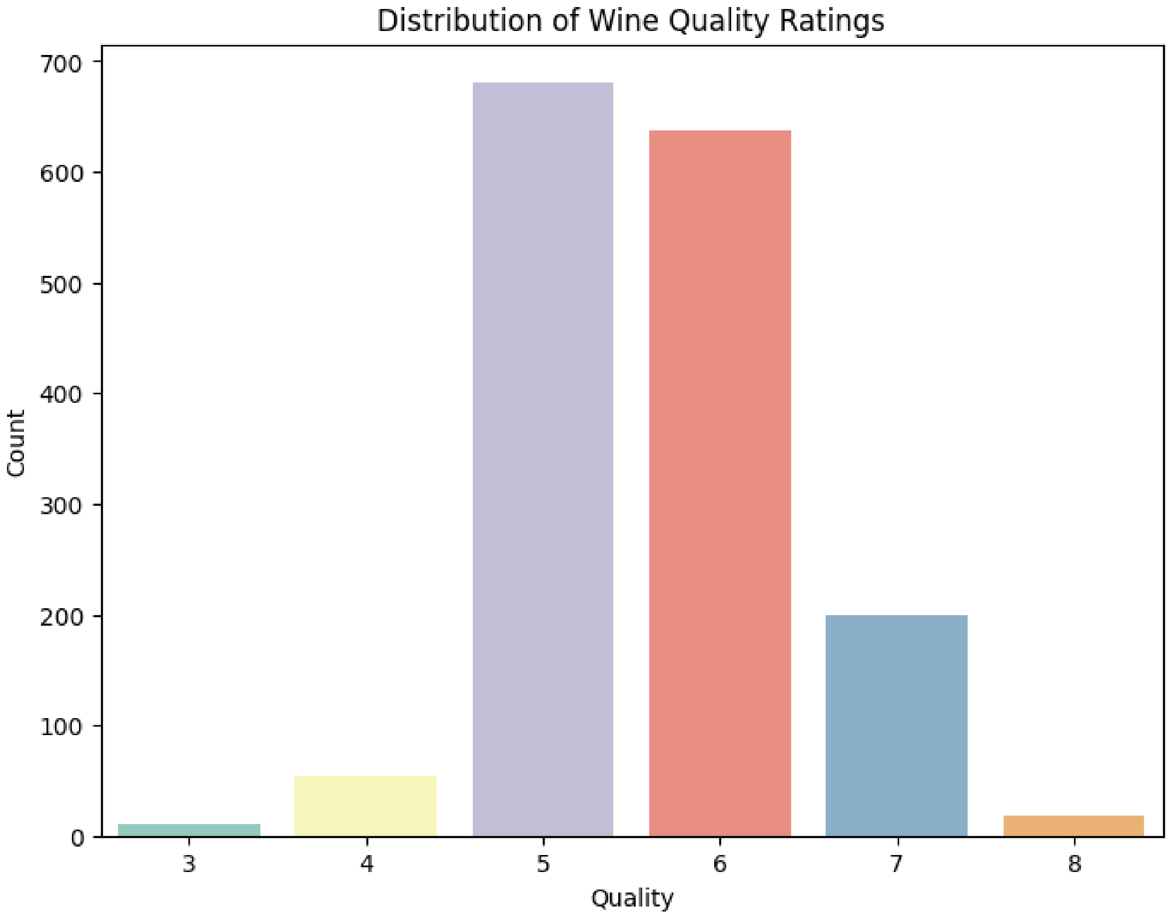
Grapes to Greatness: Machine Learning in Wine Quality Prediction

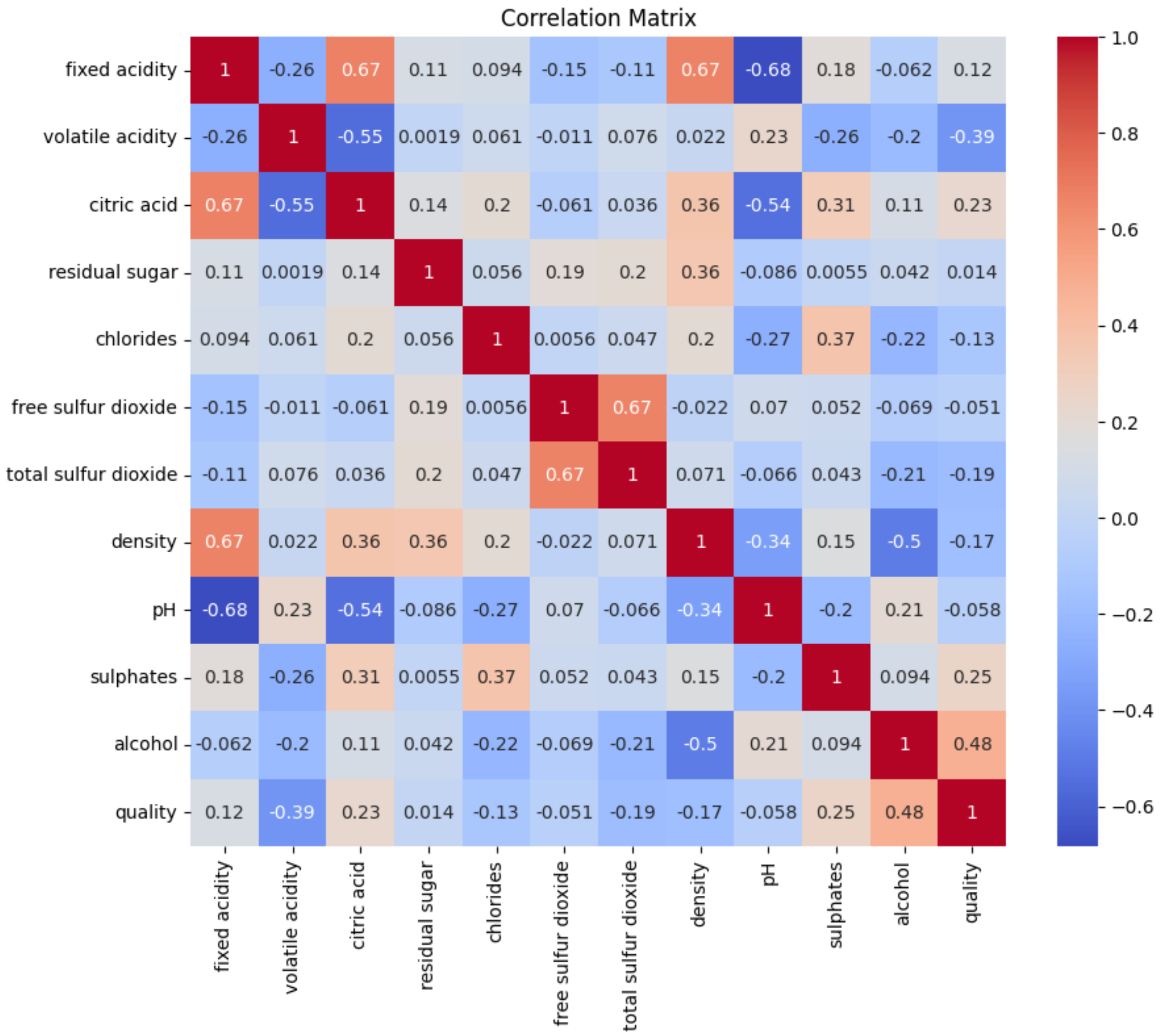
-- Hritik kumar (21BCE7815)

In [32]:
```
# Import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
data = pd.read_csv('/content/winequality-red.csv')

# Display the first few rows of the dataset to get an overview
print("First few rows of the dataset:")
print(data.head())

# Check for missing values in the dataset
missing_values = data.isnull().sum()
print("\nMissing values in the dataset:")
print(missing_values)

# Summary statistics of the dataset
print("\nSummary statistics of the dataset:")
print(data.describe())

# Visualize the distribution of wine quality ratings
plt.figure(figsize=(8, 6))
sns.countplot(x="quality", data=data, palette="Set3")
plt.title("Distribution of Wine Quality Ratings")
plt.xlabel("Quality")
plt.ylabel("Count")
plt.show()

# Visualize the correlation matrix between features
correlation_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()
```

```
First few rows of the dataset:
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076   
1            7.8              0.88         0.00             2.6      0.098   
2            7.8              0.76         0.04             2.3      0.092   
3           11.2              0.28         0.56             1.9      0.075   
4            7.4              0.70         0.00             1.9      0.076   

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56   
1                 25.0                  67.0   0.9968  3.20       0.68   
2                 15.0                  54.0   0.9970  3.26       0.65   
3                 17.0                  60.0   0.9980  3.16       0.58   
4                 11.0                  34.0   0.9978  3.51       0.56   

   alcohol  quality  
0      9.4        5  
1      9.8        5  
2      9.8        5  
3      9.8        6  
4      9.4        5  

Missing values in the dataset:
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

Summary statistics of the dataset:
       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 [33]:

```
# Import necessary libraries for machine learning
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score, accuracy_score

# Load the dataset (assuming you have already loaded the data)
# If not, you can load it here as you did previously

# Convert the quality variable to a categorical variable
data['quality'] = pd.cut(data['quality'], bins=[0, 4, 6, 8, 10], labels=[1, 2, 3, 

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(data.drop(columns=['quality'])

# Scale the features
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Build machine learning models
models = {
    'Logistic Regression': LogisticRegression(),
    'K-Nearest Neighbors': KNeighborsClassifier(),
    'Naive Bayes': GaussianNB(),
```

```python
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier()
}

# Train and evaluate each model
best_model = None
best_test_f1_score = 0
best_train_f1_score = 0
best_test_accuracy = 0
best_train_accuracy = 0

for model_name, model in models.items():
    # Train the model on the training data
    model.fit(X_train, y_train)

    # Make predictions on the test data
    y_test_pred = model.predict(X_test)

    # Calculate testing F1-score (for multi-class classification)
    test_f1_score = f1_score(y_test, y_test_pred, average='weighted')

    # Calculate testing accuracy
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Make predictions on the training data
    y_train_pred = model.predict(X_train)

    # Calculate training F1-score (for multi-class classification)
    train_f1_score = f1_score(y_train, y_train_pred, average='weighted')

    # Calculate training accuracy
    train_accuracy = accuracy_score(y_train, y_train_pred)

    print(f"{model_name} Training F1-Score:", train_f1_score)
    print(f"{model_name} Testing F1-Score:", test_f1_score)
    print(f"{model_name} Training Accuracy:", train_accuracy)
    print(f"{model_name} Testing Accuracy:", test_accuracy)

    # Check if this model has the highest testing F1-score so far
    if test_f1_score > best_test_f1_score:
        best_test_f1_score = test_f1_score
        best_train_f1_score = train_f1_score
        best_model = model_name
        best_test_accuracy = test_accuracy
        best_train_accuracy = train_accuracy

# Display the best model based on testing F1-score and accuracy
print("\nBest Model:", best_model)
print("Best Training F1-Score:", best_train_f1_score)
print("Best Testing F1-Score:", best_test_f1_score)
print("Best Training Accuracy:", best_train_accuracy)
print("Best Testing Accuracy:", best_test_accuracy)
```

```
Logistic Regression Training F1-Score: 0.8175794667961407
Logistic Regression Testing F1-Score: 0.7927467735752619
Logistic Regression Training Accuracy: 0.8467552775605942
Logistic Regression Testing Accuracy: 0.828125
K-Nearest Neighbors Training F1-Score: 0.850977912836277
K-Nearest Neighbors Testing F1-Score: 0.8196386946386948
K-Nearest Neighbors Training Accuracy: 0.872556684910086
K-Nearest Neighbors Testing Accuracy: 0.84375
Naive Bayes Training F1-Score: 0.7906844518306405
Naive Bayes Testing F1-Score: 0.8113834715501463
Naive Bayes Training Accuracy: 0.7795152462861611
Naive Bayes Testing Accuracy: 0.803125
Decision Tree Training F1-Score: 1.0
Decision Tree Testing F1-Score: 0.7919826872785591
Decision Tree Training Accuracy: 1.0
Decision Tree Testing Accuracy: 0.784375
Random Forest Training F1-Score: 1.0
Random Forest Testing F1-Score: 0.8505214139207204
Random Forest Training Accuracy: 1.0
Random Forest Testing Accuracy: 0.871875

Best Model: Random Forest
Best Training F1-Score: 1.0
Best Testing F1-Score: 0.8505214139207204
Best Training Accuracy: 1.0
Best Testing Accuracy: 0.871875
```