3. Design a statistical model to analyze wine quality using Gaussian distribution methods. Utilize synthetic data generated with NumPy or the Wine Quality Dataset

In [30]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm, kstest
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.mixture import GaussianMixture
from sklearn.metrics import accuracy_score, classification_report
```

In [31]:
```
from sklearn.datasets import fetch_openml

data = fetch_openml(name='wine-quality-red', version=1, as_frame=True)
df = data.frame
```

In [32]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype   
---  ------                --------------  -----   
 0   fixed_acidity         1599 non-null   float64 
 1   volatile_acidity      1599 non-null   float64 
 2   citric_acid           1599 non-null   float64 
 3   residual_sugar        1599 non-null   float64 
 4   chlorides             1599 non-null   float64 
 5   free_sulfur_dioxide   1599 non-null   float64 
 6   total_sulfur_dioxide  1599 non-null   float64 
 7   density               1599 non-null   float64 
 8   pH                    1599 non-null   float64 
 9   sulphates             1599 non-null   float64 
 10  alcohol               1599 non-null   float64 
 11  class                 1599 non-null   category
dtypes: category(1), float64(11)
memory usage: 139.3 KB
```

In [33]:
```
df['class'] = df['class'].astype('int64')
```

In [34]:
```
df.describe()
```

Out[34]:

	fixed_acidity	volatile_acidity	citric_acid	residual_sugar	chlorides	free_sulfur_dioxide	total_sulfur_dioxide	density	pH	sulph
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.00
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.996747	3.311113	0.65
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887	0.154386	0.16
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000	0.33
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.210000	0.55
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750	3.310000	0.62
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835	3.400000	0.73
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	4.010000	2.00

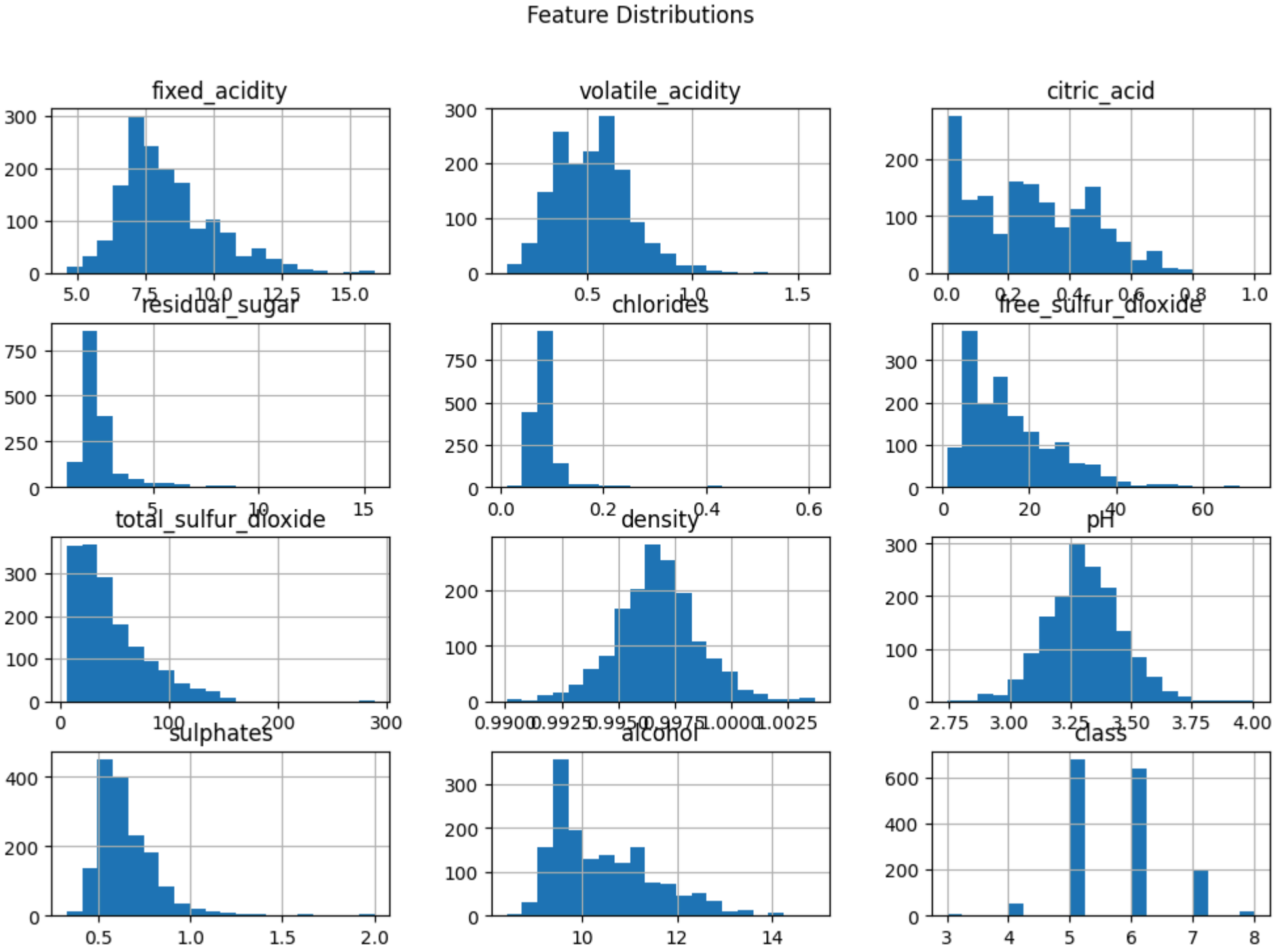
In [35]:
```
df.head()
```

Out[35]:

	fixed_acidity	volatile_acidity	citric_acid	residual_sugar	chlorides	free_sulfur_dioxide	total_sulfur_dioxide	density	pH	sulphates	alcohol	class
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [36]:
```
plt.figure(figsize=(12, 10))
df.hist(bins=20, figsize=(12, 8))
plt.suptitle("Feature Distributions")
plt.show()
```

```
<Figure size 1200x1000 with 0 Axes>
```



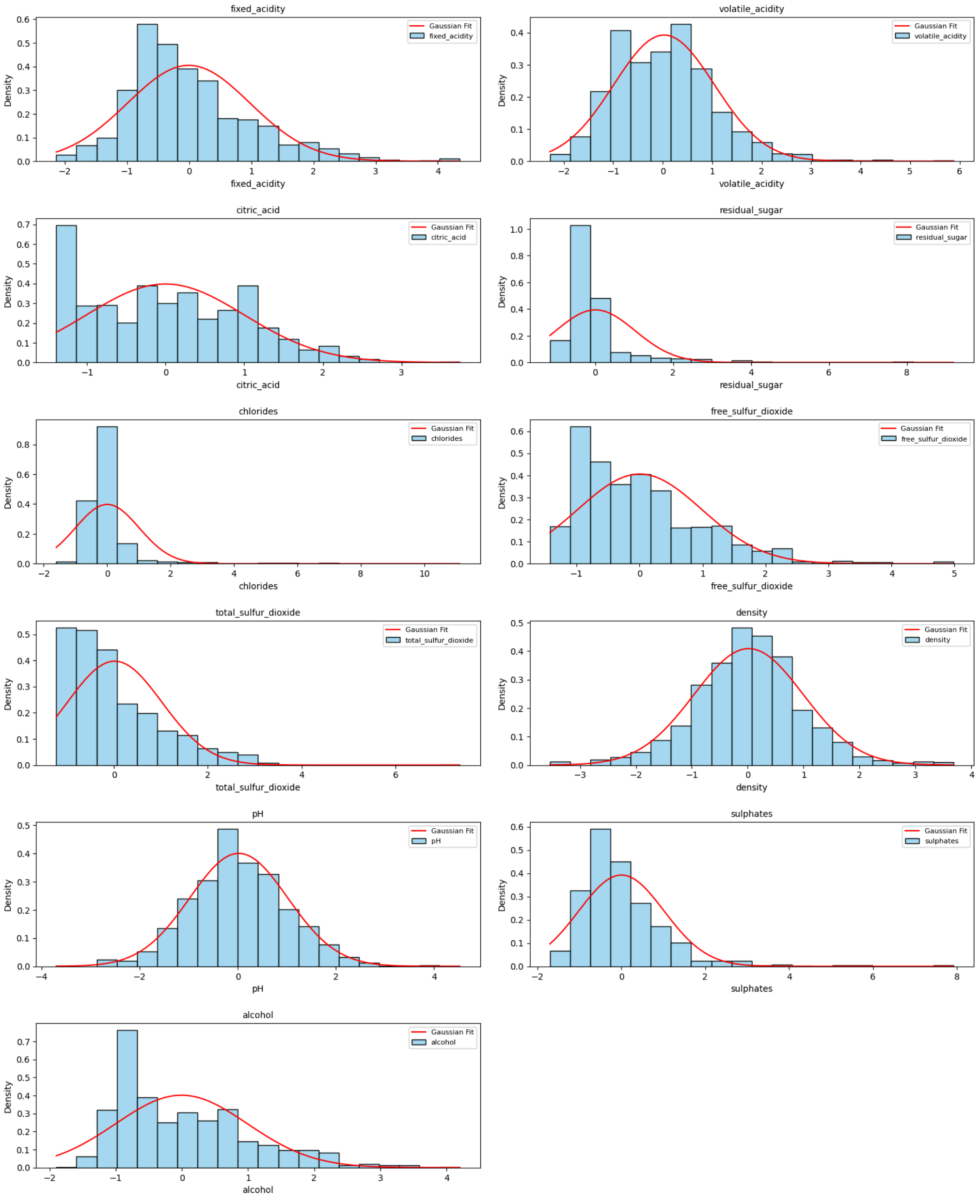
In [52]:
```
from sklearn.preprocessing import StandardScaler

X = df.drop('class', axis=1)


scaler = StandardScaler()
X = scaler.fit_transform(X)
X = pd.DataFrame(X, columns=df.columns.drop('class'))

y = df['class']
y = y.apply(lambda x: 1 if x>=6 else 0)
```

In [ ]:
```
#OPTIONAL
stats = X.agg(['mean', 'std'])
print(stats)
```

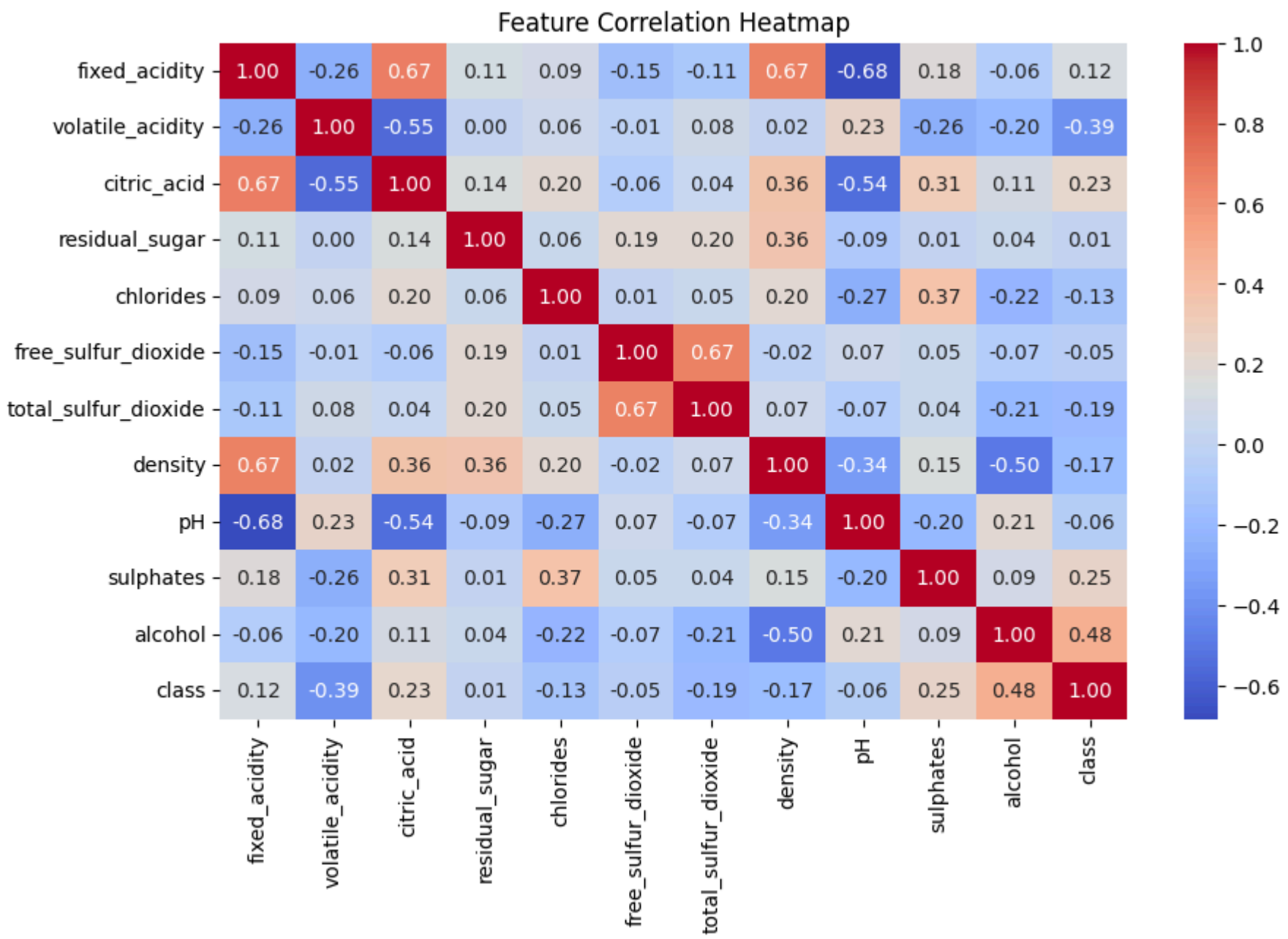
```
      fixed_acidity  volatile_acidity  ...     sulphates       alcohol
mean   3.554936e-16      1.733031e-16  ...  6.754377e-16  1.066481e-16
std    1.000313e+00      1.000313e+00  ...  1.000313e+00  1.000313e+00

[2 rows x 11 columns]
```

In [55]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [40]:
```
features = [col for col in df.columns if col != 'class']

plt.figure(figsize=(16, 20))
for i, feature in enumerate(features):
    plt.subplot((len(features)+1)//2, 2, i+1)
    mean, std = X_train[feature].mean(), X_train[feature].std()
    x = np.linspace(X_train[feature].min(), X_train[feature].max(), 100)
    pdf = norm.pdf(x, mean, std)
    sns.histplot(X_train[feature], kde=False, bins=20, stat='density', label=feature, color="skyblue", edgecolor="black")
    plt.plot(x, pdf, color='red', label="Gaussian Fit")
    plt.title(f"{feature}", fontsize=10)
    plt.legend(fontsize=8)

plt.suptitle("Gaussian Distributions of Features", fontsize=18, y=1.02)
plt.tight_layout(pad=2)
plt.show()
```



In [41]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Feature Correlation Heatmap')
plt.show()
```



In [42]:
```
gnb = GaussianNB()
gnb.fit(X_train, y_train)
y_pred = gnb.predict(X_test)
```

In [43]:
```
print("Naive Bayes Accuracy: ", accuracy_score(y_test, y_pred))
print("Classification Report: \n", classification_report(y_test, y_pred))
```

```
Naive Bayes Accuracy:  0.7416666666666667
Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.69      0.70       213
           1       0.76      0.78      0.77       267

    accuracy                           0.74       480
   macro avg       0.74      0.74      0.74       480
weighted avg       0.74      0.74      0.74       480
```

In [49]:
```
gmm = GaussianMixture(n_components=2, random_state=42)
gmm.fit(X_train)
gmm_labels = gmm.predict(X_test)
# gmm_probs = gmm.predict_proba(X_test)
# gmm_labels = (gmm_probs[:, 1] > 0.5).astype(int)
print("GMM Accuracy: ", accuracy_score(y_test, gmm_labels))
print("Classification Report: ", classification_report(y_test, gmm_labels))
```

```
GMM Accuracy:  0.4354166666666667
Classification Report:                precision    recall  f1-score   support

           0       0.43      0.80      0.56       213
           1       0.47      0.14      0.22       267

    accuracy                           0.44       480
   macro avg       0.45      0.47      0.39       480
weighted avg       0.45      0.44      0.37       480
```

In [ ]:
```
#OPTIONAL
for feature in features:
    ks_stat, p_value = kstest(X[feature], 'norm', args=(X[feature].mean(), X[feature].std()))
    print(f'KS test for {feature}: Statistics={ks_stat:.4f}, P-value={p_value:.4f}')
```

```
KS test for fixed_acidity: Statistics=0.1105, P-value=0.0000
KS test for volatile_acidity: Statistics=0.0547, P-value=0.0001
KS test for citric_acid: Statistics=0.0839, P-value=0.0000
KS test for residual_sugar: Statistics=0.2607, P-value=0.0000
KS test for chlorides: Statistics=0.2596, P-value=0.0000
KS test for free_sulfur_dioxide: Statistics=0.1112, P-value=0.0000
KS test for total_sulfur_dioxide: Statistics=0.1210, P-value=0.0000
KS test for density: Statistics=0.0448, P-value=0.0032
KS test for pH: Statistics=0.0404, P-value=0.0106
KS test for sulphates: Statistics=0.1248, P-value=0.0000
KS test for alcohol: Statistics=0.1215, P-value=0.0000
```

In [ ]: