Naive Bayes Classifier

In [1]:
```
# importing the libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, f1_score, accuracy_score, roc_auc_score
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
```

In [2]:
```
# importing the dataset
dataset = pd.read_csv('seeds_dataset.txt', sep="\t", error_bad_lines=False, warn_bad_l
dataset.columns=['area','perimeter','compactness','length_kernel','width_kernel','asym
```

```
b'Skipping line 8: expected 8 fields, saw 10\nSkipping line 36: expected 8 fields, saw 10\nSkipping line 61: expected 8 fields, saw 9\nSkipping line 69: expected 8 fields, saw 9\nSkipping line 107: expected 8 fields, saw 9\nSkipping line 136: expected 8 fields, saw 9\nSkipping line 170: expected 8 fields, saw 9\nSkipping line 171: expected 8 fields, saw 9\nSkipping line 173: expected 8 fields, saw 9\nSkipping line 202: expected 8 fields, saw 9\nSkipping line 204: expected 8 fields, saw 9\n'
```

In [3]:
```
dataset.head(5)
```

Out[3]:

	area	perimeter	compactness	length_kernel	width_kernel	asymmetry_coeff	length_of_kernel_groove	targ
0	15.26	14.84	0.8710	5.763	3.312	2.221	5.220	
1	14.88	14.57	0.8811	5.554	3.333	1.018	4.956	
2	14.29	14.09	0.9050	5.291	3.337	2.699	4.825	
3	13.84	13.94	0.8955	5.324	3.379	2.259	4.805	
4	16.14	14.99	0.9034	5.658	3.562	1.355	5.175	

In [4]:
```
# Handling Outliers by replacing them with group mean
for column in dataset.columns[:-1]:
    for target in dataset["target"].unique():
        Q1 = dataset[column][dataset["target"] == target].quantile(0.25)
        Q3 = dataset[column][dataset["target"] == target].quantile(0.75)
        IQR = Q3 - Q1 #Interquartile range
        fence_low = Q1 - (1.5 * IQR)
        fence_high = Q3 + (1.5 * IQR)

        df2 = pd.DataFrame(dataset[dataset['target'] == target][column])

        for index in df2[df2[column] < fence_low].index:
            dataset.loc[index, column] = np.nan
        for index in df2[df2[column] > fence_high].index:
            dataset.loc[index, column] = np.nan

group_mean = dataset.groupby("target").mean()
for column in dataset.columns[:-1]:
    for index in dataset[dataset[column].isna()].index:
        target = dataset.iloc[index,-1]
        dataset.loc[index, column] = group_mean[column][target]
```

In [5]:
```
data = dataset.copy()

# Separating the dataset into matrix of features and target'
X = dataset.iloc[:,:-1].values
y = dataset.iloc[:,-1].values
```

In [6]:
```
from sklearn.model_selection import train_test_split
X_train_1, X_test_1, y_train_1, y_test_1 = train_test_split(X, y, test_size=0.2, rand
```

Base Model

In [7]:
```
%%time
from sklearn.model_selection import GridSearchCV

# Fitting the Classification Model
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()

nb_params = [{'var_smoothing':[1e-10, 1e-9, 1e-5, 1e-3, 1e-1]}]
nb_grid = GridSearchCV(nb, nb_params, cv=10)
nb_grid.fit(X_train_1, y_train_1)
nb_average_score = nb_grid.cv_results_['mean_test_score'].astype(float)
result = nb_grid.cv_results_
nb_grid.best_estimator_
```

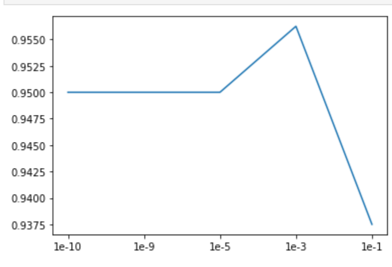
```
Wall time: 56 ms
```

Out[7]:
```
GaussianNB(var_smoothing=0.001)
```

In [8]:
```
nb_average_score
```

Out[8]:
```
array([0.95    , 0.95    , 0.95    , 0.95625, 0.9375 ])
```

In [9]:
```
plt.figure()
sns.lineplot(x=["1e-10", "1e-9", "1e-5", "1e-3", "1e-1"], y=nb_average_score)
plt.show()
```



In [10]:
```
%%time
# Building model with optimal parameters
nb_1 = GaussianNB(var_smoothing=0.001)
nb_1.fit(X_train_1, y_train_1)

print("Training Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_train_1, nb_1.predict(X_train_1)), 2)
print("F1_score: ", round(f1_score(y_train_1, nb_1.predict(X_train_1), average = 'weig
print("AUC: ", round(roc_auc_score(y_train_1, nb_1.predict_proba(X_train_1), average =
```

```
Training Set Evaluation
Accuracy:  96.23
F1_score:  0.96
AUC:  1.0
Wall time: 8.96 ms
```

In [11]:
```
# Evaluating the model on the test set
nb_pred = nb_1.predict(X_test_1)

print("Test Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_test_1, nb_pred), 2))
print("F1_score: ", round(f1_score(y_test_1, nb_pred, average = 'weighted'), 2))
print("AUC: ", round(roc_auc_score(y_test_1, nb_1.predict_proba(X_test_1), average = '
```

```
Test Set Evaluation
Accuracy:  95.0
F1_score:  0.95
AUC:  0.99
```

Notes About Smoothing Parameter

1e-3 is the best smoothing parameter with a training accuracy of 96.23% and test accuracy of 95%

A Gaussian curve can serve as a "low pass" filter, allowing only the samples close to its mean to "pass." In the context of Naive Bayes, assuming a Gaussian distribution is essentially giving more weights to the samples closer to the distribution mean. This might filter out some values that we want to "pass".

The variable, var_smoothing, artificially adds a user-defined value to the distribution's variance (whose default value is derived from the training data set). This essentially widens (or "smooths") the curve and accounts for more samples that are further away from the distribution mean.

Tuning this parameter, will also modify the variance in a way that will give the best accuracy

Improving the model computation by removing multicollinear features

In [12]:
```
dataset2 = data[['area', 'compactness' , 'width_kernel', 'asymmetry_coeff', 'length_o

# Separating the dataset into matrix of features and target'
X = dataset2.iloc[:,:-1].values
y = dataset2.iloc[:,-1].values
```

In [13]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

In [14]:
```
%%time

# Fitting the Classification Model
nb_grid.fit(X_train, y_train)
nb_average_score = nb_grid.cv_results_['mean_test_score'].astype(float)
result = nb_grid.cv_results_
nb_grid.best_estimator_
```

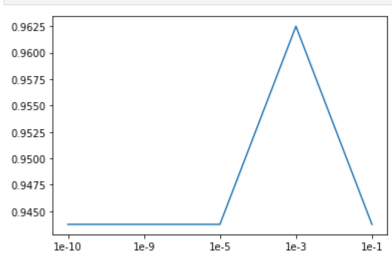
```
Wall time: 55 ms
```

Out[14]:
```
GaussianNB(var_smoothing=0.001)
```

In [15]:
```
nb_average_score
```

Out[15]:
```
array([0.94375, 0.94375, 0.94375, 0.9625 , 0.94375])
```

In [16]:
```
plt.figure()
sns.lineplot(x=["1e-10", "1e-9", "1e-5", "1e-3", "1e-1"], y=nb_average_score)
plt.show()
```



In [17]:
```
%%time
# Building model with optimal parameters
nb = GaussianNB(var_smoothing=0.001)
nb.fit(X_train, y_train)

print("Training Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_train, nb.predict(X_train)), 2))
print("F1_score: ", round(f1_score(y_train, nb.predict(X_train), average = 'weighted')
print("AUC: ", round(roc_auc_score(y_train, nb.predict_proba(X_train), average = "mac
```

```
Training Set Evaluation
Accuracy:  96.86
F1_score:  0.97
AUC:  1.0
Wall time: 10 ms
```

In [18]:
```
# Evaluating the model on the test set
nb_pred = nb.predict(X_test)

print("Test Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_test, nb_pred), 2))
print("F1_score: ", round(f1_score(y_test, nb_pred, average = 'weighted'), 2))
print("AUC: ", round(roc_auc_score(y_test, nb.predict_proba(X_test), average = "macro'
```

```
Test Set Evaluation
Accuracy:  92.5
F1_score:  0.92
AUC:  0.99
```

Effect of removing multicolinear features

- The training set accuracy increased from 96.23% to 96.86%.
- The test set accuracy reduced from 95% to 92.5%.

Improving the model by feature scaling

Standard Scaler

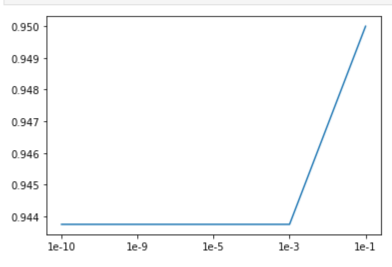
In [19]:
```
X_scaler = StandardScaler()
X_SS = X_scaler.fit_transform(X_train)
X_SS_test = X_scaler.transform(X_test)
nb_grid.fit(X_SS, y_train)
nb_average_score = nb_grid.cv_results_['mean_test_score'].astype(float)
result = nb_grid.cv_results_
nb_grid.best_estimator_
```

Out[19]:
```
GaussianNB(var_smoothing=0.1)
```

In [20]:
```
nb_average_score
```

Out[20]:
```
array([0.94375, 0.94375, 0.94375, 0.94375, 0.95   ])
```

In [21]:
```
plt.figure()
sns.lineplot(x=["1e-10", "1e-9", "1e-5", "1e-3", "1e-1"], y=nb_average_score)
plt.show()
```



In [22]:
```
%%time
# Building model with optimal parameters
nb = GaussianNB(var_smoothing=0.1)
nb.fit(X_SS, y_train)

print("Training Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_train, nb.predict(X_SS)), 2))
print("F1_score: ", round(f1_score(y_train, nb.predict(X_SS), average = 'weighted'), 2
print("AUC: ", round(roc_auc_score(y_train, nb.predict_proba(X_SS), average = "macro",
```

```
Training Set Evaluation
Accuracy:  95.6
F1_score:  0.96
AUC:  1.0
Wall time: 7.99 ms
```

In [23]:
```
# Evaluating the model on the test set
nb_pred = nb.predict(X_SS_test)

print("Test Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_test, nb_pred), 2))
print("F1_score: ", round(f1_score(y_test, nb_pred, average = 'weighted'), 2))
print("AUC: ", round(roc_auc_score(y_test, nb.predict_proba(X_SS_test), average = "ma
```

```
Test Set Evaluation
Accuracy:  90.0
F1_score:  0.9
AUC:  0.99
```

MinMax Scaler

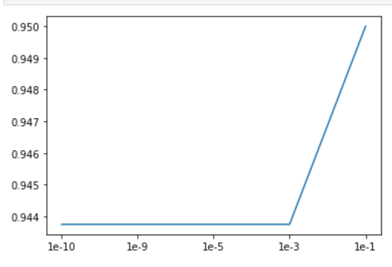
In [24]:
```
X_scaler = MinMaxScaler()
X_MMS = X_scaler.fit_transform(X_train)
X_MMS_test = X_scaler.transform(X_test)
nb_grid.fit(X_MMS, y_train)
nb_average_score = nb_grid.cv_results_['mean_test_score'].astype(float)
result = nb_grid.cv_results_
nb_grid.best_estimator_
```

Out[24]:
```
GaussianNB(var_smoothing=0.1)
```

In [25]:
```
nb_average_score
```

Out[25]:
```
array([0.94375, 0.94375, 0.94375, 0.94375, 0.95   ])
```

In [26]:
```
plt.figure()
sns.lineplot(x=["1e-10", "1e-9", "1e-5", "1e-3", "1e-1"], y=nb_average_score)
plt.show()
```



In [27]:
```
%%time
# Building model with optimal parameters
nb = GaussianNB(var_smoothing=0.1)
nb.fit(X_MMS, y_train)

print("Training Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_train, nb.predict(X_MMS)), 2))
print("F1_score: ", round(f1_score(y_train, nb.predict(X_MMS), average = 'weighted'),
print("AUC: ", round(roc_auc_score(y_train, nb.predict_proba(X_MMS), average = "macro'
```

```
Training Set Evaluation
Accuracy:  94.97
F1_score:  0.95
AUC:  0.99
Wall time: 7.95 ms
```

In [28]:
```
# Evaluating the model on the test set
nb_pred = nb.predict(X_MMS_test)

print("Test Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_test, nb_pred), 2))
print("F1_score: ", round(f1_score(y_test, nb_pred, average = 'weighted'), 2))
print("AUC: ", round(roc_auc_score(y_test, nb.predict_proba(X_MMS_test), average = "ma
```

```
Test Set Evaluation
Accuracy:  92.5
F1_score:  0.93
AUC:  0.99
```

Robust Scaler

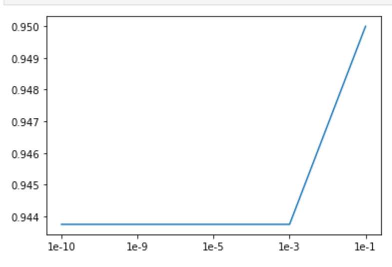
In [29]:
```
X_scaler = RobustScaler()
X_RS = X_scaler.fit_transform(X_train)
X_RS_test = X_scaler.transform(X_test)
nb_grid.fit(X_RS, y_train)
nb_average_score = nb_grid.cv_results_['mean_test_score'].astype(float)
result = nb_grid.cv_results_
nb_grid.best_estimator_
```

Out[29]:
```
GaussianNB(var_smoothing=0.1)
```

In [30]:
```
nb_average_score
```

Out[30]:
```
array([0.94375, 0.94375, 0.94375, 0.94375, 0.95   ])
```

In [31]:
```
plt.figure()
sns.lineplot(x=["1e-10", "1e-9", "1e-5", "1e-3", "1e-1"], y=nb_average_score)
plt.show()
```



In [32]:
```
%%time
# Building model with optimal parameters
nb = GaussianNB(var_smoothing=0.1)
nb.fit(X_RS, y_train)

print("Training Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_train, nb.predict(X_RS)), 2))
print("F1_score: ", round(f1_score(y_train, nb.predict(X_RS), average = 'weighted'), 2
print("AUC: ", round(roc_auc_score(y_train, nb.predict_proba(X_RS), average = "macro",
```

```
Training Set Evaluation
Accuracy:  96.23
F1_score:  0.96
AUC:  0.99
Wall time: 9.94 ms
```

In [33]:
```
# Evaluating the model on the test set
nb_pred = nb.predict(X_RS_test)

print("Test Set Evaluation")
print("Accuracy: ", round(100 * accuracy_score(y_test, nb_pred), 2))
print("F1_score: ", round(f1_score(y_test, nb_pred, average = 'weighted'), 2))
print("AUC: ", round(roc_auc_score(y_test, nb.predict_proba(X_RS_test), average = "ma
```

```
Test Set Evaluation
Accuracy:  90.0
F1_score:  0.9
AUC:  0.99
```

Notes About Feature Scaling on Naive Bayes

Effects of Scaling on Training Set

Scaling Method	Accuracy	F1 Score	AUC
Standard Scaler	95.6	0.96	1
MinMax Scaler	94.97	0.95	0.99
Robust Scaler	96.23	0.96	0.99
No Scaler	96.86	0.97	1

Effects of Scaling on Test Set

Scaling Method	Accuracy	F1 Score	AUC
Standard Scaler	90	0.9	0.99
MinMax Scaler	92.5	0.93	0.99
Robust Scaler	90	0.9	0.99
No Scaler	92.5	0.92	0.99

The Naive Bayes classifier performs better without feature scaling. Naive Bayes is not very sensitive to distance between values like KNN, so we did not expect much improvement from Feature Scaling.

In [ ]: