```python
# Wine Quality Binary Classification Pipeline — Complete

# ✅ Imports
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 StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier

from sklearn.metrics import classification_report, confusion_matrix

# ✅ Load dataset
df = pd.read_csv("/kaggle/input/winequalityred/winequality-red.csv",
sep=",")
print("Initial shape:", df.shape)

# ✅ Target: Convert quality to binary
df['quality_label'] = df['quality'].apply(lambda q: 1 if q >= 7 else
0)
df.drop('quality', axis=1, inplace=True)

# ✅ No categorical features, skip encoding

# ✅ EDA: Correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Feature Correlation Heatmap")
plt.show()

# ✅ EDA: Target balance
sns.countplot(x='quality_label', data=df)
plt.title("Target Class Distribution")
plt.show()

# ✅ Feature matrix and target
X = df.drop('quality_label', axis=1)
y = df['quality_label']

# ✅ Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, stratify=y, random_state=42)

# ✅ Scaling
scaler = StandardScaler()
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X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# □ Feature importance using Random Forest (for feature selection)
rf_fs = RandomForestClassifier(random_state=42)
rf_fs.fit(X_train_scaled, y_train)

feat_importances = pd.Series(rf_fs.feature_importances_,
index=X.columns)
feat_importances.sort_values(ascending=False).plot(kind='bar',
title='Feature Importances')
plt.show()

# (Optional): Drop low-importance features manually if needed

# 🤖 Models
models = {
    "Logistic Regression": LogisticRegression(),
    "Random Forest": RandomForestClassifier(random_state=42),
    "SVM": SVC(),
    "XGBoost": XGBClassifier(use_label_encoder=False,
eval_metric='logloss')
}

# □ Train and evaluate models
results = {}

for name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)
    report = classification_report(y_test, y_pred, output_dict=True)
    results[name] = {
        "Accuracy": report["accuracy"],
        "Precision": report["1"]["precision"],
        "Recall": report["1"]["recall"],
        "F1-score": report["1"]["f1-score"]
    }
    print(f"\n□ {name} Evaluation:")
    print(classification_report(y_test, y_pred))

# □ Comparison
result_df = pd.DataFrame(results).T
print("\n□ Model Comparison:")
print(result_df.sort_values("F1-score", ascending=False))

# □ Best model: Choose based on F1-score
best_model = result_df.sort_values("F1-score",
ascending=False).index[0]
print(f"\n□ Best Model Based on F1-score: {best_model}")
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```python
# □ Bonus: GridSearchCV for Random Forest
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5]
}

grid = GridSearchCV(RandomForestClassifier(random_state=42),
param_grid, cv=3, scoring='f1')
grid.fit(X_train_scaled, y_train)
print("\n□ Best Random Forest Params from GridSearch:")
print(grid.best_params_)
print("Best F1-score from GridSearch:", grid.best_score_)
```

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Initial shape: (1596, 12)
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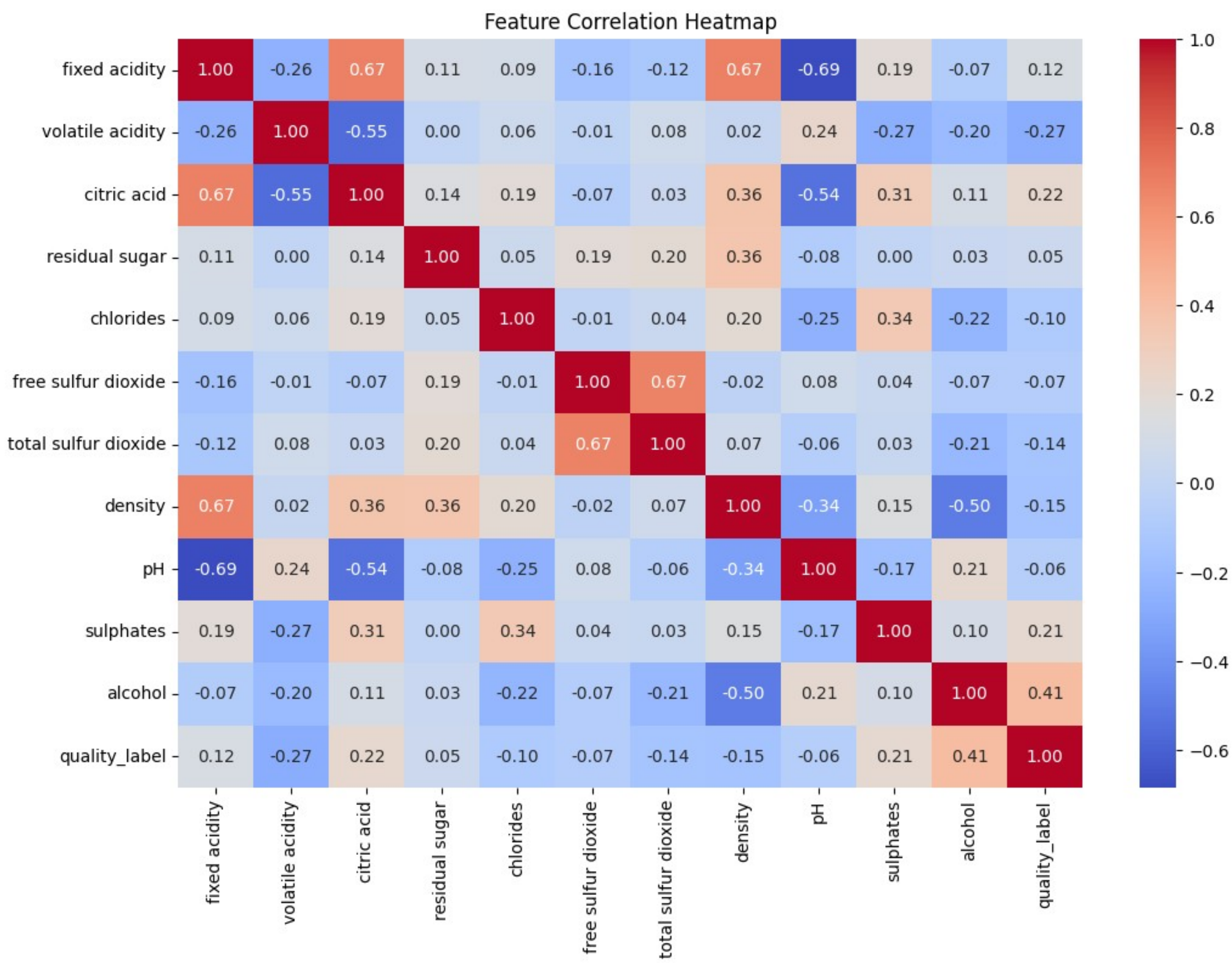
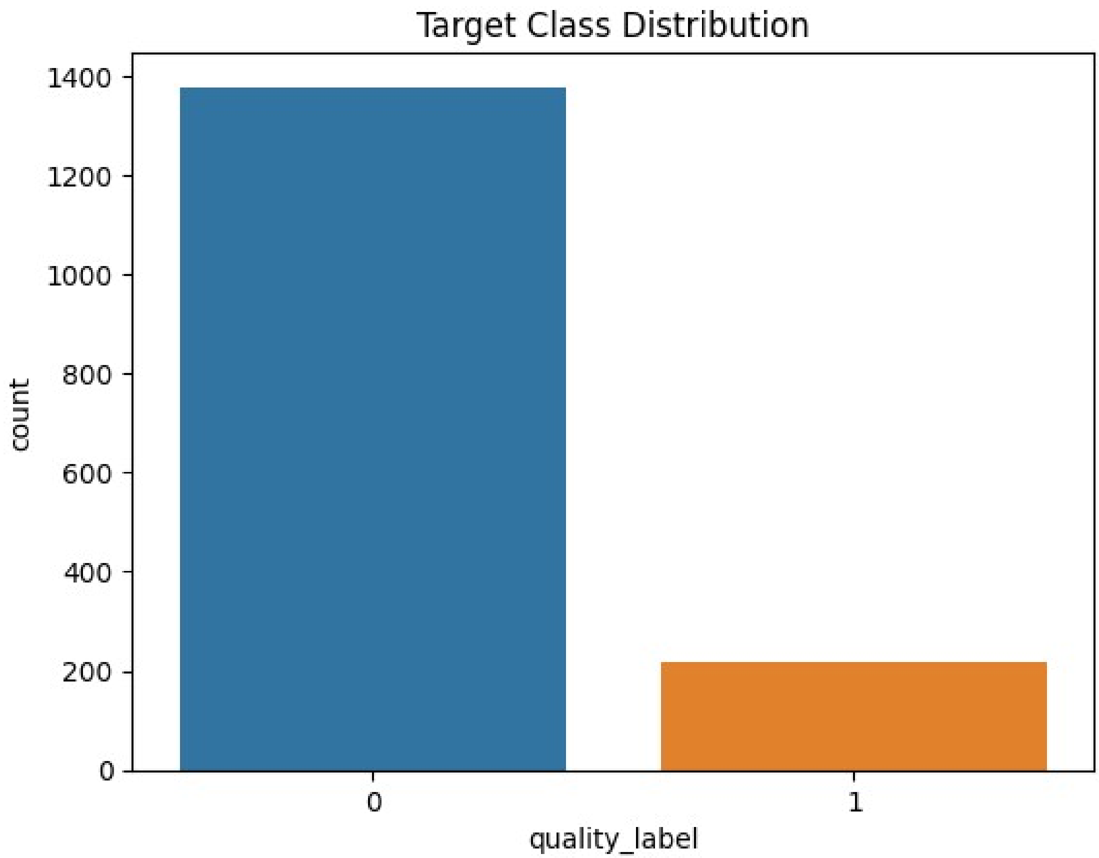
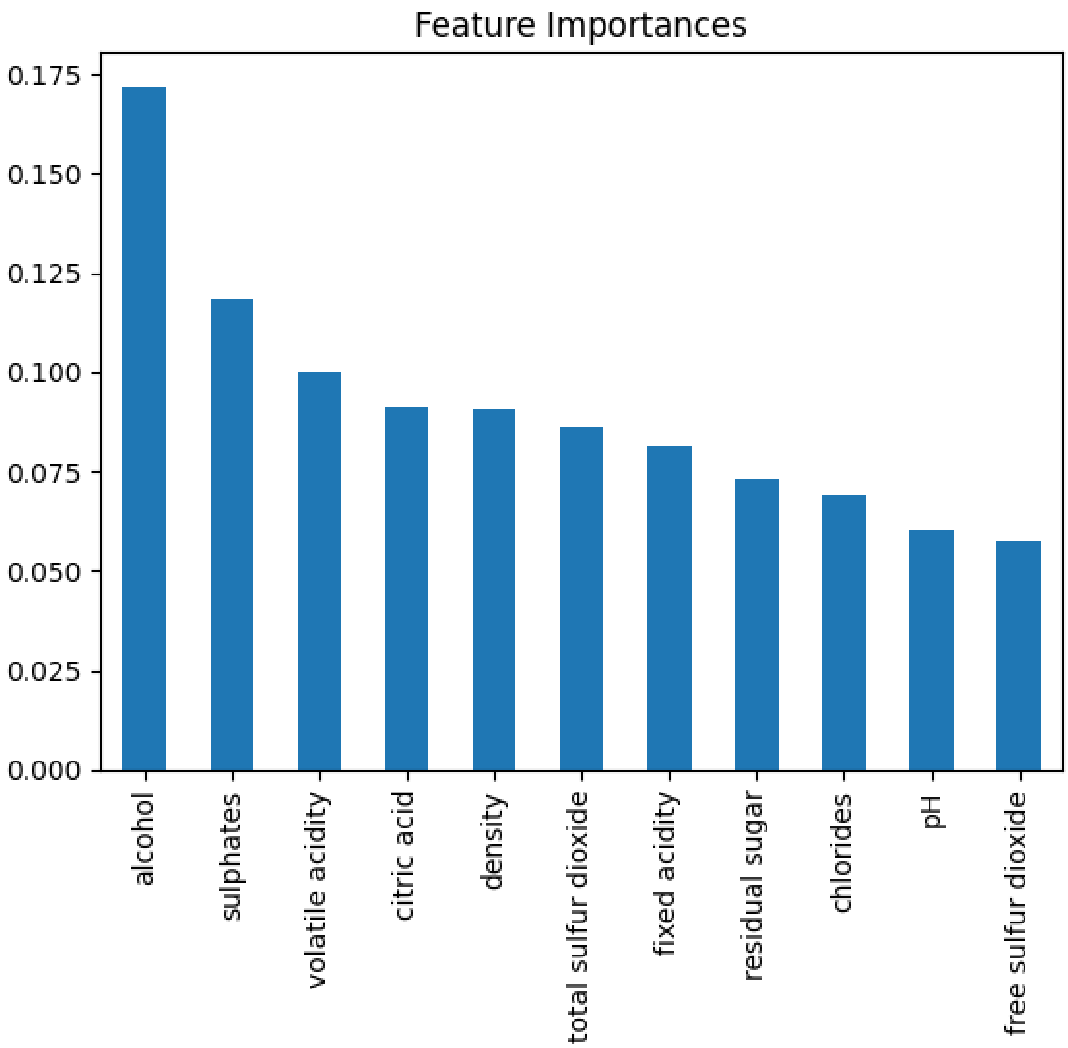



Target Class Distribution
1400
1200
1000
800
600
400
200
0
count
0
1
quality_label

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□ Logistic Regression Evaluation:
              precision    recall  f1-score   support

           0       0.91      0.99      0.94       276
           1       0.80      0.36      0.50        44

    accuracy                           0.90       320
   macro avg       0.85      0.67      0.72       320
weighted avg       0.89      0.90      0.88       320


□ Random Forest Evaluation:
              precision    recall  f1-score   support

           0       0.95      0.99      0.97       276
           1       0.91      0.66      0.76        44
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    accuracy                           0.94       320
   macro avg       0.93      0.82      0.87       320
weighted avg       0.94      0.94      0.94       320


□ SVM Evaluation:
              precision    recall  f1-score   support

           0       0.91      0.99      0.95       276
           1       0.81      0.39      0.52        44

    accuracy                           0.90       320
   macro avg       0.86      0.69      0.73       320
weighted avg       0.90      0.90      0.89       320


□ XGBoost Evaluation:
              precision    recall  f1-score   support

           0       0.96      0.99      0.97       276
           1       0.89      0.75      0.81        44

    accuracy                           0.95       320
   macro avg       0.93      0.87      0.89       320
weighted avg       0.95      0.95      0.95       320


□ Model Comparison:
                     Accuracy  Precision    Recall  F1-score
XGBoost              0.953125   0.891892  0.750000  0.814815
Random Forest        0.943750   0.906250  0.659091  0.763158
SVM                  0.903125   0.809524  0.386364  0.523077
Logistic Regression  0.900000   0.800000  0.363636  0.500000

□ Best Model Based on F1-score: XGBoost

□ Best Random Forest Params from GridSearch:
{'max_depth': 10, 'min_samples_split': 2, 'n_estimators': 100}
Best F1-score from GridSearch: 0.5379273504273504
```