About Wine

import warnings

Wine is One of the most complex beverages in the world ,with a rich history and a variety of flovours that can be inflenced by numerous factors. In this notebook, we will explore a dataset of wine characteristics to uncover interesting insights and potentially build a predictive model. If you find this notebook useful, please consider upvoting it.

```
warnings.filterwarnings('ignore')
In [24]:
          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
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
In [25]: df = pd.read csv("Wine Dataset.csv")
In [26]: df.head()
Out[26]:
             Malic
                           Alcalinity
                                                    Total
                                                                        Nonflavanoid
                                                                                                         Color
                                                           Flavanoidse
                                                                                                                OD280
                    Ashe
                                     Magnesium
                                                                                     Proanthocyanins
                                                                                                                        OD31 Proline
              acid
                             of ashe
                                                 phenols
                                                                            phenols
                                                                                                      intensity
          0 14.23
                     1.71
                                2.43
                                            15.6
                                                      127
                                                                  2.80
                                                                                3.06
                                                                                                 0.28
                                                                                                           2.29
                                                                                                                   5.64
                                                                                                                         1.04
                                                                                                                                  3.92
                                                                  2.65
                                                                                                                                  3.40
             13 20
                     1 78
                               2 14
                                            112
                                                     100
                                                                                2 76
                                                                                                 0.26
                                                                                                           1 28
                                                                                                                  4 38
                                                                                                                         1 05
                                                      101
                                                                  2.80
           2 13.16
                     2.36
                               2.67
                                            18.6
                                                                                3.24
                                                                                                 0.30
                                                                                                           2.81
                                                                                                                  5.68
                                                                                                                         1.03
                                                                                                                                  3.17
             14.37
                     1.95
                                2.50
                                            16.8
                                                      113
                                                                  3.85
                                                                                3.49
                                                                                                 0.24
                                                                                                           2.18
                                                                                                                  7.80
                                                                                                                         0.86
                                                                                                                                 3.45
           4 13.24
                     2.59
                               2.87
                                            21.0
                                                     118
                                                                  2.80
                                                                                2.69
                                                                                                 0.39
                                                                                                           1.82
                                                                                                                  4.32
                                                                                                                         1.04
                                                                                                                                 2.93
          4
```

Now,let's check for any missing values in dataset.

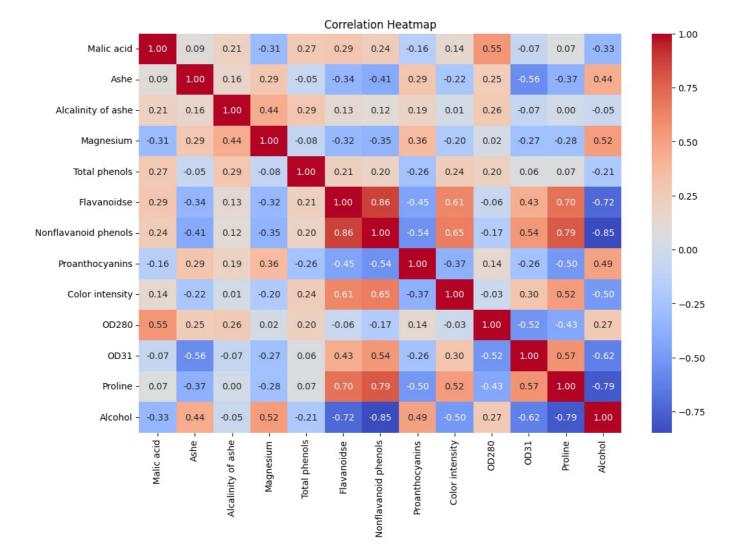
```
In [27]: df.isnull().sum()
Out[27]: Malic acid
                                   0
                                   0
          Ashe
          Alcalinity of ashe
                                   0
          Magnesium
                                   0
          Total phenols
                                   0
          Flavanoidse
                                   0
          Nonflavanoid phenols
                                   0
                                   0
          Proanthocyanins
          Color intensity
                                   0
          0D280
                                   0
          0D31
                                   0
          Proline
                                   0
          Alcohol
                                   0
          dtype: int64
```

Correlation Heatmap

Let's start by visualizing the correlation batween diferent features in the dataset

```
In [28]: # Select only numeric columns for correlation heatmap
    numeric_df = df.select_dtypes(include=[np.number])

# Plot the correlation heatmap
    plt.figure(figsize=(12, 8))
    sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
    plt.title('Correlation Heatmap')
    plt.show()
```



Pairplot

A pairplot can help us visualize the relationships between different features.

```
In [ ]: # Plot pairplot
    sns.pairplot(numeric_df)
    plt.show()
```

Feature Distribution

Let's visualize the distribution of each feature to understand their individual charactrestics

```
In [ ]: # Plot distribution of each feature
  numeric_df.hist(bins=15, figsize=(15, 10), layout=(4, 4))
  plt.tight_layout()
  plt.show()
```

Building a Predictive Model

Based on the dataset, it seems plausible to predict the type of wine based on its characteristics. Let's build a Random Forest Classifier to see how well we can predict the wine type.

```
In []: # Define features and target variable
X = numeric_df.drop('Alcohol', axis=1) # Assuming 'Alcohol' is the target variable
y = numeric_df['Alcohol']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize and train the Random Forest Classifier
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
```

```
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
accuracy, conf_matrix, class_report
```

Conclusion and Future Work

In this notebook, we explored the wine dataset, visualized the relationships between different features, and built a predictive model to classify wine types based on their characteristics. The Random Forest Classifier provided us with an accuracy score, which gives us an idea of how well the model performs.

For future analysis, we could consider:

- 1. Tuning the hyperparameters of the Random Forest model to improve accuracy.
- 2. Tuning the hyperparameters of the Random Forest model to improve accuracy.
- 3. Investigating the impact of each feature on the prediction using feature importance.

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