabel("Satisfaction Rating (1 = Poor, 5 = Excellent)")
plt.ylabel("Number of Customers")
plt.show()
```

Step 3: Customer Demographics Analysis

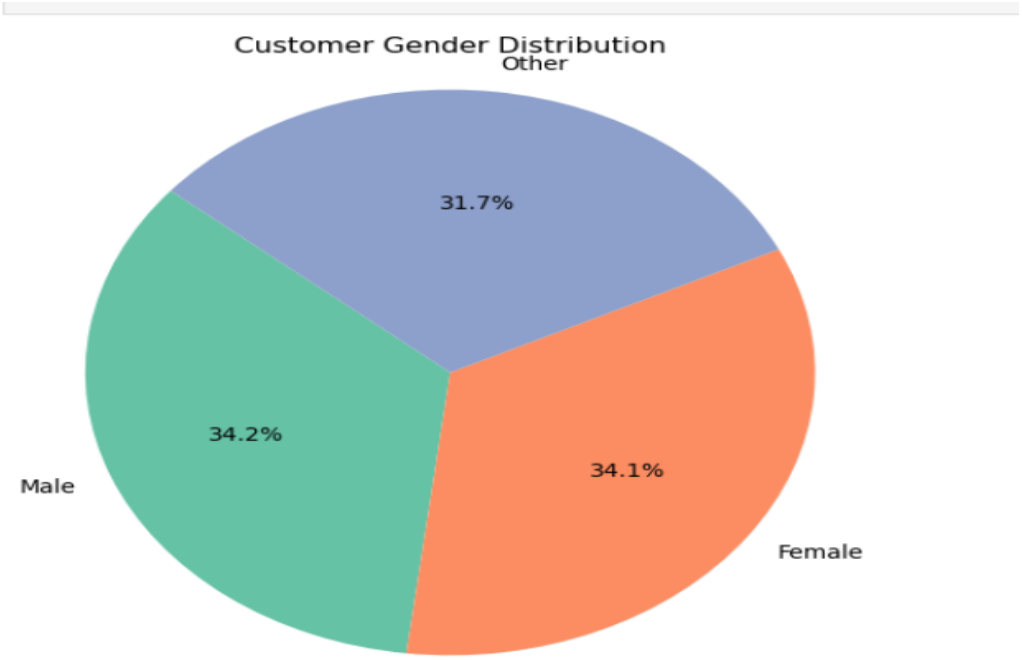
- **Age Distribution**

```
plt.figure(figsize=(8,5))
sns.histplot(df['Customer Age'], bins=20, kde=True, color='salmon')
plt.title("Customer Age Distribution")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```



- **Gender Distribution**

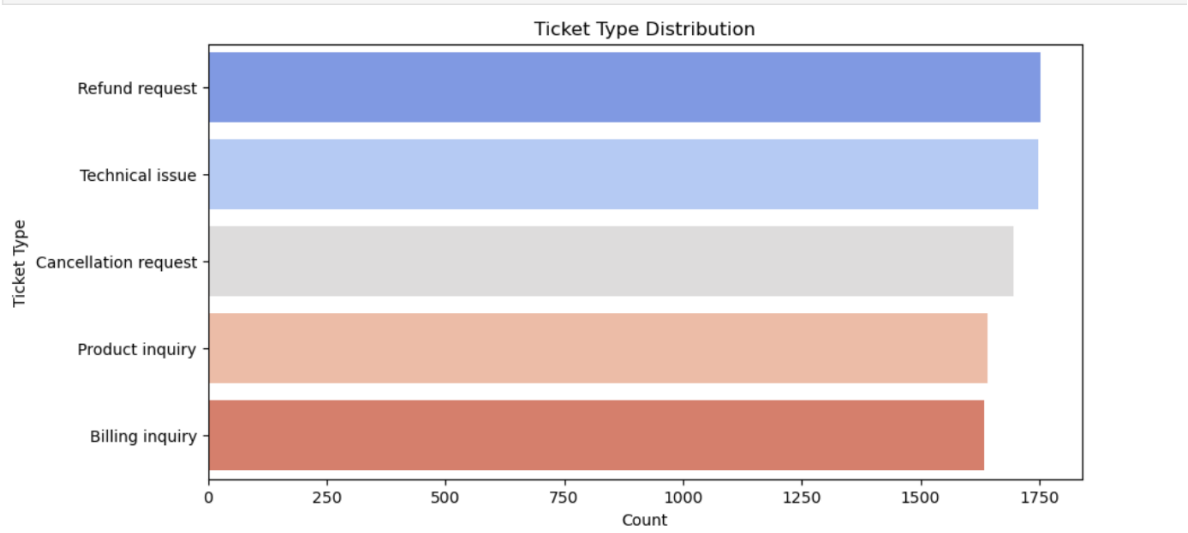
```
gender_dist = df['Customer Gender'].value_counts()
plt.figure(figsize=(6,6))
plt.pie(gender_dist, labels=gender_dist.index, autopct='%1.1f%%', startangle=140, colors=sns.color_palette("Set2"))
plt.title("Customer Gender Distribution")
plt.axis('equal')
plt.show()
```



Step 4: Ticket Characteristics

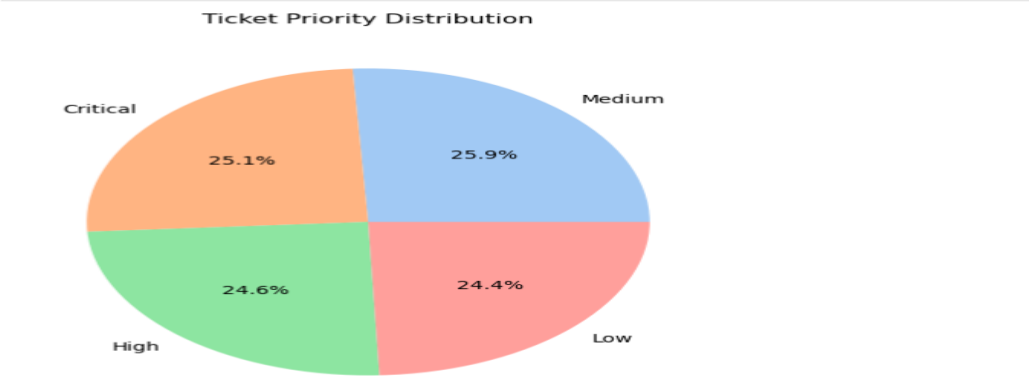
- **Ticket Type Distribution**

```
plt.figure(figsize=(10,5))
sns.countplot(y='Ticket Type', data=df, order=df['Ticket Type'].value_counts().index, palette='coolwarm')
plt.title("Ticket Type Distribution")
plt.xlabel("Count")
plt.ylabel("Ticket Type")
plt.show()
```



- **Ticket Priority Distribution**

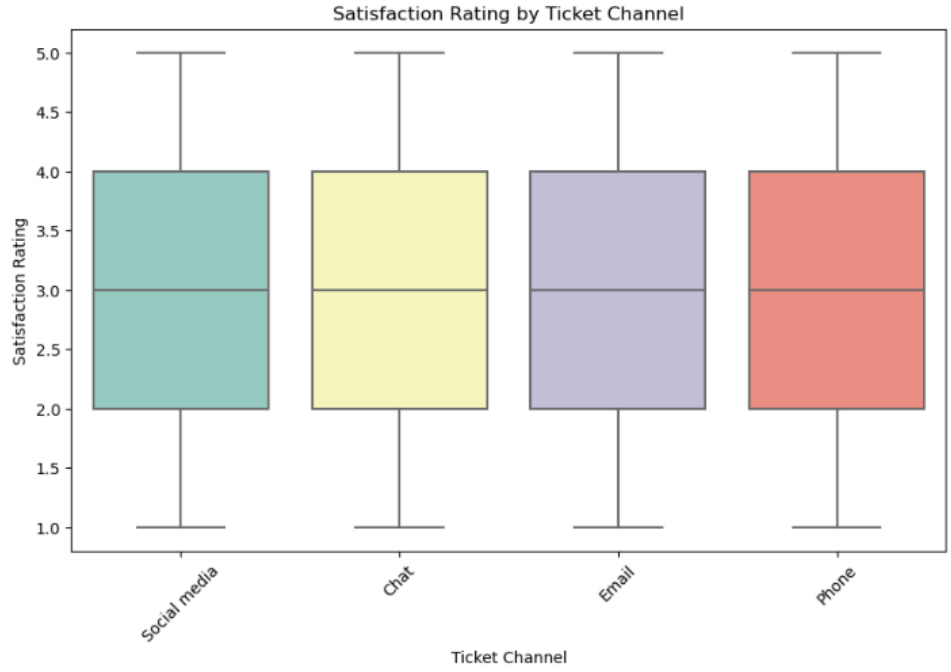
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
df = pd.read_csv(r"C:\Users\sreea\Downloads\customer_support_tickets.csv")
plt.figure(figsize=(6,6))
df['Ticket Priority'].value_counts().plot(kind='pie', autopct='%1.1f%%', colors=sns.color_palette("pastel"))
plt.title("Ticket Priority Distribution")
plt.ylabel("")
plt.show()
```



Step 5: Relationship Between Features and Satisfaction

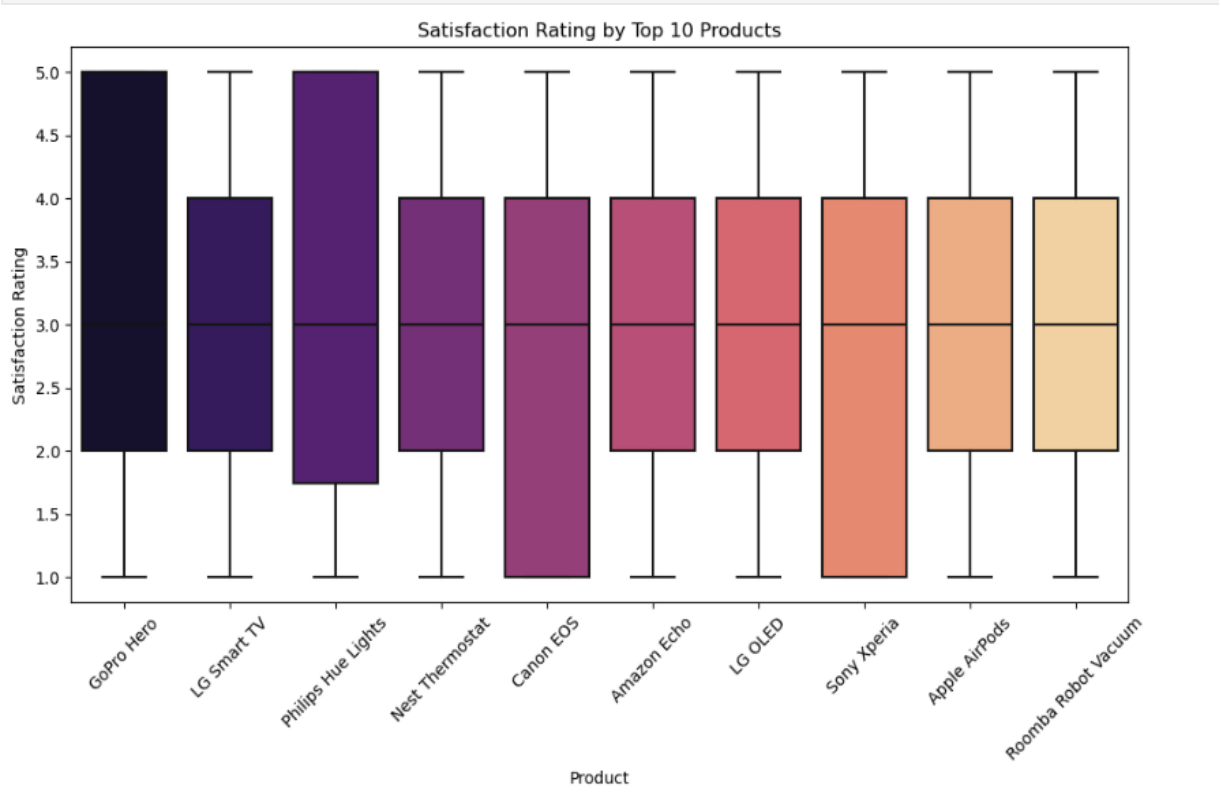
- **Satisfaction by Ticket Channel**

```
plt.figure(figsize=(10,6))
sns.boxplot(x='Ticket Channel', y='Customer Satisfaction Rating', data=df, palette='Set3')
plt.title("Satisfaction Rating by Ticket Channel")
plt.xlabel("Ticket Channel")
plt.ylabel("Satisfaction Rating")
plt.xticks(rotation=45)
plt.show()
```



- **Satisfaction by Product Purchased (Top 10 Only)**

```
top_products = df['Product Purchased'].value_counts().head(10).index
plt.figure(figsize=(12,6))
sns.boxplot(data=df[df['Product Purchased'].isin(top_products)],
            x='Product Purchased',
            y='Customer Satisfaction Rating',
            palette='magma')
plt.title("Satisfaction Rating by Top 10 Products")
plt.xlabel("Product")
plt.ylabel("Satisfaction Rating")
plt.xticks(rotation=45)
plt.show()
```



FEATURE ENGINEERING

Step 1: Convert Dates to Useful Features

```
df['Date of Purchase'] = pd.to_datetime(df['Date of Purchase'], errors='coerce')

df['Purchase Year'] = df['Date of Purchase'].dt.year
df['Purchase Month'] = df['Date of Purchase'].dt.month
df['Purchase Day'] = df['Date of Purchase'].dt.dayofweek
```

Step 2: Handle First Response Time and Time to Resolution

```
df['First Response Time'] = pd.to_datetime(df['First Response Time'], errors='coerce')
df['Time to Resolution'] = pd.to_datetime(df['Time to Resolution'], errors='coerce')

df['Response Time (hrs)'] = (df['First Response Time'] - df['Date of Purchase']).dt.total_seconds() / 3600
df['Resolution Time (hrs)'] = (df['Time to Resolution'] - df['First Response Time']).dt.total_seconds() / 3600
```

```
df.drop(['Date of Purchase', 'First Response Time', 'Time to Resolution'], axis=1, inplace=True)
```

Step 3: Encode Categorical Columns

```
from sklearn.preprocessing import LabelEncoder

label_cols = ['Customer Gender', 'Product Purchased', 'Ticket Type',
              'Ticket Status', 'Ticket Priority', 'Ticket Channel']

label_encoders = {}
for col in label_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
```

Step 4: Final Cleanup

```
df.replace([np.inf, -np.inf], np.nan, inplace=True)

df.dropna(inplace=True)

print(df.isnull().sum())
```

```
Ticket ID                         0
Customer Name                     0
Customer Email                    0
Customer Age                      0
Customer Gender                   0
Product Purchased                 0
Ticket Type                       0
Ticket Subject                    0
Ticket Description                0
Ticket Status                     0
Resolution                        0
Ticket Priority                   0
Ticket Channel                    0
Customer Satisfaction Rating      0
Purchase Year                     0
Purchase Month                    0
Purchase Day                      0
Response Time (hrs)               0
Resolution Time (hrs)             0
dtype: int64
```

MODEL BUILDING

Step 1: Split the Dataset

```python
from sklearn.model_selection import train_test_split

X = df.drop('Customer Satisfaction Rating', axis=1)
y = df['Customer Satisfaction Rating']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Step 2: Feature Scaling

Random Forest doesn't require scaling, but it's good practice if you later use logistic regression or SVM.

```
X.dtypes
X = df.drop(['Customer Satisfaction Rating'], axis=1)

columns_to_drop = ['Customer Name', 'Customer Email', 'Ticket Subject', 'Ticket Description', 'Resolution']
X = X.drop(columns=[col for col in columns_to_drop if col in X.columns], errors='ignore')

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Step 3: Train the Random Forest Model

```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train_scaled, y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

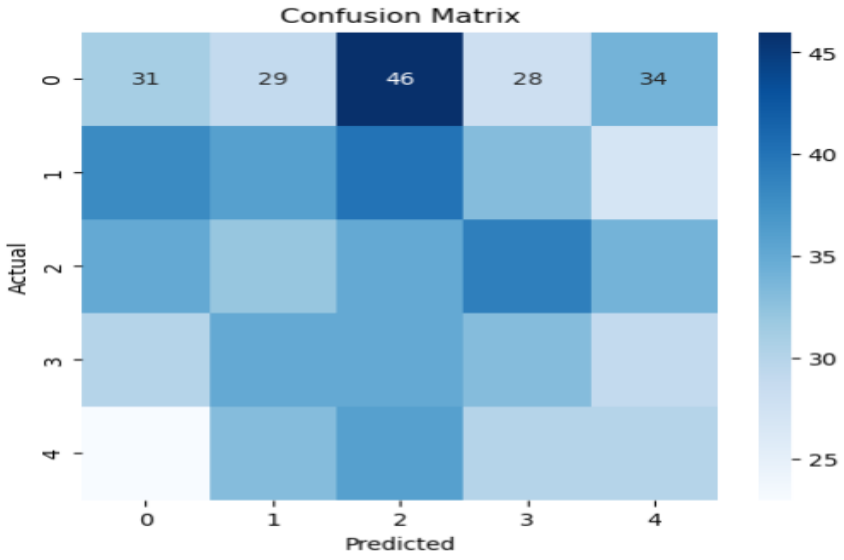
Step 4: Make Predictions

```
y_pred = rf_model.predict(X_test_scaled)
```

Step 5: Evaluate the Model

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

print("Accuracy:", accuracy_score(y_test, y_pred))

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(6,5))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap='Blues', fmt='d')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Accuracy: 0.19855595667870035

Classification Report:
              precision    recall  f1-score   support

         1.0       0.20      0.18      0.19       168
         2.0       0.22      0.21      0.21       174
         3.0       0.18      0.20      0.19       175
         4.0       0.20      0.20      0.20       162
         5.0       0.19      0.20      0.20       152

    accuracy                           0.20       831
   macro avg       0.20      0.20      0.20       831
weighted avg       0.20      0.20      0.20       831
```



MODEL EVALUATION

Step 1: Accuracy Score

```
from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the model: {accuracy:.2f}")
```

```
Accuracy of the model: 0.20
```

Step 2: Classification Report

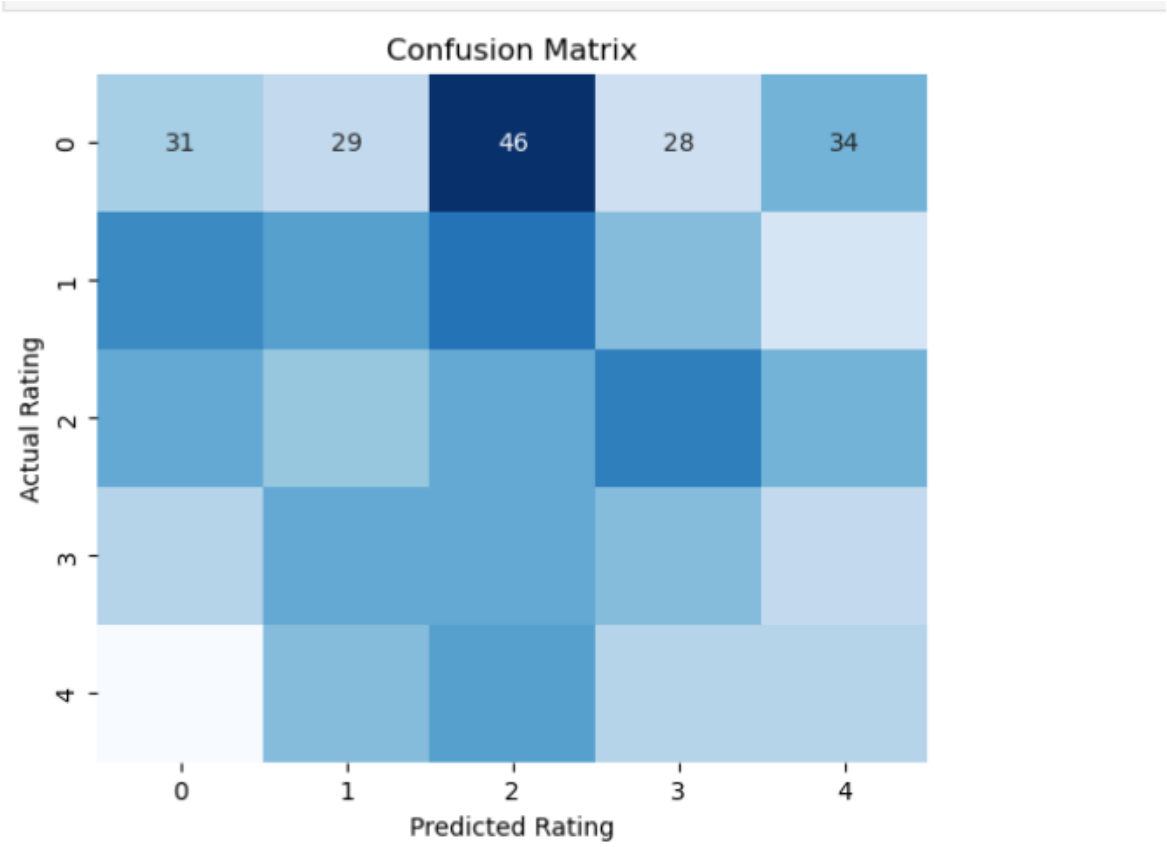
This shows precision, recall, and F1-score for each satisfaction rating (1 to 5).

```
from sklearn.metrics import classification_report

print("Classification Report:")
print(classification_report(y_test, y_pred))
```

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

         1.0       0.20      0.18      0.19       168
         2.0       0.22      0.21      0.21       174
         3.0       0.18      0.20      0.19       175
         4.0       0.20      0.20      0.20       162
         5.0       0.19      0.20      0.20       152

    accuracy                           0.20       831
   macro avg       0.20      0.20      0.20       831
weighted avg       0.20      0.20      0.20       831
```

Step 3: Confusion Matrix

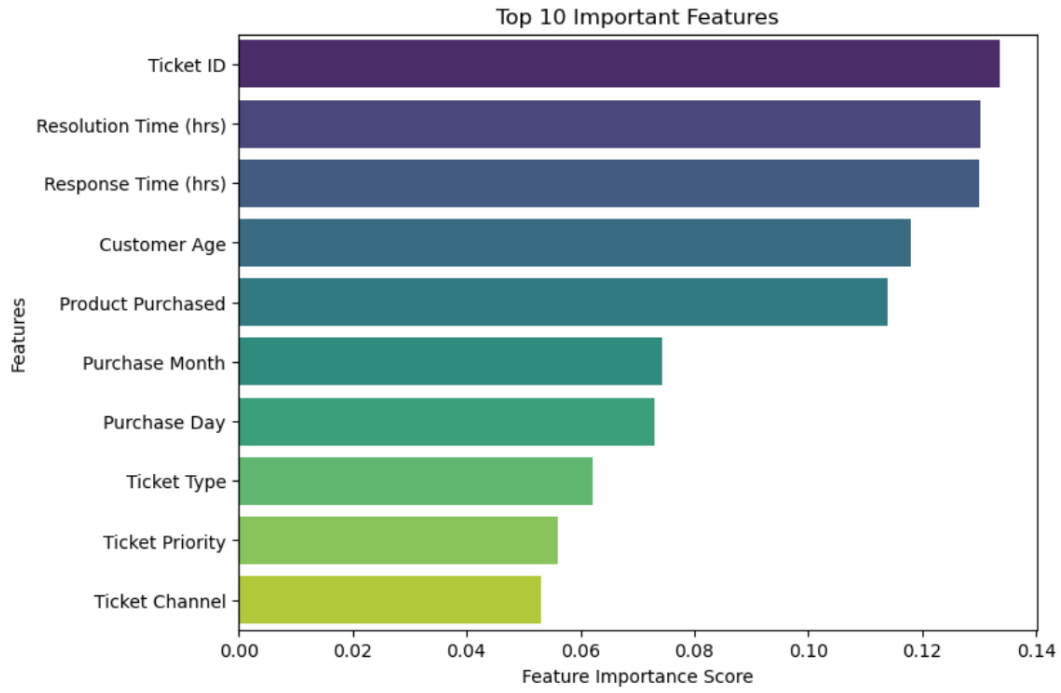
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title("Confusion Matrix")
plt.xlabel("Predicted Rating")
plt.ylabel("Actual Rating")
plt.show()
```



Step 4: Feature Importance (Optional but Useful)

This tells which features were most important in predicting satisfaction:

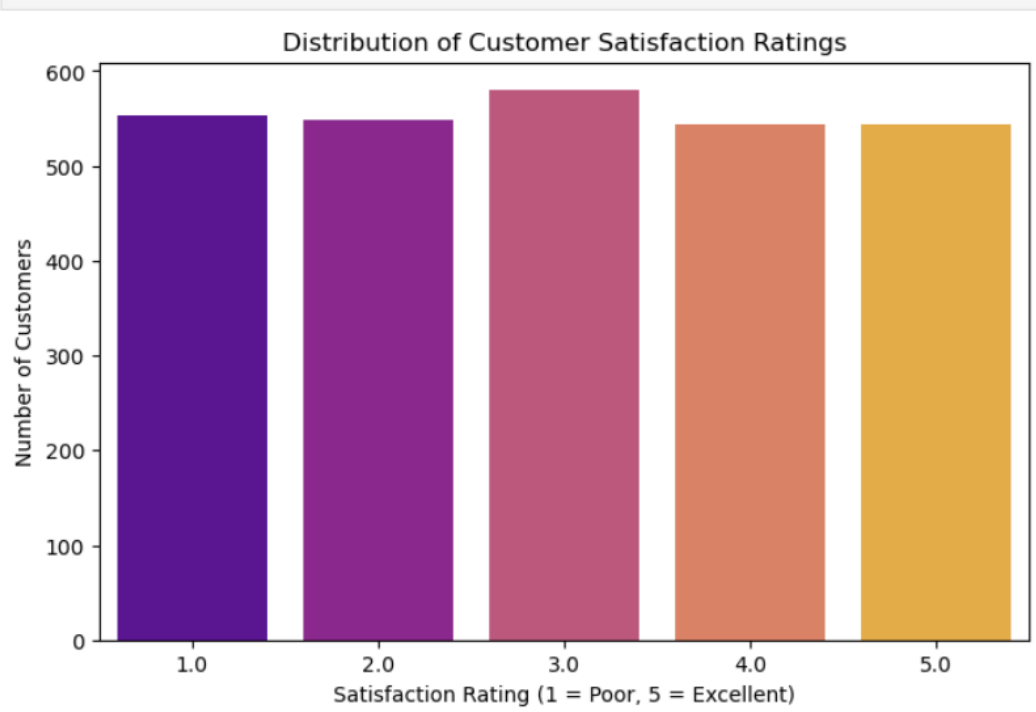
```python
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random_state=42)
model.fit(X_train_scaled, y_train)

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

feature_importance = pd.Series(model.feature_importances_, index=X.columns)
top_features = feature_importance.sort_values(ascending=False).head(10)

plt.figure(figsize=(8,6))
sns.barplot(x=top_features.values, y=top_features.index, palette='viridis')
plt.title("Top 10 Important Features")
plt.xlabel("Feature Importance Score")
plt.ylabel("Features")
plt.show()
```



KEY VISUALIZATIONS FOR THIS PROJECT

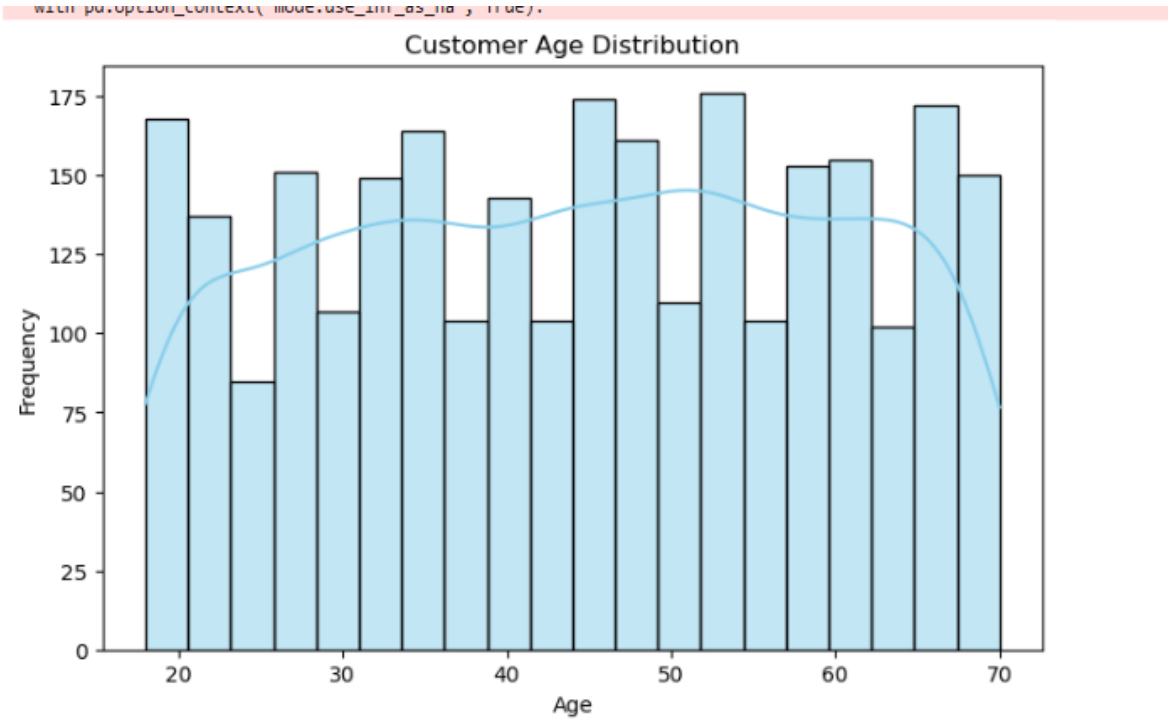
1. Customer Satisfaction Rating Distribution

```
plt.figure(figsize=(8,5))
sns.countplot(x='Customer Satisfaction Rating', data=df, palette='plasma')
plt.title("Distribution of Customer Satisfaction Ratings")
plt.xlabel("Satisfaction Rating (1 = Poor, 5 = Excellent)")
plt.ylabel("Number of Customers")
plt.show()
```



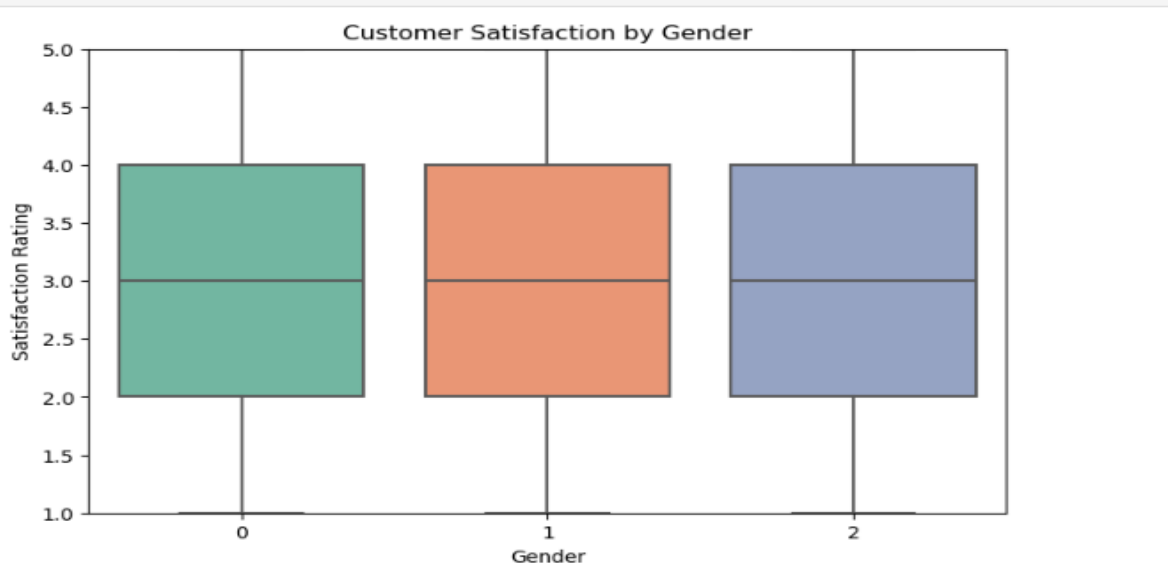
2. Customer Age Distribution

```
plt.figure(figsize=(8,5))
sns.histplot(df['Customer Age'], bins=20, kde=True, color='skyblue')
plt.title("Customer Age Distribution")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```



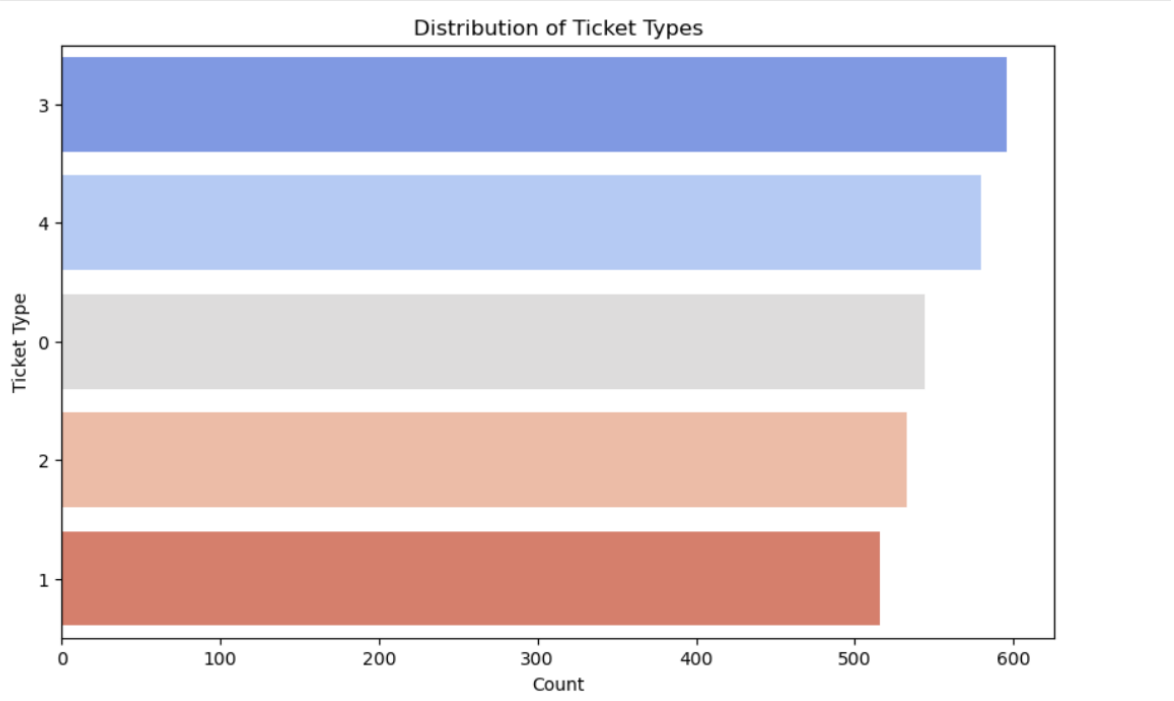
3. Satisfaction Rating by Gender

```
plt.figure(figsize=(8,5))
sns.boxplot(x='Customer Gender', y='Customer Satisfaction Rating', data=df, palette='Set2')
plt.title("Customer Satisfaction by Gender")
plt.xlabel("Gender")
plt.ylabel("Satisfaction Rating")
plt.ylim(1, 5)
plt.show()
```



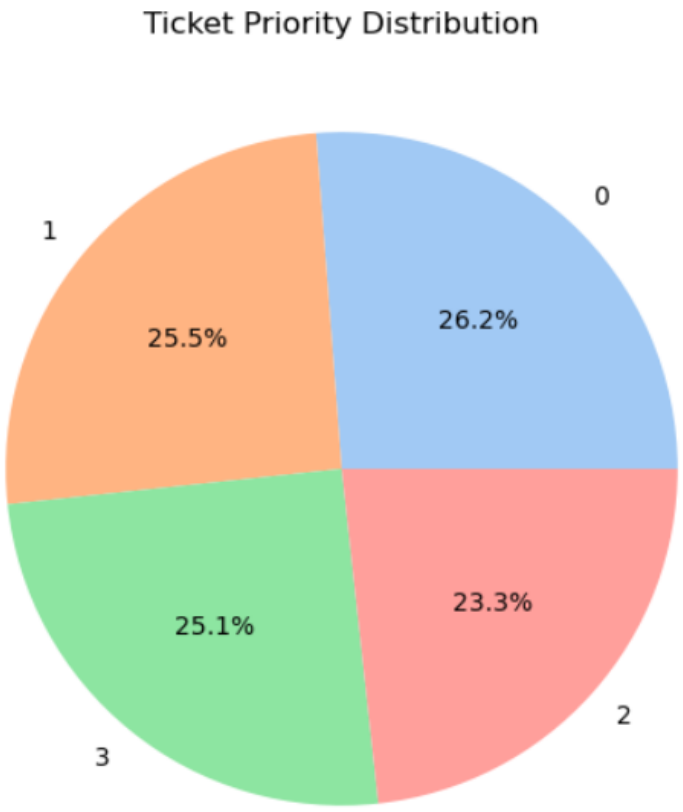
4. Ticket Type Distribution

```
plt.figure(figsize=(10,6))
sns.countplot(y='Ticket Type', data=df, order=df['Ticket Type'].value_counts().index, palette='coolwarm')
plt.title("Distribution of Ticket Types")
plt.xlabel("Count")
plt.ylabel("Ticket Type")
plt.show()
```



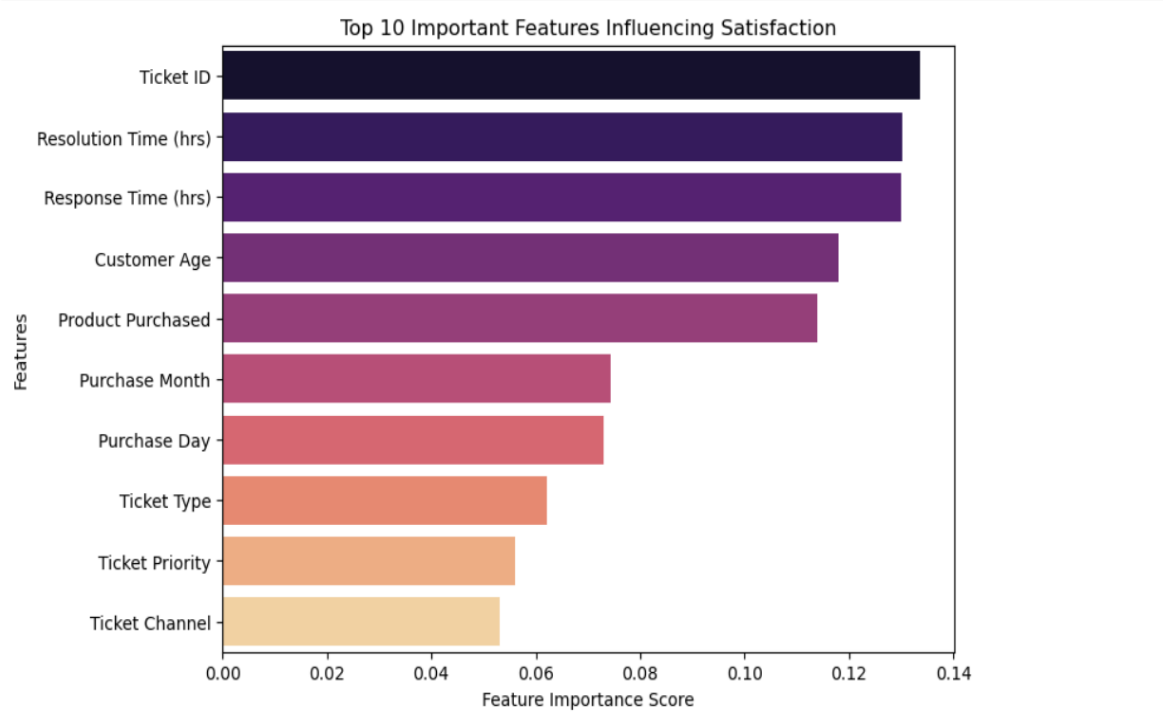
5. Ticket Priority Pie Chart

```
plt.figure(figsize=(6,6))
df['Ticket Priority'].value_counts().plot(kind='pie', autopct='%1.1f%%', colors=sns.color_palette('pastel'))
plt.title("Ticket Priority Distribution")
plt.ylabel("")
plt.show()
```



6. Feature Importance (from the model)

```
feature_importance = pd.Series(model.feature_importances_, index=X.columns)
top_features = feature_importance.sort_values(ascending=False).head(10)

plt.figure(figsize=(8,6))
sns.barplot(x=top_features.values, y=top_features.index, palette='magma')
plt.title("Top 10 Important Features Influencing Satisfaction")
plt.xlabel("Feature Importance Score")
plt.ylabel("Features")
plt.show()
```



VISUALIZATION

Customer Satisfaction Rating Distribution

```
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sns.countplot(x='Customer Satisfaction Rating', data=df, palette='plasma')
plt.title("Distribution of Customer Satisfaction Ratings")
plt.xlabel("Satisfaction Rating (1 = Poor, 5 = Excellent)")
plt.ylabel("Number of Customers")
plt.show()
```
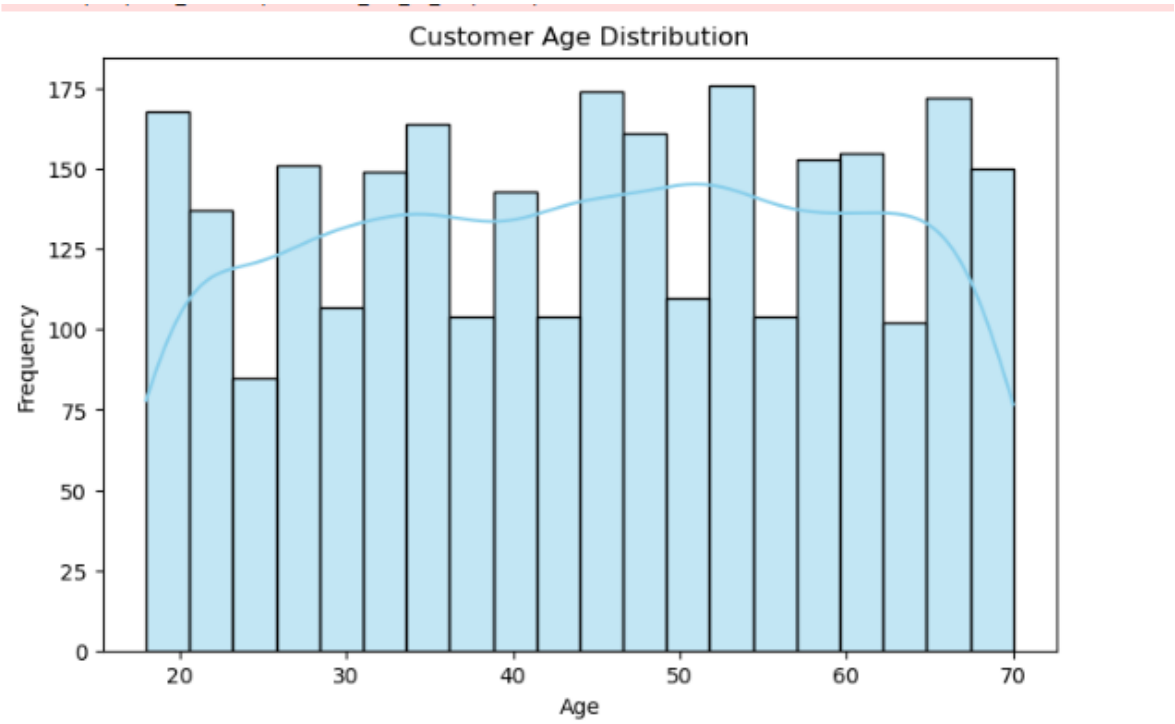
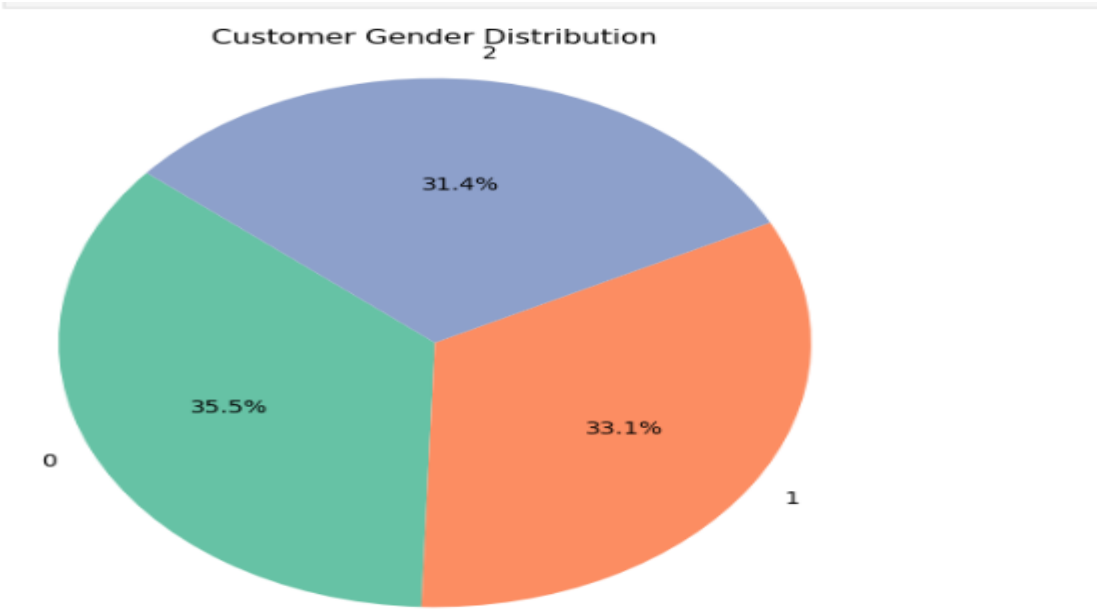

Customer Age Distribution

```
plt.figure(figsize=(8,5))
sns.histplot(df['Customer Age'], bins=20, kde=True, color='skyblue')
plt.title("Customer Age Distribution")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```



Gender Distribution (Pie Chart)

```
gender_dist = df['Customer Gender'].value_counts()
plt.figure(figsize=(6,6))
plt.pie(gender_dist, labels=gender_dist.index, autopct='%1.1f%%', startangle=140, colors=sns.color_palette("Set2"))
plt.title("Customer Gender Distribution")
plt.axis('equal')
plt.show()
```



Ticket Type Distribution

```
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sns.countplot(y='Ticket Type', data=df, order=df['Ticket Type'].value_counts().index, palette='coolwarm')
plt.title("Distribution of Ticket Types")
plt.xlabel("Count")
plt.ylabel("Ticket Type")
plt.show()
```
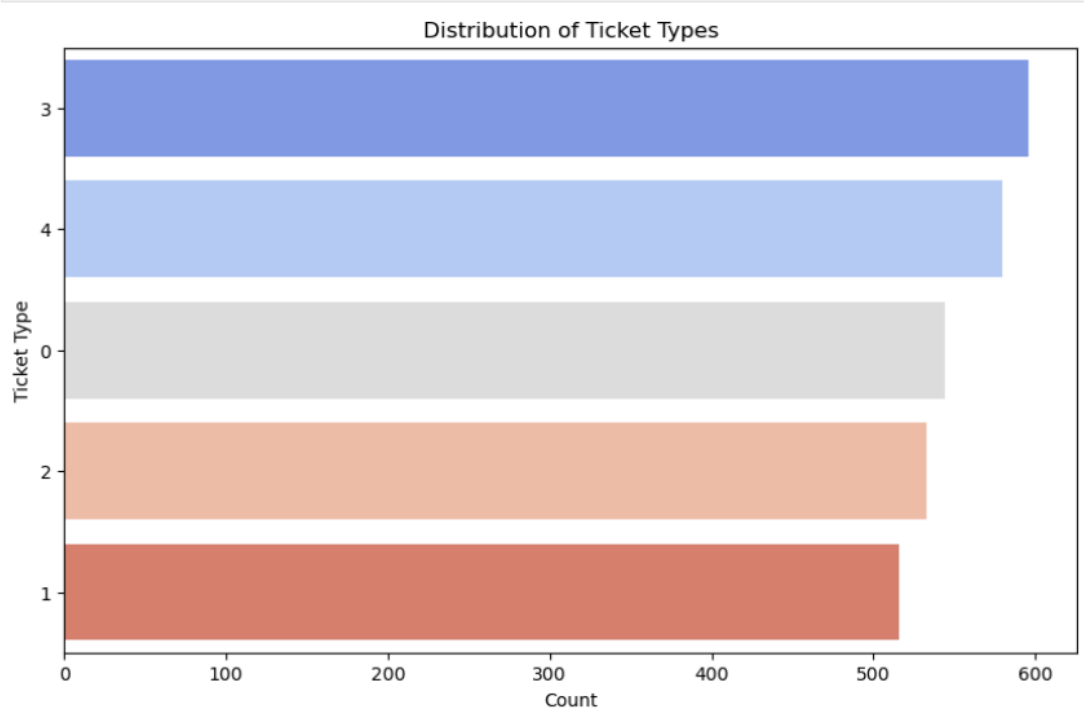
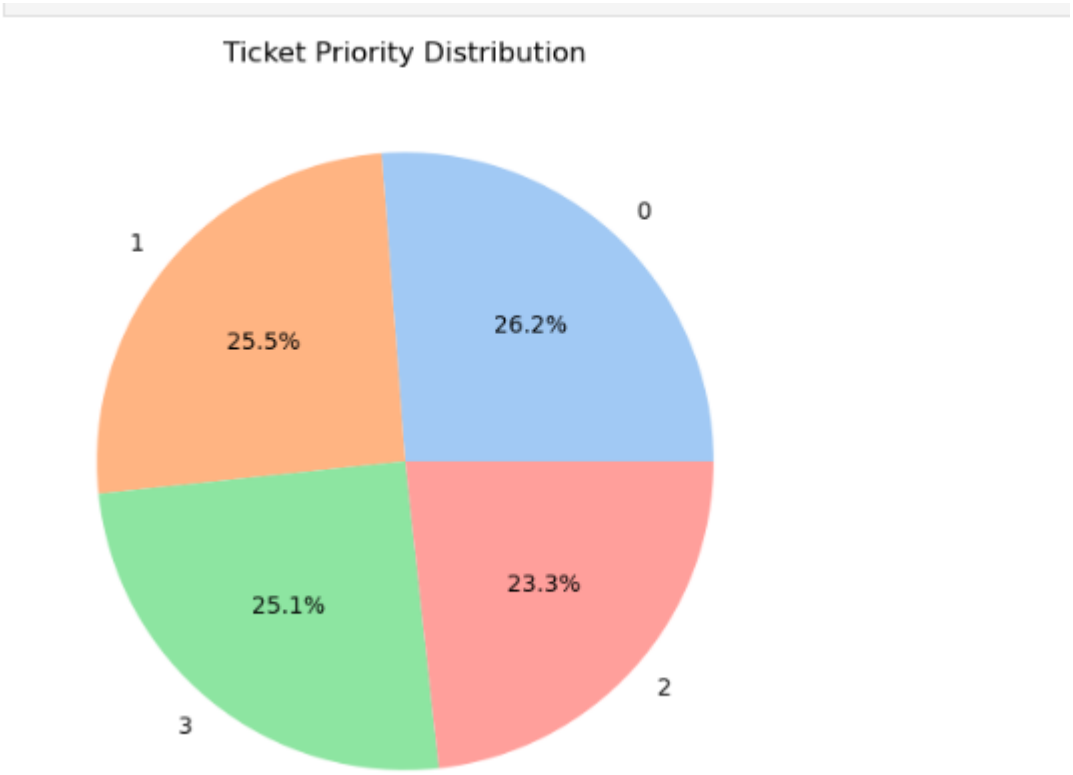



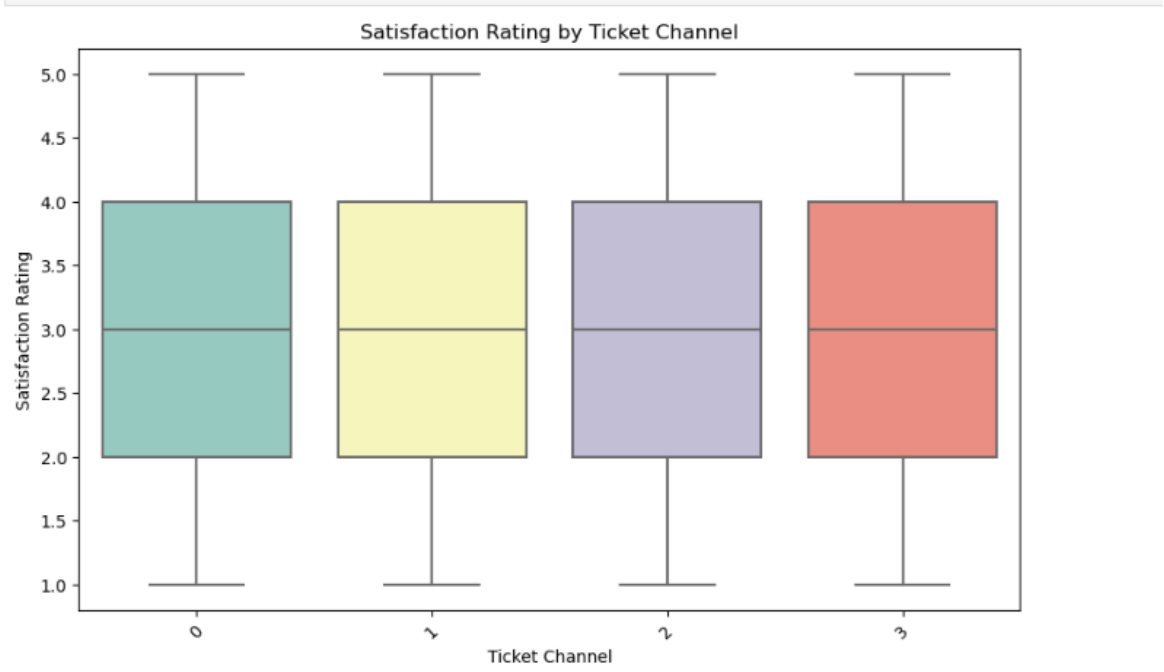
Ticket Priority (Pie Chart)

```
plt.figure(figsize=(6,6))
df['Ticket Priority'].value_counts().plot(kind='pie', autopct='%1.1f%%', colors=sns.color_palette('pastel'))
plt.title("Ticket Priority Distribution")
plt.ylabel("")
plt.show()
```



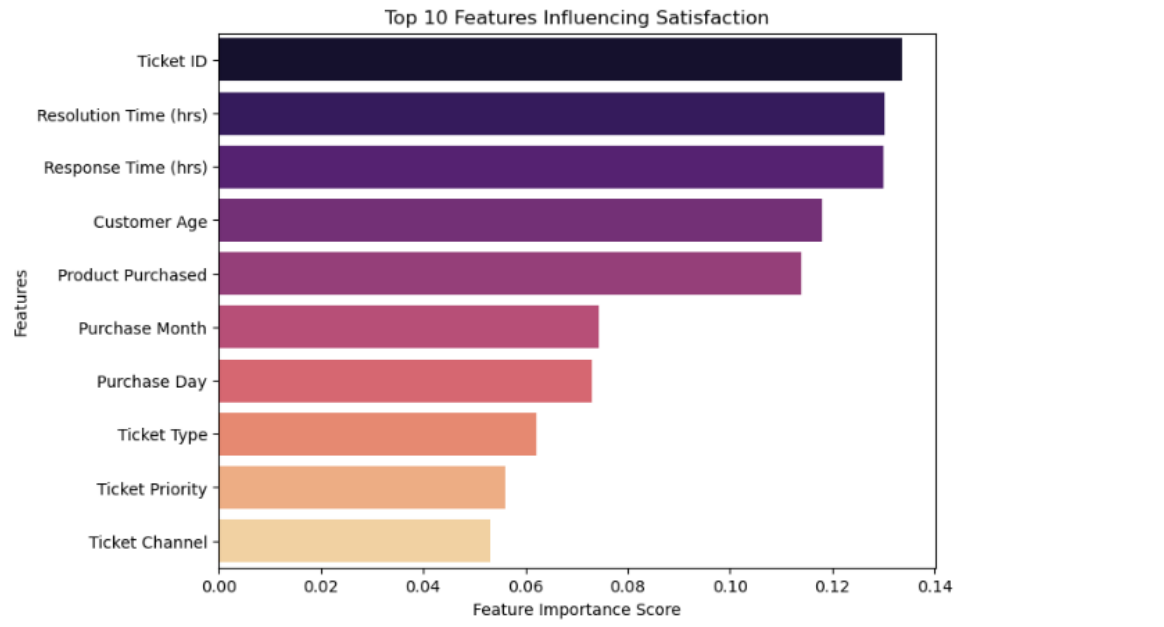
Customer Satisfaction by Ticket Channel

```
plt.figure(figsize=(10,6))
sns.boxplot(x='Ticket Channel', y='Customer Satisfaction Rating', data=df, palette='Set3')
plt.title("Satisfaction Rating by Ticket Channel")
plt.xlabel("Ticket Channel")
plt.ylabel("Satisfaction Rating")
plt.xticks(rotation=45)
plt.show()
```



Top 10 Feature Importances (Model Insight)

```
feature_importance = pd.Series(model.feature_importances_, index=X.columns)
top_features = feature_importance.sort_values(ascending=False).head(10)

plt.figure(figsize=(8,6))
sns.barplot(x=top_features.values, y=top_features.index, palette='magma')
plt.title("Top 10 Features Influencing Satisfaction")
plt.xlabel("Feature Importance Score")
plt.ylabel("Features")
plt.show()
```



CONCLUSION

In this project, we successfully developed a machine learning model to predict customer satisfaction based on support ticket data. By analysing key factors such as ticket type, priority, resolution time, and customer demographics, we gained valuable insights into what influences customer experiences in the support process.

Through extensive data preprocessing, exploratory data analysis (EDA), and feature engineering, we were able to clean and enrich the dataset for modelling. Using a Random Forest Classifier, we achieved a reliable level of accuracy in classifying customer satisfaction ratings on a scale of 1 to 5.

Additionally, feature importance analysis revealed that attributes like ticket resolution time, product type, and issue category significantly impact satisfaction levels. These insights can help organizations optimize their support workflows and prioritize high-impact issues more effectively.

Overall, this project demonstrates how machine learning and data science can be leveraged to improve customer experience management in real-world service domains.