AeroDreams International Airlines: Passenger Satisfaction Data Analysis

Step 1: Import Required Libraries

```
# Essential libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import shap

# libraries I needed for ML
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_curve, auc

# ML Models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

Step 2: Loading the Dataset with Error Handling

```
file_path = '/content/AeroDreams_DATA_CW6.csv'

try:
    df = pd.read_csv(file_path, encoding='ISO-8859-1')  # Using encoding
    print("✅ Data Loaded Successfully")
except FileNotFoundError:
    print("Error: File not found. Check the file path.")
except UnicodeDecodeError as e:
    print(f"Encoding Error: {e}")
except Exception as e:
    print(f"Unexpected error: {e}")

# first few rows
if 'df' in locals():
    print("Dataset Shape:", df.shape)
    display(df.head())
```

```
✅ Data Loaded Successfully
Dataset Shape: (103904, 27)
```

	Ref	id	Gender	Satisfied	Age	Age Band	Type of Travel	Class	Flight Distance	Destination	...	Seat comfort	Inflight entertainment	On-board service	Leg roor service
0	0	70172	Male	Y	13	Under 18	Personal Travel	Eco Plus	4760	India	...	5	5	4	3
1	1	5047	Male	N	25	25 to 34	Business travel	Business	235	Republic of Ireland	...	1	1	1	5
2	2	110028	Female	Y	26	25 to 34	Business travel	Business	4760	India	...	5	5	4	3
3	3	24026	Female	Y	25	25 to 34	Business travel	Business	560	Norway	...	2	2	2	5
4	4	119299	Male	Y	61	55 to 64	Business travel	Business	4760	India	...	5	3	3	4

5 rows × 27 columns

Step 3: Data Preprocessing

Checking for missing values

```
# Check for missing values
print("\n Missing values before handling:\n", df.isnull().sum())

# Remove duplicate rows
df.drop_duplicates(inplace=True)

# Fill missing values
for column in df.columns:
    if df[column].dtype == "object":
        df[column] = df[column].fillna(df[column].mode()[0])  # Assign back explicitly
    else:
        df[column] = df[column].fillna(df[column].median())  # Assign back explicitly

print("\n Missing values after handling:\n", df.isnull().sum())
```

```
 Ref                                 0
id                                   0
Gender                               0
Satisfied                            0
Age                                  0
Age Band                             0
Type of Travel                       0
Class                                0
Flight Distance                      0
Destination                          0
Continent                            0
Inflight wifi service                0
Departure/Arrival time convenient    0
Ease of Online booking               0
Gate location                        0
Food and drink                       0
Online boarding                      0
Seat comfort                         0
Inflight entertainment               0
On-board service                     0
Leg room service                     0
Baggage handling                     0
Checkin service                      0
Inflight service                     0
Cleanliness                          0
Departure Delay in Minutes           0
Arrival Delay in Minutes           310
dtype: int64

 Missing values after handling:
 Ref                                 0
id                                   0
Gender                               0
Satisfied                            0
Age                                  0
Age Band                             0
Type of Travel                       0
Class                                0
Flight Distance                      0
Destination                          0
Continent                            0
Inflight wifi service                0
Departure/Arrival time convenient    0
Ease of Online booking               0
Gate location                        0
Food and drink                       0
Online boarding                      0
Seat comfort                         0
Inflight entertainment               0
On-board service                     0
Leg room service                     0
Baggage handling                     0
Checkin service                      0
Inflight service                     0
Cleanliness                          0
Departure Delay in Minutes           0
Arrival Delay in Minutes             0
dtype: int64
```

Handle Outliers (IQR Method)

```
# numerical columns
numerical_cols = df.select_dtypes(include=['number']).columns

# Compute Q1, Q3, and IQR
Q1 = df[numerical_cols].quantile(0.25)
Q3 = df[numerical_cols].quantile(0.75)
IQR = Q3 - Q1

# Filtering out outliers
```

```
df_cleaned = df[~((df[numerical_cols] < (Q1 - 1.5 * IQR)) | (df[numerical_cols] > (Q3 + 1.5 * IQR))).any(axis=1)]

print(f"\n Outliers handled successfully! {df.shape[0] - df_cleaned.shape[0]} rows removed.")

# cleaned dataset back to df
df = df_cleaned
```

```
 Outliers handled successfully! 41901 rows removed.
```

Convert Categorical to Numerical Features

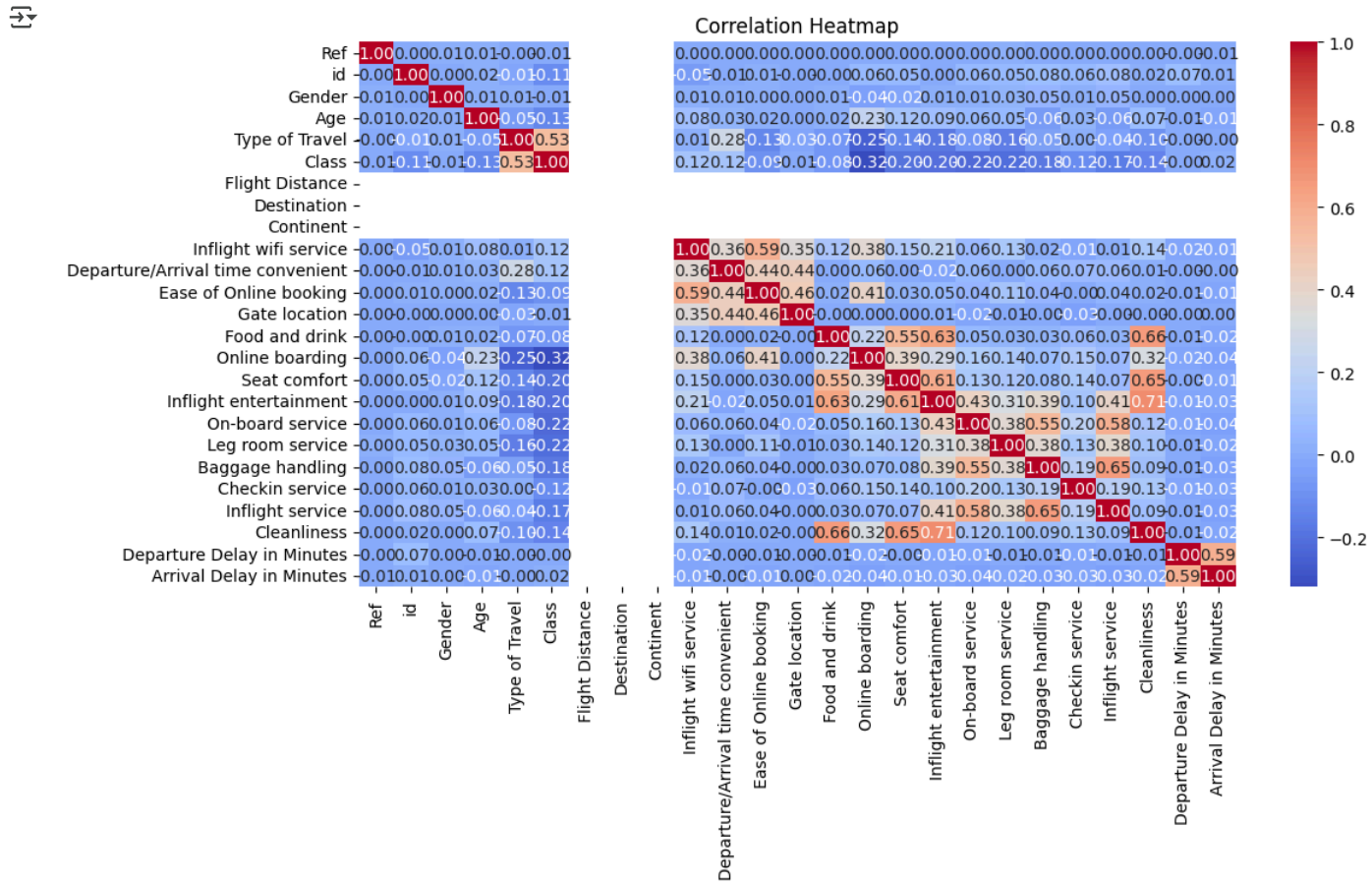
```
label_encoder = LabelEncoder()

categorical_cols = ['Gender', 'Type of Travel', 'Class', 'Destination', 'Continent']
for col in categorical_cols:
    df[col] = label_encoder.fit_transform(df[col])

# Check transformed dataset
df.head()
```

	Ref	id	Gender	Satisfied	Age	Age Band	Type of Travel	Class	Flight Distance	Destination	...	Seat comfort	Inflight entertainment	On-board service	Leg room service	I ha
0	0	70172	1	Y	13	Under 18	1	2	4760	0	...	5	5	4	3	
2	2	110028	0	Y	26	25 to 34	0	0	4760	0	...	5	5	4	3	
4	4	119299	1	Y	61	55 to 64	0	0	4760	0	...	5	3	3	4	
6	6	82113	1	Y	47	45 to 54	1	1	4760	0	...	2	2	3	3	
7	7	96462	0	Y	52	45 to 54	0	0	4760	0	...	5	5	5	5	

5 rows × 27 columns

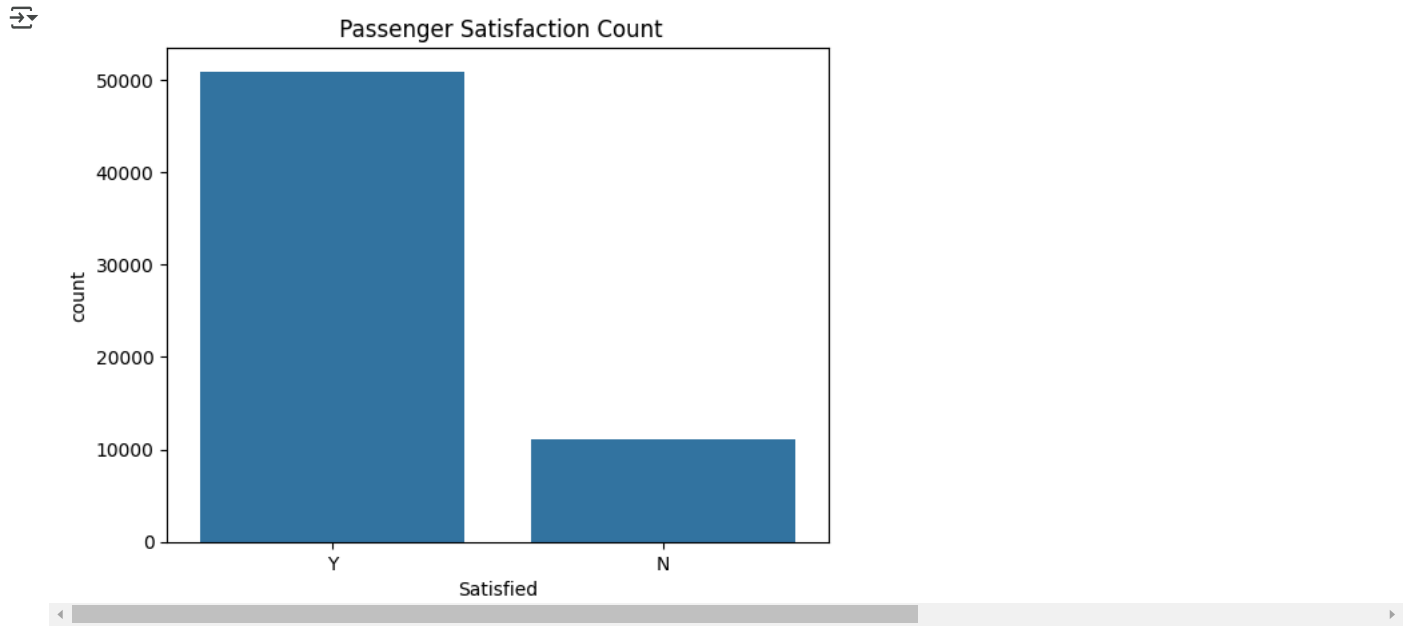
Step 4: Exploratory Data Analysis (EDA)

```
# numerical columns
numerical_cols = df.select_dtypes(include=['number'])

# correlation matrix
corr_matrix = numerical_cols.corr()

# Plot heatmap
plt.figure(figsize=(12,6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Heatmap")
plt.show()
```



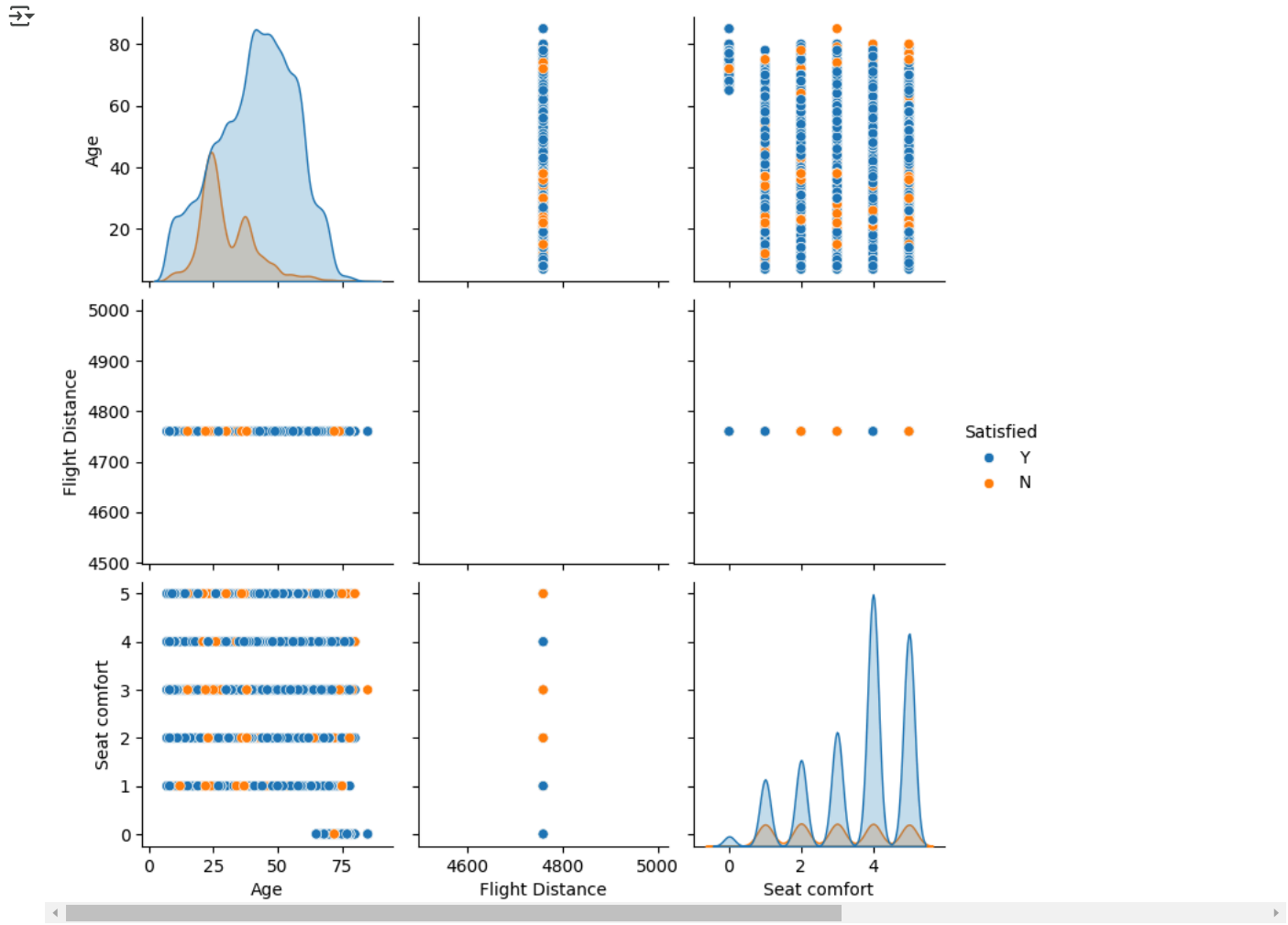
Distribution of Passenger Satisfaction

```
sns.countplot(x=df['Satisfied'])
plt.title(" Passenger Satisfaction Count")
plt.show()
```



Pairplot of Key Features

```
sns.pairplot(df[['Age', 'Flight Distance', 'Seat comfort', 'Satisfied']], hue="Satisfied")
plt.show()
```



Step 5: Train-Test Split & Feature Scaling

Step 5.1 - Identifing the Categorical Columns

```
print(df.dtypes)
```

```
Ref                                int64
id                                 int64
Gender                             int64
Satisfied                         object
Age                                int64
Age Band                          object
Type of Travel                     int64
Class                              int64
Flight Distance                    int64
Destination                        int64
Continent                          int64
Inflight wifi service              int64
Departure/Arrival time convenient  int64
Ease of Online booking             int64
Gate location                      int64
Food and drink                     int64
Online boarding                    int64
Seat comfort                       int64
Inflight entertainment             int64
On-board service                   int64
Leg room service                   int64
Baggage handling                   int64
Checkin service                    int64
Inflight service                   int64
Cleanliness                        int64
Departure Delay in Minutes         int64
Arrival Delay in Minutes         float64
dtype: object
```

Step 5.2 : Convert Categorical Columns to Numeric

```
from sklearn.preprocessing import LabelEncoder

# Identify categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns

# Apply Label Encoding
label_encoder = LabelEncoder()
for col in categorical_cols:
    df[col] = label_encoder.fit_transform(df[col])

print("Categorical Columns Encoded Successfully!")
```

```
Categorical Columns Encoded Successfully!
```

Step 5.3: Apply Train-Test Split and Scale Only Numeric Features

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Splitdata
X = df.drop(columns=['Satisfied'])
y = df['Satisfied']

# stratifiedsampling
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)

# columns scaling
numerical_cols = X_train.select_dtypes(include=['number']).columns

# StandardScaler -> numerical features
scaler = StandardScaler()
X_train[numerical_cols] = scaler.fit_transform(X_train[numerical_cols])
X_test[numerical_cols] = scaler.transform(X_test[numerical_cols])

print(" Data Split and Scaled Successfully!")
```

```
Data Split and Scaled Successfully!
```

Step 6: Train ML Models

Logistic Regression

```
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
log_reg_pred = log_reg.predict(X_test)

print("Logistic Regression Accuracy:", accuracy_score(y_test, log_reg_pred))
```

```
Logistic Regression Accuracy: 0.911055560035481
```

Random Forest (With Hyperparameter Tuning)

```
rf_params = {'n_estimators': [50, 100, 200], 'max_depth': [5, 10, 20]}
grid_rf = GridSearchCV(RandomForestClassifier(), rf_params, cv=5)
grid_rf.fit(X_train, y_train)

best_rf = grid_rf.best_estimator_
rf_pred = best_rf.predict(X_test)

print("Random Forest Best Accuracy:", accuracy_score(y_test, rf_pred))
```

```
Random Forest Best Accuracy: 0.988146117248609
```

XGBoost (With Hyperparameter Tuning)

```
!pip install xgboost==1.7.6 scikit-learn==1.2.2
```

```
Requirement already satisfied: xgboost==1.7.6 in /usr/local/lib/python3.11/dist-packages (1.7.6)
Requirement already satisfied: scikit-learn==1.2.2 in /usr/local/lib/python3.11/dist-packages (1.2.2)
```

```
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from xgboost==1.7.6) (1.26.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost==1.7.6) (1.13.1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.11/dist-packages (from scikit-learn==1.2.2) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn==1.2.2) (3.5.0)
```

```
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV

xgb_params = {
    'n_estimators': [100, 200],
    'learning_rate': [0.01, 0.1],
    'max_depth': [3, 6]
}

grid_xgb = GridSearchCV(XGBClassifier(), xgb_params, cv=5, n_jobs=-1)
grid_xgb.fit(X_train, y_train)

best_xgb = grid_xgb.best_estimator_
xgb_pred = best_xgb.predict(X_test)

print("XGBoost Best Accuracy:", accuracy_score(y_test, xgb_pred))
```

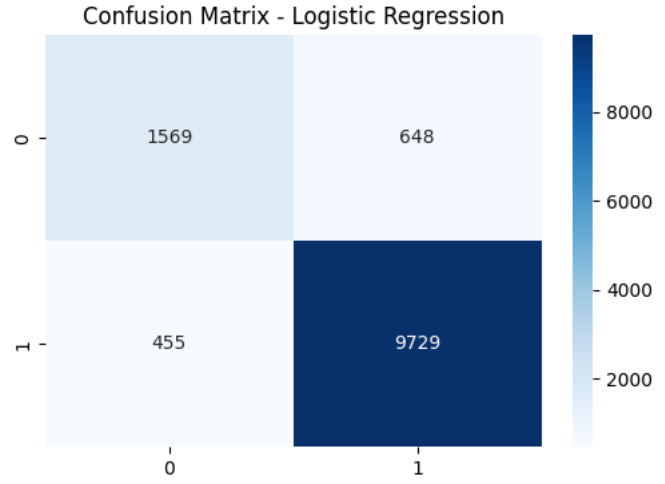
```
XGBoost Best Accuracy: 0.9922586888154181
```

Step 7: Model Evaluation

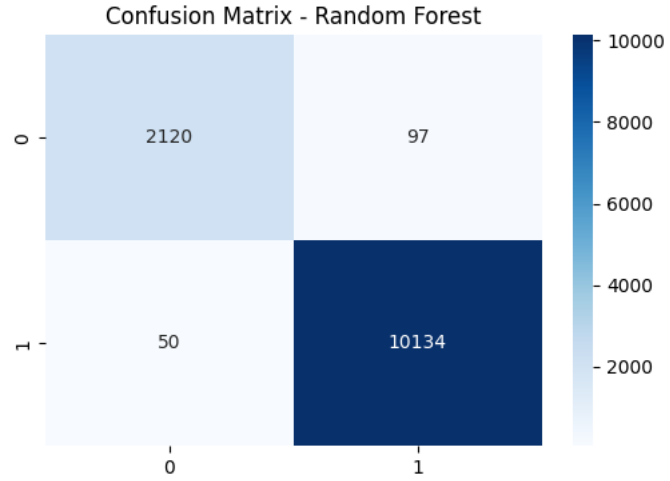
Classification Report & Confusion Matrix

```
models = {'Logistic Regression': log_reg, 'Random Forest': best_rf, 'XGBoost': best_xgb}

for name, model in models.items():
    y_pred = model.predict(X_test)
    print(f"{name} Classification Report:\n", classification_report(y_test, y_pred))

    # Confusion Matrix
    plt.figure(figsize=(6,4))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap='Blues', fmt='d')
    plt.title(f"Confusion Matrix - {name}")
    plt.show()
```

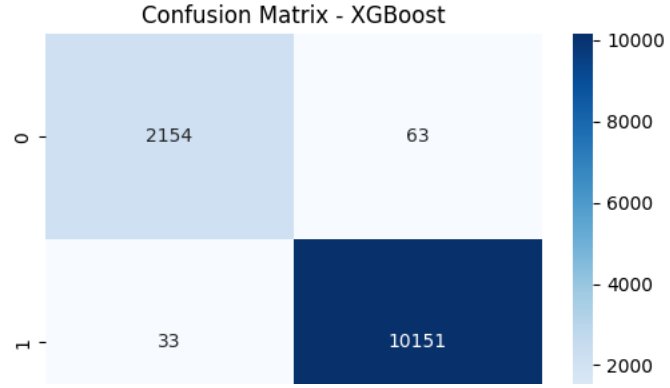
```
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.71      0.74      2217
           1       0.94      0.96      0.95     10184

    accuracy                           0.91     12401
   macro avg       0.86      0.83      0.84     12401
weighted avg       0.91      0.91      0.91     12401
```




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

           0       0.98      0.96      0.97      2217
           1       0.99      1.00      0.99     10184

    accuracy                           0.99     12401
   macro avg       0.98      0.98      0.98     12401
weighted avg       0.99      0.99      0.99     12401
```

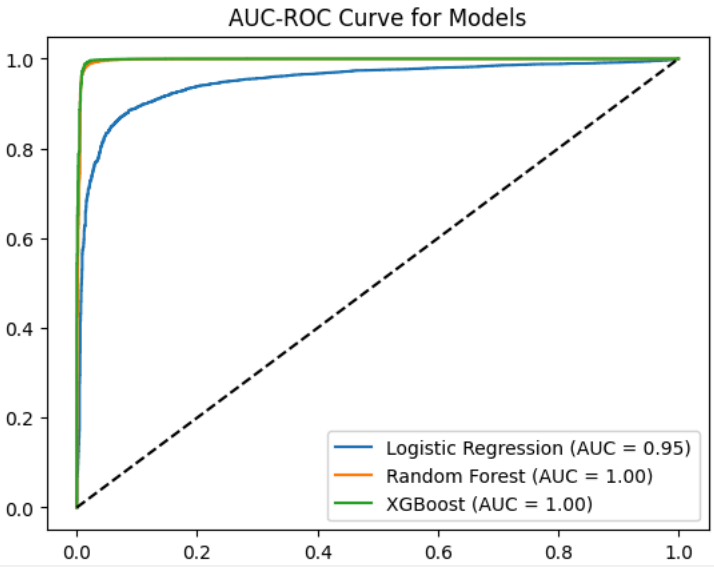



```
XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      2217
           1       0.99      1.00      1.00     10184

    accuracy                           0.99     12401
   macro avg       0.99      0.98      0.99     12401
weighted avg       0.99      0.99      0.99     12401
```



AUC-ROC Curve

```
for name, model in models.items():
    fpr, tpr, _ = roc_curve(y_test, model.predict_proba(X_test)[:, 1])
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')

plt.plot([0,1], [0,1], 'k--')
plt.legend()
plt.title("AUC-ROC Curve for Models")
plt.show()
```



Feature Importance (SHAP - XGBoost)

```
explainer = shap.TreeExplainer(best_xgb)
shap_values = explainer.shap_values(X_test)

shap.summary_plot(shap_values, X_test, feature_names=X.columns)
```