Tools

In [26]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("darkgrid")
```

Dataset

In [27]:
```
# from google.colab import drive
# drive.mount('/content/drive')
```

In [28]:
```
# data = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/dataset/MLF/BreastCanc
# data.head(10)
```

Dataset directly uploaded to google colab runtime disk and accessed

In [29]:
```
data = pd.read_csv("BreastCancerData.csv")
data.head(10)
```

Out[29]:

	mean_radius	mean_texture	mean_perimeter	mean_area	mean_smoothness	diagnosis
0	17.99	10.38	122.80	1001.0	0.11840	0
1	20.57	17.77	132.90	1326.0	0.08474	0
2	19.69	21.25	130.00	1203.0	0.10960	0
3	11.42	20.38	77.58	386.1	0.14250	0
4	20.29	14.34	135.10	1297.0	0.10030	0
5	12.45	15.70	82.57	477.1	0.12780	0
6	18.25	19.98	119.60	1040.0	0.09463	0
7	13.71	20.83	90.20	577.9	0.11890	0
8	13.00	21.82	87.50	519.8	0.12730	0
9	12.46	24.04	83.97	475.9	0.11860	0

Function for generating all-round results

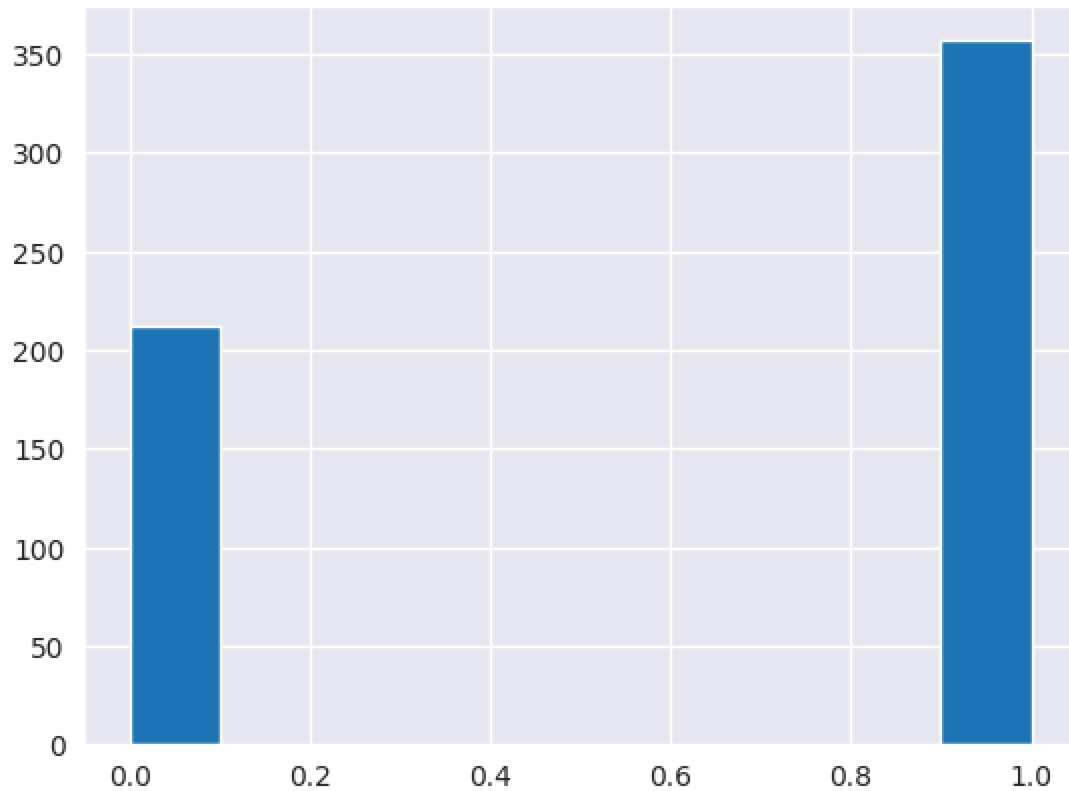
In [30]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import roc_curve, RocCurveDisplay, roc_auc_score, log_loss


def generate_results(y_test, y_pred, y_proba=None):
```

```
print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
print(f"Precision: {precision_score(y_test, y_pred)}")
print(f"Recall: {recall_score(y_test, y_pred)}")
print(f"F1 Score: {f1_score(y_test, y_pred)}")

cm = confusion_matrix(y_test, y_pred)
auc = roc_auc_score(y_test, y_pred)

print(f"\nAUC: {auc}")
print(f"\nLog loss: {log_loss(y_test, y_pred)}\n")

fpr, tpr, thresholds = roc_curve(y_test, y_proba if y_proba is not None else y_pr

fig, ax = plt.subplots(1, 2, figsize=(12, 6))

ConfusionMatrixDisplay(confusion_matrix=cm).plot(ax=ax[0])
ax[0].set_title('Confusion Matrix')

roc_display = RocCurveDisplay(fpr=fpr, tpr=tpr)
roc_display.plot(ax=ax[1])
ax[1].plot([0, 1], [0, 1], color='green', linestyle='--')
ax[1].set_title('ROC Curve')

plt.tight_layout()
plt.show()
```

Basic EDA

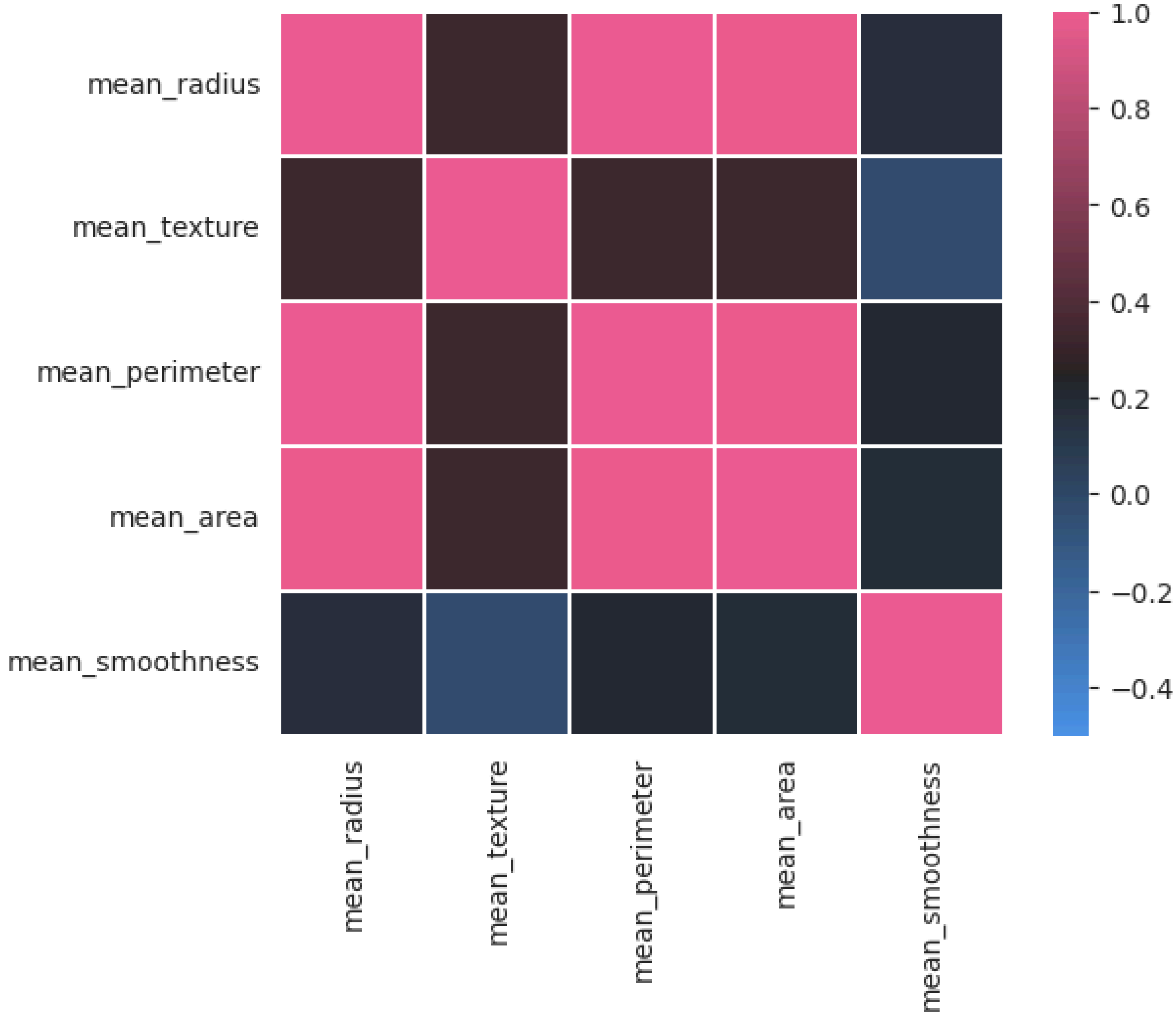
In [31]:
```
data["diagnosis"].hist()
```

Out[31]: <Axes: >



In [32]:
```
corr = data.iloc[:,:-1].corr(method="pearson")
cmap = sns.diverging_palette(250,354,80,60,center='dark',as_cmap=True)
sns.heatmap(corr, vmax=1, vmin=-.5, cmap=cmap, square=True, linewidths=.2)
```

Out[32]: <Axes: >



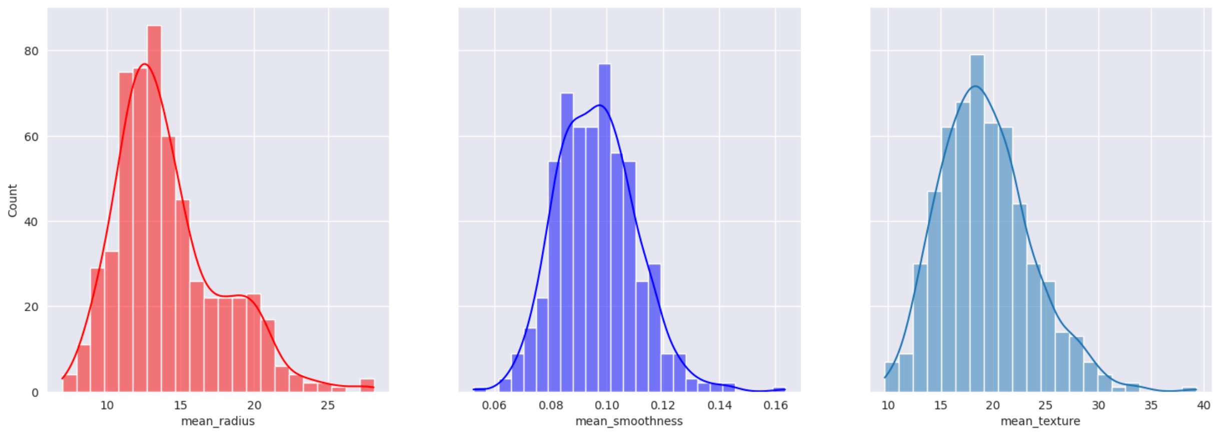
In [33]:
```
data = data[["mean_radius", "mean_texture", "mean_smoothness", "diagnosis"]]
data.head(10)
```

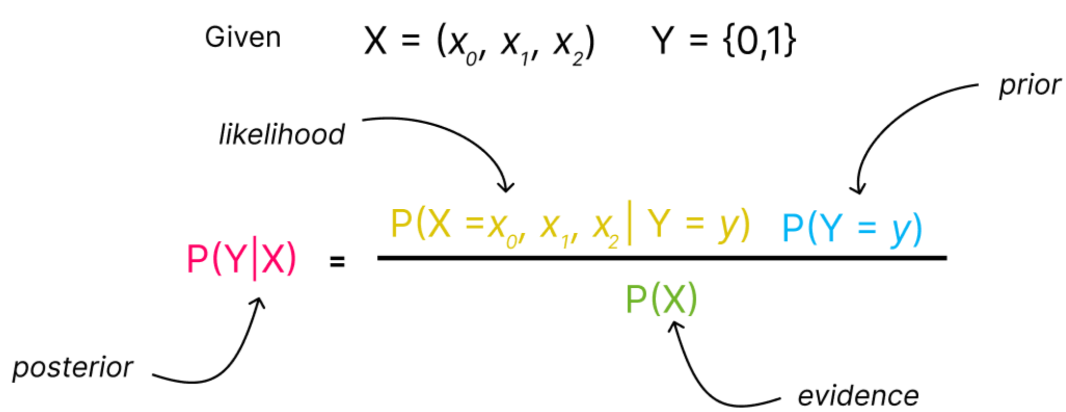
Out[33]:

	mean_radius	mean_texture	mean_smoothness	diagnosis
0	17.99	10.38	0.11840	0
1	20.57	17.77	0.08474	0
2	19.69	21.25	0.10960	0
3	11.42	20.38	0.14250	0
4	20.29	14.34	0.10030	0
5	12.45	15.70	0.12780	0
6	18.25	19.98	0.09463	0
7	13.71	20.83	0.11890	0
8	13.00	21.82	0.12730	0
9	12.46	24.04	0.11860	0

In [34]:
```
fig, axes = plt.subplots(1, 3, figsize=(18, 6), sharey=True)
sns.histplot(data, ax=axes[0], x="mean_radius", kde=True, color='r')
sns.histplot(data, ax=axes[1], x="mean_smoothness", kde=True, color='b')
sns.histplot(data, ax=axes[2], x="mean_texture", kde=True)
```

Out[34]: `<Axes: xlabel='mean_texture', ylabel='Count'>`





Calculate P(Y=y) for all possible y

In [35]:
```
def calculate_prior(df, Y):
    classes = sorted(list(df[Y].unique()))
    prior = []
    for i in classes:
        prior.append(len(df[df[Y]==i])/len(df))
    return prior
```

Approach 1: Calculate P(X=x|Y=y) using Gaussian dist.

In [36]:
```
def calculate_likelihood_gaussian(df, feat_name, feat_val, Y, label):
    feat = list(df.columns)
    df = df[df[Y]==label]
    mean, std = df[feat_name].mean(), df[feat_name].std()
```

```
    p_x_given_y = (1 / (np.sqrt(2 * np.pi) * std)) *  np.exp(-((feat_val-mean)**2 /
    return p_x_given_y
```

Calculate P(X=x1|Y=y)P(X=x2|Y=y)...P(X=xn|Y=y) * P(Y=y) for all y and find the maximum

In [37]:
```
def naive_bayes_gaussian(df, X, Y):
    # get feature names
    features = list(df.columns)[:-1]

    # calculate prior
    prior = calculate_prior(df, Y)

    Y_pred = []
    # loop over every data sample
    for x in X:
        # calculate likelihood
        labels = sorted(list(df[Y].unique()))
        likelihood = [1]*len(labels)
        for j in range(len(labels)):
            for i in range(len(features)):
                likelihood[j] *= calculate_likelihood_gaussian(df, features[i], x[i

        # calculate posterior probability (numerator only)
        post_prob = [1]*len(labels)
        for j in range(len(labels)):
            post_prob[j] = likelihood[j] * prior[j]

        Y_pred.append(np.argmax(post_prob))

    return np.array(Y_pred)
```

Test Gaussian model

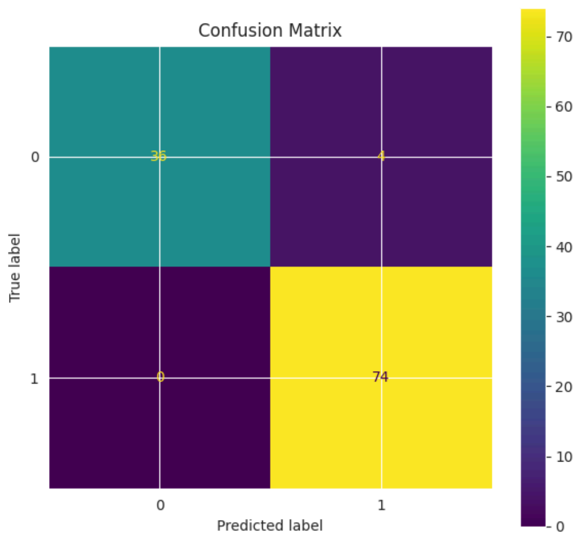
In [38]:
```
from sklearn.model_selection import train_test_split
train, test = train_test_split(data, test_size=.2, random_state=41)

X_test = test.iloc[:,:-1].values
Y_test = test.iloc[:,-1].values
Y_pred = naive_bayes_gaussian(train, X=X_test, Y="diagnosis")

from sklearn.metrics import confusion_matrix, f1_score
print(confusion_matrix(Y_test, Y_pred))
print(f1_score(Y_test, Y_pred))
```

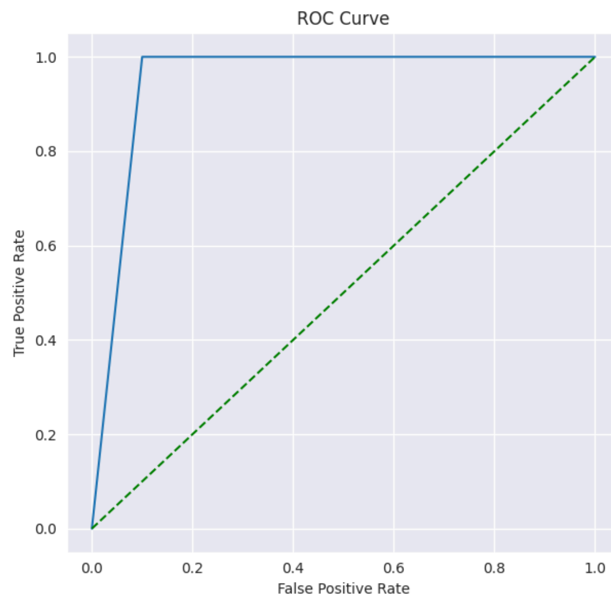
```
[[36  4]
 [ 0 74]]
0.9736842105263158
```

what does means 0? false negative ... and what about 4? false positive

In [39]:
```
# all-round results
generate_results(Y_test, Y_pred)
```

```
Accuracy: 0.9649122807017544
Precision: 0.9487179487179487
Recall: 1.0
F1 Score: 0.9736842105263158

AUC: 0.9500000000000001

Log loss: 1.2646895926006019
```





Convert continuous features to Categorical features

In [40]:
```
data_encoded = data.copy()
data_encoded["cat_mean_radius"] = pd.cut(data_encoded["mean_radius"].values, bins =
data_encoded["cat_mean_texture"] = pd.cut(data_encoded["mean_texture"].values, bins
data_encoded["cat_mean_smoothness"] = pd.cut(data_encoded["mean_smoothness"].values

data_encoded = data_encoded.drop(columns=["mean_radius", "mean_texture", "mean_smoo
data_encoded = data_encoded[["cat_mean_radius", "cat_mean_texture",     "cat_mean_s
data_encoded.head(10)
```

Out[40]:

	cat_mean_radius	cat_mean_texture	cat_mean_smoothness	diagnosis
0	1	0	1	0
1	1	0	0	0
2	1	1	1	0
3	0	1	2	0
4	1	0	1	0
5	0	0	2	0
6	1	1	1	0
7	0	1	1	0
8	0	1	2	0
9	0	1	1	0

Approach 2: Calculate P(X=x|Y=y) categorically

In [41]:
```
def calculate_likelihood_categorical(df, feat_name, feat_val, Y, label):
    feat = list(df.columns)
    df = df[df[Y]==label]
    p_x_given_y = len(df[df[feat_name]==feat_val]) / len(df)
    return p_x_given_y
```

Calculate P(X=x1|Y=y)P(X=x2|Y=y)...P(X=xn|Y=y) * P(Y=y) for all y and find the maximum

In [42]:
```
def naive_bayes_categorical(df, X, Y):
    # get feature names
    features = list(df.columns)[:-1]

    # calculate prior
    prior = calculate_prior(df, Y)

    Y_pred = []
    # loop over every data sample
    for x in X:
        # calculate likelihood
        labels = sorted(list(df[Y].unique()))
        likelihood = [1]*len(labels)
        for j in range(len(labels)):
            for i in range(len(features)):
                likelihood[j] *= calculate_likelihood_categorical(df, features[i],

        # calculate posterior probability (numerator only)
        post_prob = [1]*len(labels)
        for j in range(len(labels)):
```

```
            post_prob[j] = likelihood[j] * prior[j]

        Y_pred.append(np.argmax(post_prob))

    return np.array(Y_pred)
```

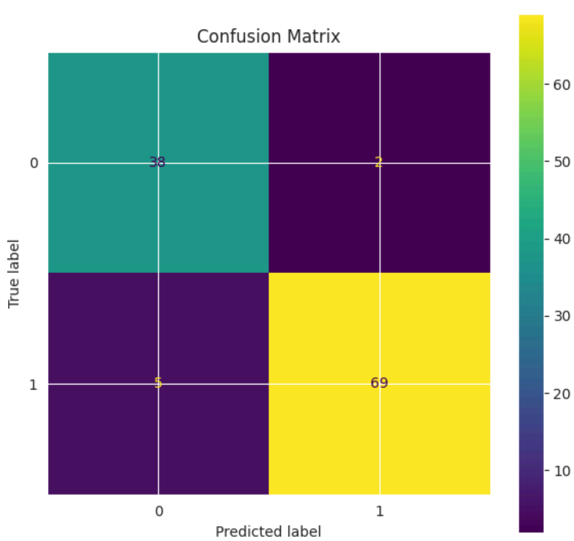
Test Categorical model

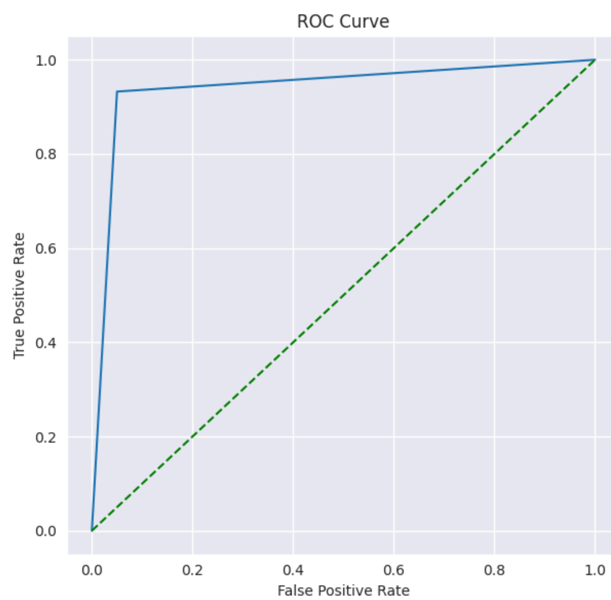
In [43]:
```
from sklearn.model_selection import train_test_split
train, test = train_test_split(data_encoded, test_size=.2, random_state=41)

X_test = test.iloc[:,:-1].values
Y_test = test.iloc[:,-1].values
Y_pred = naive_bayes_categorical(train, X=X_test, Y="diagnosis")

from sklearn.metrics import confusion_matrix, f1_score
print(confusion_matrix(Y_test, Y_pred))
print(f1_score(Y_test, Y_pred))
```

```
[[38  2]
 [ 5 69]]
0.9517241379310345
```

In [44]:
```
# all-round results
generate_results(Y_test, Y_pred)
```

```
Accuracy: 0.9385964912280702
Precision: 0.971830985915493
Recall: 0.9324324324324325
F1 Score: 0.9517241379310345

AUC: 0.9412162162162161

Log loss: 2.2132067870510532
```



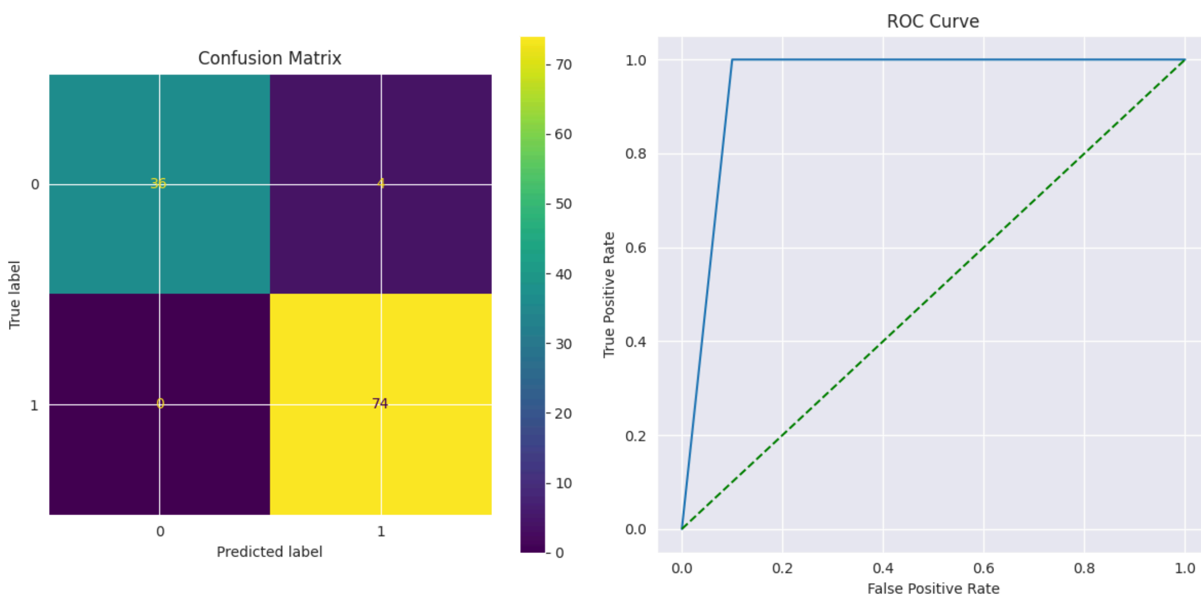


Comparision with Scikit-learn library implementations

Gaussian Naive Bayes with sklearn library

In [45]:
```
from sklearn.naive_bayes import GaussianNB

X_train, X_test, y_train, y_test = train_test_split(data.drop('diagnosis', axis=1),


gnb = GaussianNB()
gnb.fit(X_train, y_train)
y_pred_gnb = gnb.predict(X_test)

generate_results(y_test, y_pred_gnb)
```

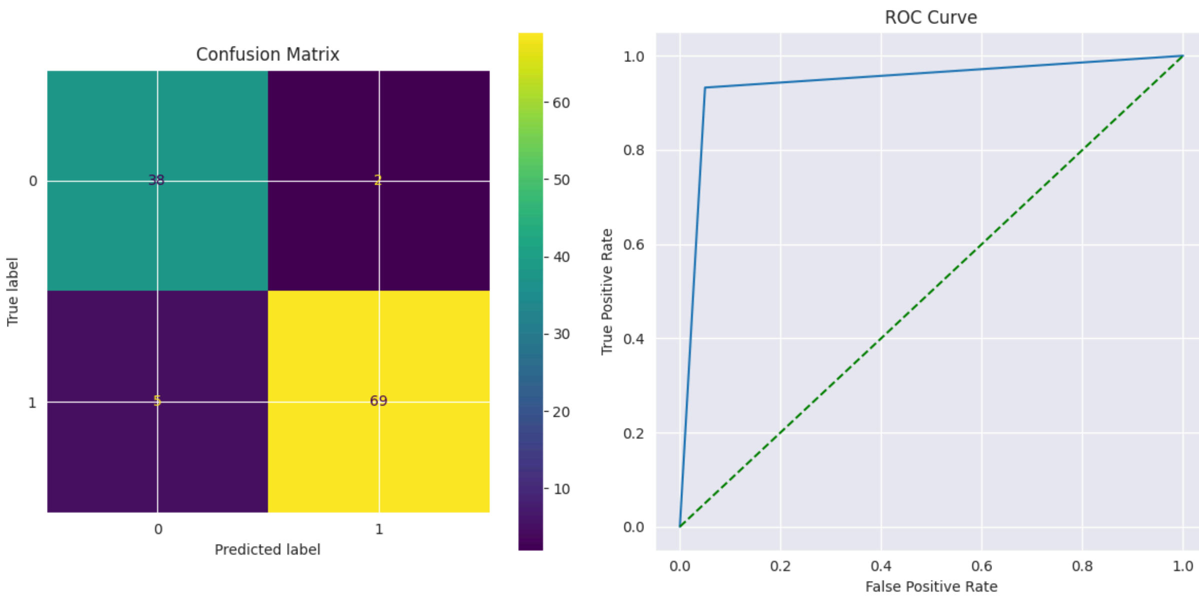
```
Accuracy: 0.9649122807017544
Precision: 0.9487179487179487
Recall: 1.0
F1 Score: 0.9736842105263158

AUC: 0.9500000000000001

Log loss: 1.2646895926006019
```



Categorial Naive Bayes with sklearn library

In [46]:
```
from sklearn.naive_bayes import CategoricalNB

X_train, X_test, y_train, y_test = train_test_split(data_encoded.drop('diagnosis',

cat_nb = CategoricalNB()
cat_nb.fit(X_train, y_train)
y_pred_cat = cat_nb.predict(X_test)

generate_results(y_test, y_pred_cat)
```

```
Accuracy: 0.9385964912280702
Precision: 0.971830985915493
Recall: 0.9324324324324325
F1 Score: 0.9517241379310345

AUC: 0.9412162162162161

Log loss: 2.2132067870510532
```



Conclusion

The results indicate a high level of consistency between the scratch implementation and the scikit-learn implementation for both Gaussian Naive Bayes and Categorical Naive Bayes.

In [46]: