1. Business Understanding

Objective: To predict whether a wine is of good quality based on its physicochemical properties.

Target Variable: Wine quality (binary classification: quality ≥ 6 as "good", else "not good").

2. Data Collection and Preparation

2.1 Data Collection

In [1]:
```
import pandas as pd
import numpy as np

# Load the dataset
file_path = 'Red wine Quality.csv'
data = pd.read_csv(file_path)
data.head()
```

Out[1]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4

2.2 Initial Data Assessment

In [2]:
```
# Check the shape of the dataset
print(f"Dataset shape: {data.shape}")
```

```
Dataset shape: (1599, 12)
```

In [3]:
```
# Check for missing values
print(data.isnull().sum())
```

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

In [4]:
```
# Summary statistics
print(data.describe())
```

```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    1599.000000       1599.000000  1599.000000     1599.000000
mean        8.319637          0.527821     0.270976        2.538806
std         1.741096          0.179060     0.194801        1.409928
min         4.600000          0.120000     0.000000        0.900000
25%         7.100000          0.390000     0.090000        1.900000
50%         7.900000          0.520000     0.260000        2.200000
75%         9.200000          0.640000     0.420000        2.600000
max        15.900000          1.580000     1.000000       15.500000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  1599.000000          1599.000000           1599.000000  1599.000000
mean      0.087467            15.874922             46.467792     0.996747
std       0.047065            10.460157             32.895324     0.001887
min       0.012000             1.000000              6.000000     0.990070
25%       0.070000             7.000000             22.000000     0.995600
50%       0.079000            14.000000             38.000000     0.996750
75%       0.090000            21.000000             62.000000     0.997835
max       0.611000            72.000000            289.000000     1.003690

                pH    sulphates      alcohol      quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean      3.311113     0.658149    10.422983     5.636023
std       0.154386     0.169507     1.065668     0.807569
min       2.740000     0.330000     8.400000     3.000000
25%       3.210000     0.550000     9.500000     5.000000
50%       3.310000     0.620000    10.200000     6.000000
75%       3.400000     0.730000    11.100000     6.000000
max       4.010000     2.000000    14.900000     8.000000
```

In [5]:
```
# Check target variable distribution
print(data['quality'].value_counts())
```

```
5    681
6    638
7    199
4     53
8     18
3     10
Name: quality, dtype: int64
```

2.3 Data Preprocessing

In [6]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder
from sklearn.impute import SimpleImputer

# Define target variable
# Assuming 'quality' is the target, converting it to binary classification
# e.g., quality >=7 as 'good' and <7 as 'not good'
data['quality_label'] = data['quality'].apply(lambda x: 1 if x >= 7 else 0)

# Drop original 'quality' if not needed
data = data.drop('quality', axis=1)


# Check for missing values again
print(data.isnull().sum())

# Feature scaling
```

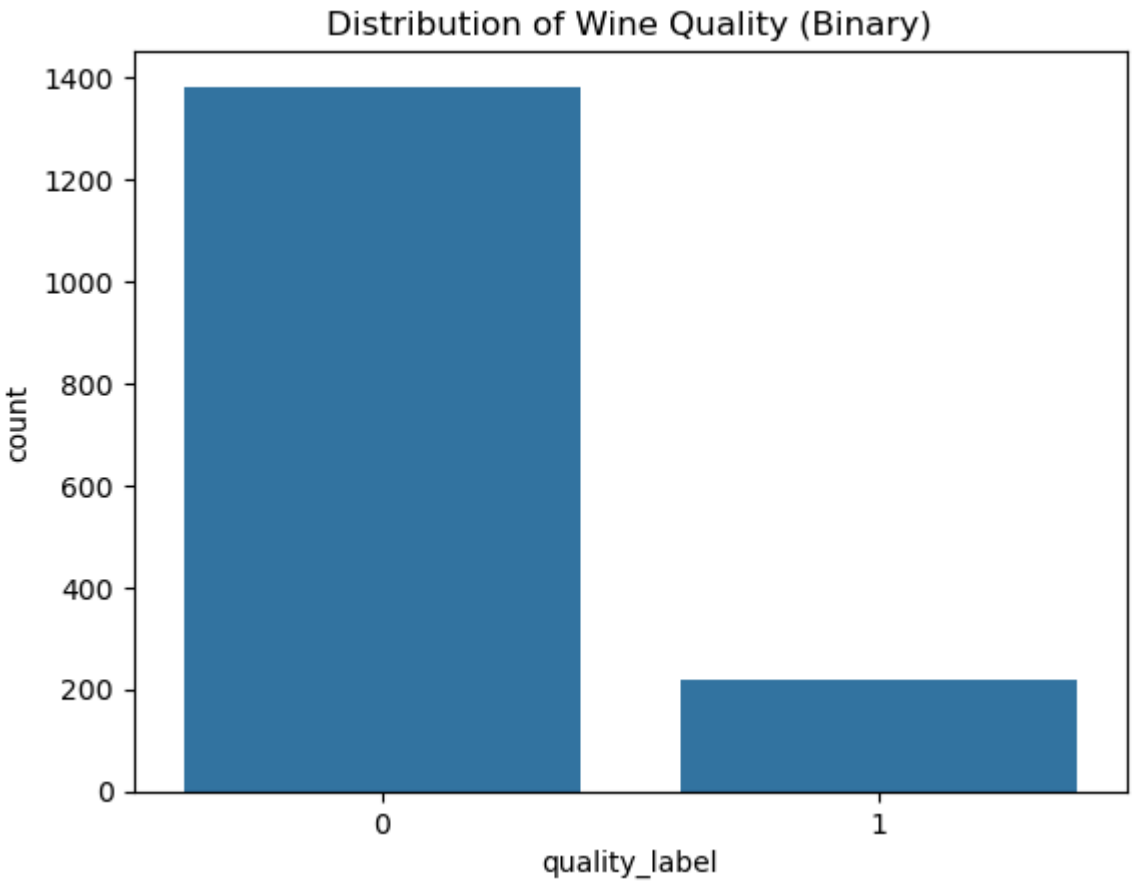
```
features = data.drop('quality_label', axis=1).columns
scaler = StandardScaler()
data[features] = scaler.fit_transform(data[features])

# Verify scaling
print(data.head())
```

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality_label           0
dtype: int64
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0      -0.528360          0.961877    -1.391472       -0.453218  -0.243707
1      -0.298547          1.967442    -1.391472        0.043416   0.223875
2      -0.298547          1.297065    -1.186070       -0.169427   0.096353
3       1.654856         -1.384443     1.484154       -0.453218  -0.264960
4      -0.528360          0.961877    -1.391472       -0.453218  -0.243707

   free sulfur dioxide  total sulfur dioxide   density        pH  sulphates  \
0            -0.466193             -0.379133  0.558274  1.288643  -0.579207
1             0.872638              0.624363  0.028261 -0.719933   0.128950
2            -0.083669              0.229047  0.134264 -0.331177  -0.048089
3             0.107592              0.411500  0.664277 -0.979104  -0.461180
4            -0.466193             -0.379133  0.558274  1.288643  -0.579207

    alcohol  quality_label
0 -0.960246              0
1 -0.584777              0
2 -0.584777              0
3 -0.584777              0
4 -0.960246              0
```

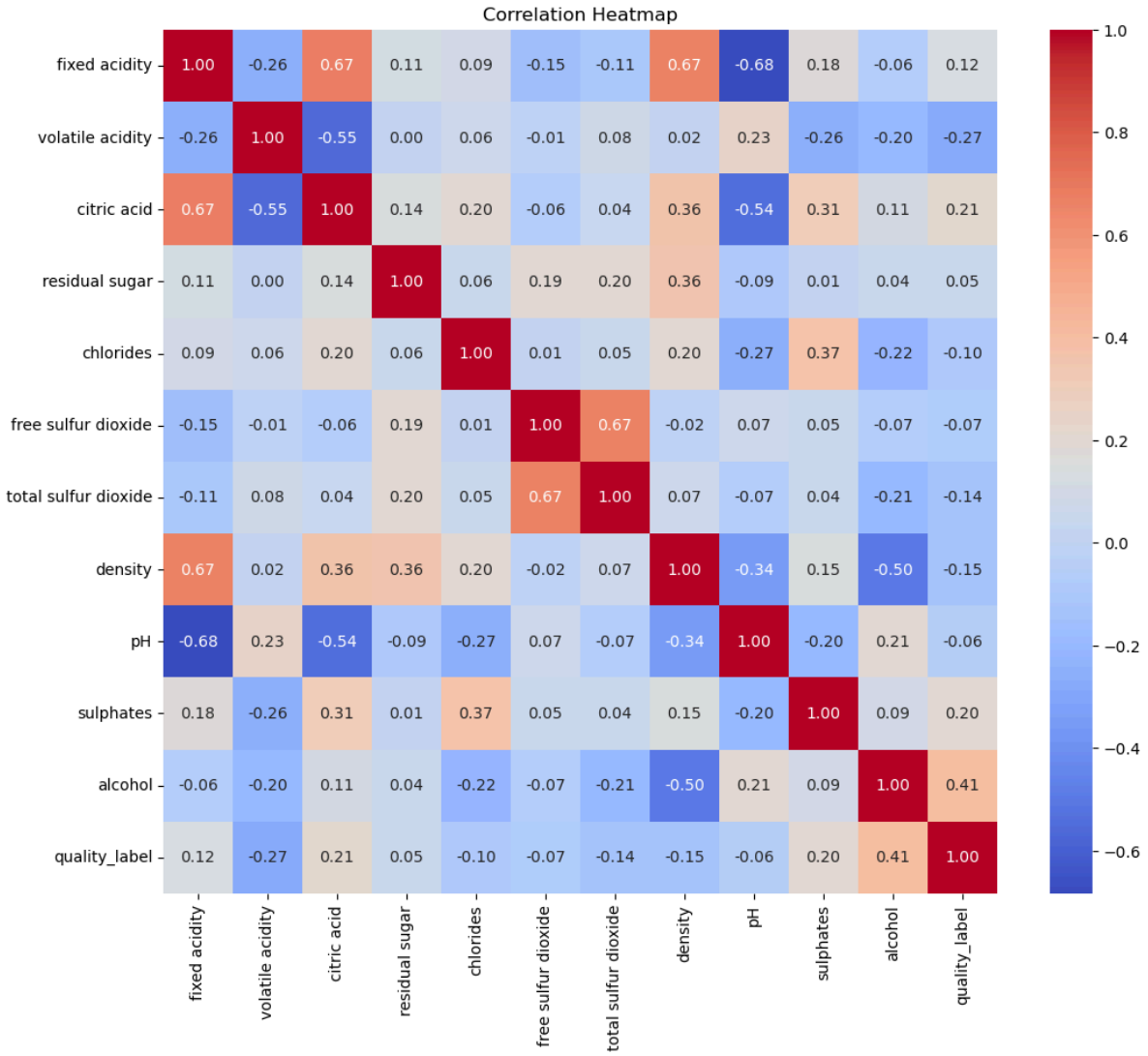
3. Exploratory Data Analysis (EDA)

In [7]:

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

# Distribution of target variable
sns.countplot(x='quality_label', data=data)
plt.title('Distribution of Wine Quality (Binary)')
plt.show()
```

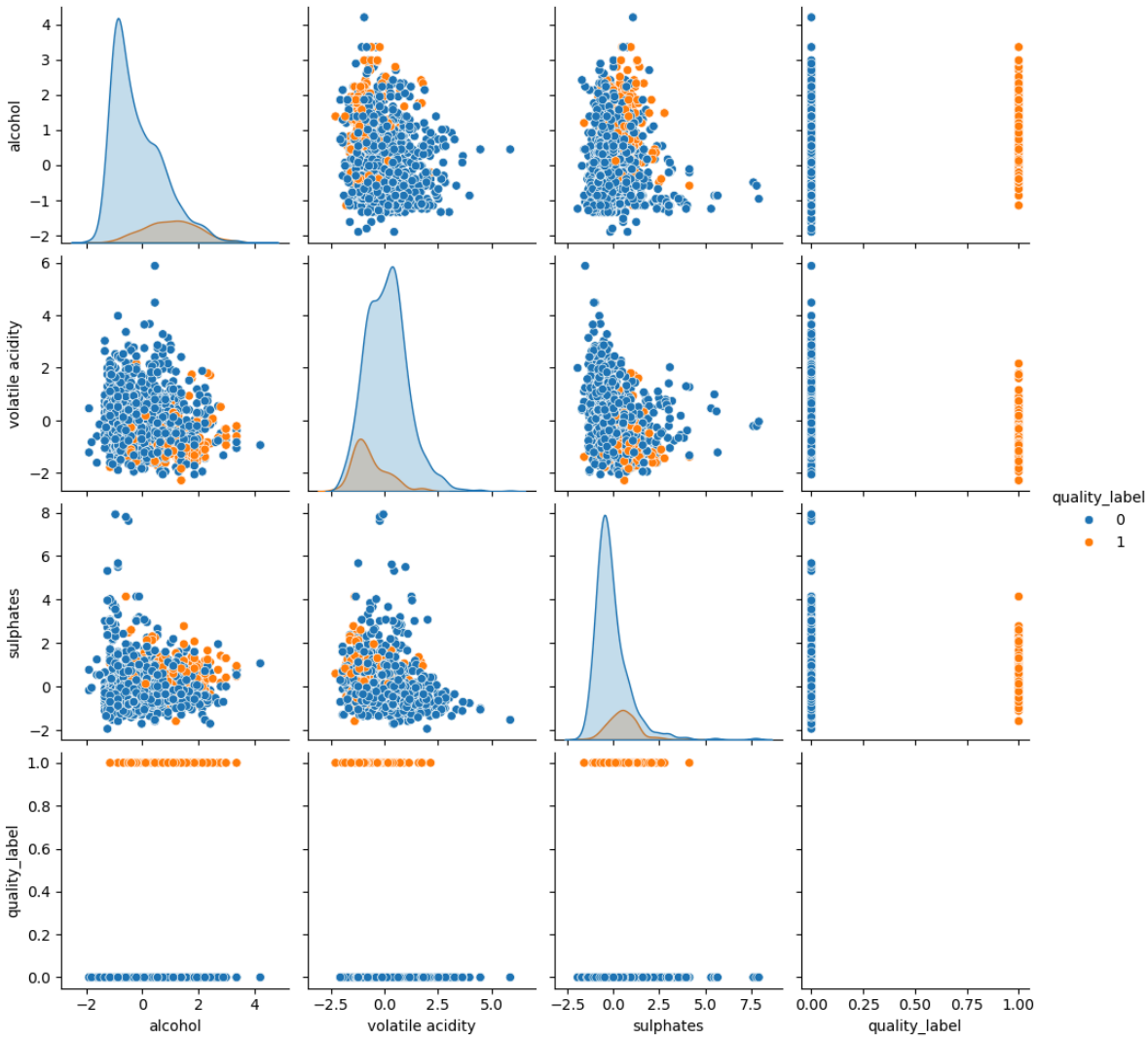


In [8]:
```
# Correlation heatmap
plt.figure(figsize=(12,10))
sns.heatmap(data.corr(), annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



In [9]:
```
# Pairplot for a subset of features
sns.pairplot(data, vars=['alcohol', 'volatile acidity', 'sulphates', 'quality_label
plt.show()
```

```
C:\Users\chira\anaconda3\Lib\site-packages\seaborn\axisgrid.py:123: UserWarning: T
he figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



4. Feature Engineering and Selection

4.1 Feature Engineering and Feature Selection

In [10]:
```
%pipeline = Pipeline([('logreg', logreg)  # Assuming 'logreg' is your logistic regr
```

```
UsageError: Line magic function `%pipeline` not found.
```

In [11]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression

# Define feature matrix X and target y
X = data.drop('quality_label', axis=1)
y = data['quality_label']

# Initialize logistic regression estimator
logreg = LogisticRegression(max_iter=1000, solver='liblinear')

# Recursive Feature Elimination
rfe = RFE(logreg, n_features_to_select=10)
rfe = rfe.fit(X, y)

# Select features
selected_features = X.columns[rfe.support_]
print("Selected Features:", selected_features)

# Update X with selected features
X = X[selected_features]
```

```
Selected Features: Index(['fixed acidity', 'volatile acidity', 'citric acid', 'res
idual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'sulphates', 'alcohol'],
      dtype='object')
```

In [12]:
```python
from sklearn.preprocessing import StandardScaler

# Separating the features and the target
X = data.drop(columns=['quality_label'])
y = data['quality_label']

# Feature scaling (Standardization)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

5. Model Development

5.1 Data Splitting

In [13]:
```python
from sklearn.model_selection import train_test_split

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, rar
```

In [14]:
```python
from sklearn.model_selection import train_test_split, StratifiedKFold

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

# Cross-validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

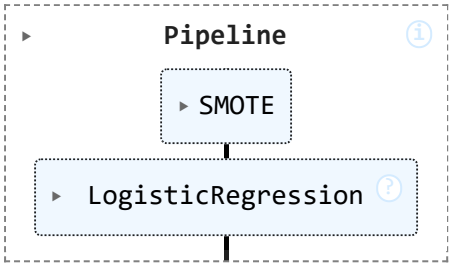
5.2 Model Building

In [15]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score

# Initialize the logistic regression model
log_reg = LogisticRegression()

# Train the model
log_reg.fit(X_train, y_train)

# Make predictions
y_pred = log_reg.predict(X_test)
y_pred_proba = log_reg.predict_proba(X_test)[:, 1]
```

In [17]:
```python
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline

# Handle class imbalance using SMOTE
smote = SMOTE(random_state=42)

# Define logistic regression with L2 regularization
logreg = LogisticRegression(
    penalty='l2',
    solver='liblinear',
```

```
    class_weight='balanced',
    max_iter=1000
)

# Create pipeline
pipeline = Pipeline([
    ('smote', smote),
    ('logreg', logreg)
])

# Fit the model
pipeline.fit(X_train, y_train)
```

Out[17]:



In [24]:

```
from sklearn.model_selection import GridSearchCV

# Define hyperparameter grid
param_grid = {
    'logreg__C': [0.01, 0.1, 1, 10, 100],
    'logreg__penalty': ['l1', 'l2']
}

# Initialize GridSearchCV
grid = GridSearchCV(
    estimator=pipeline,
    param_grid=param_grid,
    cv=cv,
    scoring='roc_auc',
    n_jobs=-1,
    verbose=1
)

# Fit GridSearch
grid.fit(X_train, y_train)

# Best parameters
print("Best Parameters:", grid.best_params_)

# Update pipeline with best estimator
best_pipeline = grid.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Best Parameters: {'logreg__C': 0.1, 'logreg__penalty': 'l2'}
```

6. Model Evaluation

In [68]:

```
model = LogisticRegression()
model.fit(X_train,y_train)
```

Out[68]:

LogisticRegression

```
LogisticRegression()
```

In [28]:
```
y_pred = model.predict(X_test)
y_pred
```

Out[28]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [29]:
```
accuracy = accuracy_score(y_test,y_pred)
conf_matrix = confusion_matrix(y_test,y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test,y_pred)
f1 = f1_score(y_test,y_pred)

print("Logistic Regression Model Results:")
print("Accuracy:", accuracy)
print("confusion Matrix :", conf_matrix)
print("Precision:", precision)
print("recall:", recall)
print("F1 Score", f1)
```

```
Logistic Regression Model Results:
Accuracy: 0.89375
confusion Matrix : [[270   7]
 [ 27  16]]
Precision: 0.6956521739130435
recall: 0.37209302325581395
F1 Score 0.48484848484848486
```

Decision tree classification

In [31]:
```
from sklearn.tree import DecisionTreeClassifier

model1 = DecisionTreeClassifier()
model1.fit(X_train,y_train)
```

Out[31]:
```
DecisionTreeClassifier()
```

In [33]:
```
y_pred1 = model1.predict(X_test)
y_pred1
```

Out[33]:
```
array([0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [34]:
```
accuracy1 = accuracy_score(y_test,y_pred1)
conf_matrix1 = confusion_matrix(y_test,y_pred1)
precision1 = precision_score(y_test, y_pred1)
recall1 = recall_score(y_test,y_pred1)
f11 = f1_score(y_test,y_pred1)

print("Decision Tree Classification Model Results:")
print("Accuracy:", accuracy1)
print("confusion Matrix :", conf_matrix1)
print("Precision:", precision1)
print("recall:", recall1)
print("F1 Score", f11)
```

```
Decision Tree Classification Model Results:
Accuracy: 0.9125
confusion Matrix : [[262  15]
 [ 13  30]]
Precision: 0.6666666666666666
recall: 0.6976744186046512
F1 Score 0.6818181818181818
```

In [35]:
```
model.score(X_train, y_train)
```

Out[35]:
```
0.8811571540265832
```

In [36]:
```
model.score(X_test,y_test)
```

Out[36]:
```
0.89375
```

Random Forest

In [41]:
```
from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier
model2 = RandomForestClassifier()
model2.fit(X_train,y_train)
```

Out[41]:

▾ RandomForestClassifier

```
RandomForestClassifier()
```

In [42]:
```
y_pred2 = model2.predict(X_test)
y_pred2
```

Out[42]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [43]:
```
accuracy2 = accuracy_score(y_test,y_pred2)
conf_matrix2 = confusion_matrix(y_test,y_pred2)
precision2 = precision_score(y_test, y_pred2)
recall2 = recall_score(y_test,y_pred2)
f12 = f1_score(y_test,y_pred2)

print("Random Forest Classification Model Results:")
print("Accuracy:", accuracy2)
print("confusion Matrix :", conf_matrix2)
print("Precision:", precision2)
print("recall:", recall2)
print("F1 Score", f12)
```

```
Random Forest Classification Model Results:
Accuracy: 0.9375
confusion Matrix : [[273   4]
 [ 16  27]]
Precision: 0.8709677419354839
recall: 0.627906976744186
F1 Score 0.7297297297297297
```

Support Vector Machine

In [45]:
```
from sklearn.svm import SVC
model3 = SVC()
model3.fit(X_train, y_train)
```

Out[45]:

SVC

SVC()

In [47]:
```
y_pred3 = model3.predict(X_test)
y_pred3
```

Out[47]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [48]:
```
accuracy3 = accuracy_score(y_test,y_pred3)
conf_matrix3 = confusion_matrix(y_test,y_pred3)
precision3 = precision_score(y_test, y_pred3)
recall3 = recall_score(y_test,y_pred3)
f13 = f1_score(y_test,y_pred3)

print("SVM Model Results:")
print("Accuracy:", accuracy3)
print("confusion Matrix :", conf_matrix3)
print("Precision:", precision3)
print("recall:", recall3)
print("F1 Score", f13)
```

```
SVM Model Results:
Accuracy: 0.9
confusion Matrix : [[272   5]
 [ 27  16]]
Precision: 0.7619047619047619
recall: 0.37209302325581395
F1 Score 0.5
```

Navie bayes Calassifier

In [54]:
```
from sklearn.naive_bayes import GaussianNB
model4 = GaussianNB()
model4.fit(X_train, y_train)
y_pred4 = model4.predict(X_test)
y_pred4
```

Out[54]:
```
array([0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [55]:
```
accuracy4 = accuracy_score(y_test,y_pred4)
conf_matrix4 = confusion_matrix(y_test,y_pred4)
precision4 = precision_score(y_test, y_pred4)
```

```
recall4 = recall_score(y_test,y_pred4)
f14 = f1_score(y_test,y_pred4)

print("Navie Bayes Model Results:")
print("Accuracy:", accuracy4)
print("confusion Matrix :", conf_matrix4)
print("Precision:", precision4)
print("recall:", recall4)
print("F1 Score", f14)
```

```
Navie Bayes Model Results:
Accuracy: 0.859375
confusion Matrix : [[244  33]
 [ 12  31]]
Precision: 0.484375
recall: 0.7209302325581395
F1 Score 0.5794392523364486
```

KNeighborsClassifier

In [56]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [59]:
```
model5 = KNeighborsClassifier(n_neighbors=3)
model5.fit(X_train, y_train)
```

Out[59]:

KNeighborsClassifier

KNeighborsClassifier(n_neighbors=3)

In [61]:
```
 y_pred5 = model5.predict(X_test)
y_pred5
```

Out[61]:
```
array([0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [62]:
```
accuracy5 = accuracy_score(y_test, y_pred5)
conf_matrix5 = confusion_matrix(y_test, y_pred5)
precision5 = precision_score(y_test, y_pred5)
recall5 = recall_score(y_test, y_pred5)
f15 = f1_score(y_test, y_pred5)
print("KNN Model Results:")
print("Accuracy:", accuracy5)
print("Confusion Matrix:", conf_matrix5)
print("Precision:", precision5)
print("Recall:", recall5)
print("F1 Score:", f15)
```

```
KNN Model Results:
Accuracy: 0.89375
Confusion Matrix: [[265  12]
 [ 22  21]]
Precision: 0.6363636363636364
Recall: 0.4883720930232558
F1 Score: 0.5526315789473685
```

GradientBoostingClassifier

In [65]:
```
model6 = GradientBoostingClassifier()
model6.fit(X_train, y_train)
```

Out[65]:
```
GradientBoostingClassifier()
```

In [66]:
```
y_pred6 = model6.predict(X_test)
y_pred6
```

Out[66]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0], dtype=int64)
```

In [67]:
```
accuracy6 = accuracy_score(y_test, y_pred6)
conf_matrix6 = confusion_matrix(y_test, y_pred6)
precision6 = precision_score(y_test, y_pred6)
recall6 = recall_score(y_test, y_pred6)
f16 = f1_score(y_test, y_pred6)
print("Gradient Boosting Model Results:")
print("Accuracy:", accuracy6)
print("Confusion Matrix:", conf_matrix6)
print("Precision:", precision6)
print("Recall:", recall6)
print("F1 Score:", f16)
```

```
Gradient Boosting Model Results:
Accuracy: 0.915625
Confusion Matrix: [[271   6]
 [ 21  22]]
Precision: 0.7857142857142857
Recall: 0.5116279069767442
F1 Score: 0.6197183098591549
```

6.1 Performance Metrics

In [19]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Predict on test set
y_pred = best_pipeline.predict(X_test)
```

```
y_proba = best_pipeline.predict_proba(X_test)[:,1]

# Calculate metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_proba)
conf_matrix = confusion_matrix(y_test, y_pred)

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
print(f"ROC-AUC: {roc_auc:.4f}")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8094
Precision: 0.3953
Recall: 0.7907
F1-Score: 0.5271
ROC-AUC: 0.8857
Confusion Matrix:
[[225  52]
 [  9  34]]
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.81      0.88       277
           1       0.40      0.79      0.53        43

    accuracy                           0.81       320
   macro avg       0.68      0.80      0.70       320
weighted avg       0.89      0.81      0.83       320
```

6.2 Model Validation

In [20]:

```
from sklearn.model_selection import cross_val_score

# Cross-validation scores
cv_scores = cross_val_score(best_pipeline, X_train, y_train, cv=cv, scoring='roc_au
print(f"Cross-Validation ROC-AUC Scores: {cv_scores}")
print(f"Mean CV ROC-AUC: {cv_scores.mean():.4f}")
```

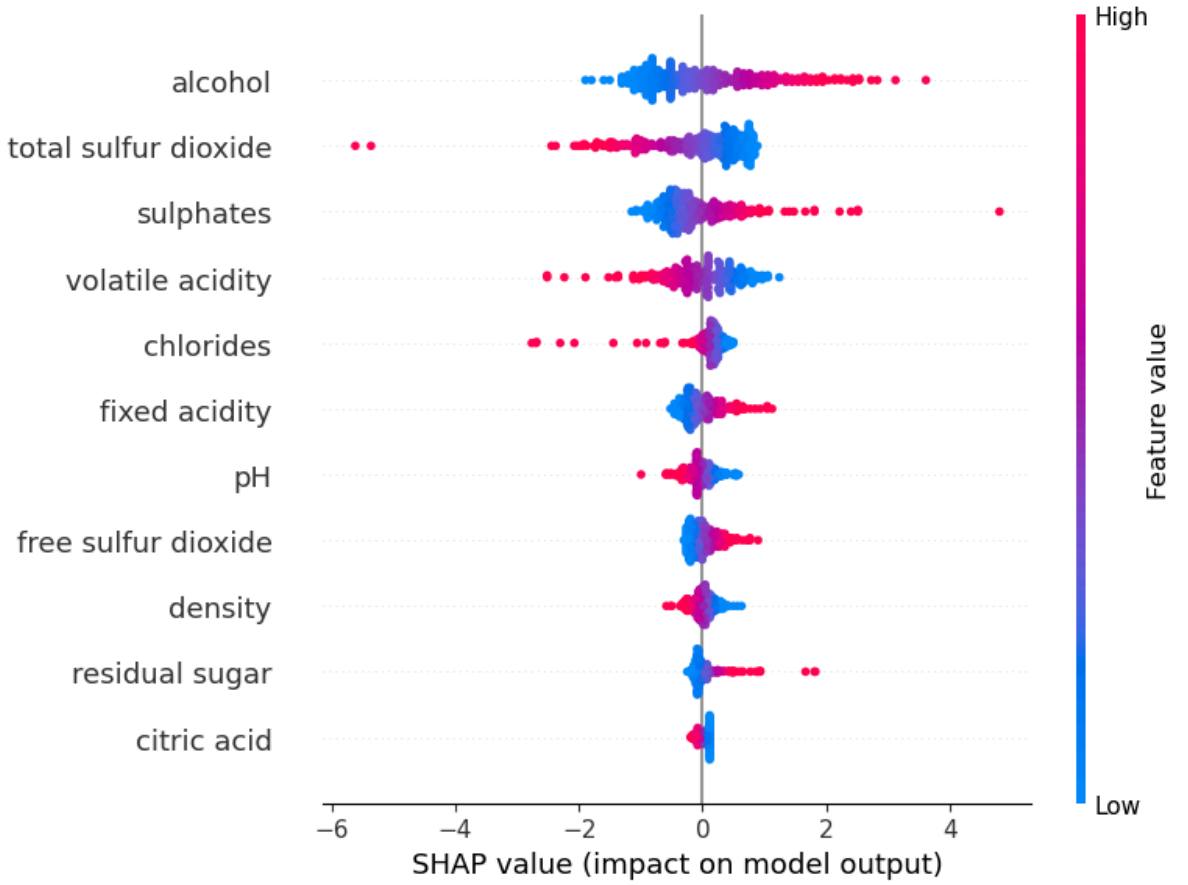
```
Cross-Validation ROC-AUC Scores: [0.87149321 0.86658048 0.88248222 0.87847447 0.85
427203]
Mean CV ROC-AUC: 0.8707
```

7. Model Interpretation

In [21]:

```
import shap

# Initialize SHAP explainer
explainer = shap.Explainer(best_pipeline.named_steps['logreg'], X_train)

# Calculate SHAP values
shap_values = explainer(X_test)

# Summary plot
```

```
shap.summary_plot(shap_values, X_test)

# Feature importance based on coefficients
coefficients = best_pipeline.named_steps['logreg'].coef_[0]
feature_importance = pd.Series(coefficients, index=X.columns).sort_values(key=lambd
print("Feature Importance:")
print(feature_importance)

# Odds ratios
odds_ratios = np.exp(coefficients)
odds_ratios_df = pd.DataFrame({
    'Feature': X.columns,
    'Odds Ratio': odds_ratios
}).sort_values(by='Odds Ratio', ascending=False)
print(odds_ratios_df)
```



```
Feature Importance:
alcohol                1.047385
total sulfur dioxide  -0.755582
sulphates              0.626066
volatile acidity      -0.555635
chlorides             -0.400651
fixed acidity          0.277810
residual sugar         0.224651
free sulfur dioxide    0.224292
pH                    -0.211960
density               -0.175287
citric acid           -0.077341
dtype: float64
                 Feature  Odds Ratio
10               alcohol    2.850189
9              sulphates    1.870239
0          fixed acidity    1.320235
3         residual sugar    1.251886
5    free sulfur dioxide    1.251436
2           citric acid    0.925574
7               density    0.839216
8                    pH    0.808997
4             chlorides    0.669884
1      volatile acidity    0.573708
6   total sulfur dioxide    0.469737
```

8. Model Deployment and Monitoring

Deployment and monitoring typically involve creating APIs, setting up pipelines, and monitoring tools which are beyond the scope of this script. However, here's a basic example of saving the model for deployment.

In [22]:
```python
import joblib

# Save the model
joblib.dump(best_pipeline, 'logistic_regression_wine_model.pkl')

print("Model saved as 'logistic_regression_wine_model.pkl'")
```

```
Model saved as 'logistic_regression_wine_model.pkl'
```

In [69]:
```python
import numpy as np
from sklearn.ensemble import RandomForestClassifier

# Assuming you have a trained GradientBoostingClassifier object called 'model'
model2 = RandomForestClassifier()

# Sample input data
Testing_data_value = np.array([ 7.4, 0.7, 0.1,0.086, 1.9, 11.0,34.0,0.9976,3.52,0.5

# Reshape the input data to a 2D array
Testing_data_value_reshape = Testing_data_value.reshape(1, -1)

# Predict the class using the reshaped input data
prediction = model.predict(Testing_data_value_reshape)

if prediction[0] == 1:
    print("GOOD QUALITY WINE.")
else:
    print("GOOD QUALITY BAD.")
```

```
GOOD QUALITY BAD.
```

```
C:\Users\chira\anaconda3\Lib\site-packages\sklearn\base.py:493: UserWarning: X doe
s not have valid feature names, but LogisticRegression was fitted with feature nam
es
  warnings.warn(
```

In [ ]: