Loading and Preprocessing Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV, KFold, train_test_split
from sklearn.utils.class_weight import compute_class_weight
from sklearn import metrics
from sklearn.metrics import roc_curve, roc_auc_score

# Ignore warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

```
data = pd.read_csv('/content/DATA File.csv')
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   ID                  569 non-null    int64  
 1   Diagnosis           569 non-null    object 
 2   radius1             569 non-null    float64
 3   texture1            569 non-null    float64
 4   perimeter1          569 non-null    float64
 5   area1               569 non-null    float64
 6   smoothness1         569 non-null    float64
 7   compactness1        569 non-null    float64
 8   concavity1          569 non-null    float64
 9   concave_points1     569 non-null    float64
 10  symmetry1           569 non-null    float64
 11  fractal_dimension1  569 non-null    float64
 12  radius2             569 non-null    float64
 13  texture2            569 non-null    float64
 14  perimeter2          569 non-null    float64
 15  area2               569 non-null    float64
 16  smoothness2         569 non-null    float64
 17  compactness2        569 non-null    float64
 18  concavity2          569 non-null    float64
 19  concave_points2     569 non-null    float64
 20  symmetry2           569 non-null    float64
 21  fractal_dimension2  569 non-null    float64
 22  radius3             569 non-null    float64
 23  texture3            569 non-null    float64
 24  perimeter3          569 non-null    float64
 25  area3               569 non-null    float64
 26  smoothness3         569 non-null    float64
 27  compactness3        569 non-null    float64
 28  concavity3          569 non-null    float64
 29  concave_points3     569 non-null    float64
 30  symmetry3           569 non-null    float64
 31  fractal_dimension3  569 non-null    float64
dtypes: float64(30), int64(1), object(1)
memory usage: 142.4+ KB
```

```
data
```

	ID	Diagnosis	radius1	texture1	perimeter1	area1	smoothness1	compactness1	concav
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1
...	...	...	...	...	...	...	...	...	
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.2
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.1
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.0
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.3
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.0

569 rows × 32 columns

```
# Counting missing values
missing_values = data.isnull().sum()
missing_values
```

```
ID                    0
Diagnosis             0
radius1               0
texture1              0
perimeter1            0
area1                 0
smoothness1           0
compactness1          0
concavity1            0
concave_points1       0
symmetry1             0
fractal_dimension1    0
radius2               0
```

```
texture2             0
perimeter2           0
area2                0
smoothness2          0
compactness2         0
concavity2           0
concave_points2      0
symmetry2            0
fractal_dimension2   0
radius3              0
texture3             0
perimeter3           0
area3                0
smoothness3          0
compactness3         0
concavity3           0
concave_points3      0
symmetry3            0
fractal_dimension3   0
dtype: int64
```

```
# Identify duplicate rows
duplicates = data.duplicated()
print("Duplicate Rows:\n", data[duplicates])

# Count the number of duplicate rows
num_duplicates = duplicates.sum()
print(f"Number of Duplicate Rows: {num_duplicates}")
```

```
Duplicate Rows:
 Empty DataFrame
Columns: [ID, Diagnosis, radius1, texture1, perimeter1, area1, smoothness1, compactness1, concavity1, concave_points1, symmetry1, fractal_dimension1, r
Index: []

[0 rows x 32 columns]
Number of Duplicate Rows: 0
```

```
# Drop 'ID' column
new_data = data.drop(['ID'], axis=1)
```

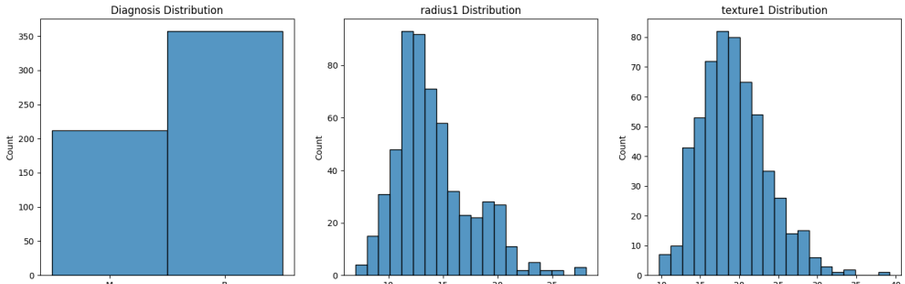
```
print(new_data.describe())
```

```
           radius1    texture1  perimeter1        area1  smoothness1  \
count  569.000000  569.000000  569.000000   569.000000   569.000000
mean    14.127292   19.289649   91.969033   654.889104     0.096360
std      3.524049    4.301036   24.298981   351.914129     0.014064
min      6.981000    9.710000   43.790000   143.500000     0.052630
25%     11.700000   16.170000   75.170000   420.300000     0.086370
50%     13.370000   18.840000   86.240000   551.100000     0.095870
75%     15.780000   21.800000  104.100000   782.700000     0.105300
max     28.110000   39.280000  188.500000  2501.000000     0.163400

       compactness1  concavity1  concave_points1   symmetry1  \
count    569.000000  569.000000       569.000000  569.000000
mean       0.104341    0.088799         0.048919    0.181162
std        0.052813    0.079720         0.038803    0.027414
min        0.019380    0.000000         0.000000    0.106000
25%        0.064920    0.029560         0.020310    0.161900
50%        0.092630    0.061540         0.033500    0.179200
75%        0.130400    0.130700         0.074000    0.195700
max        0.345400    0.426800         0.201200    0.304000

       fractal_dimension1  ...     radius3    texture3  perimeter3  \
count          569.000000  ...  569.000000  569.000000  569.000000
mean             0.062798  ...   16.269190   25.677223  107.261213
std              0.007060  ...    4.833242    6.146258   33.602542
min              0.049960  ...    7.930000   12.020000   50.410000
25%              0.057700  ...   13.010000   21.080000   84.110000
50%              0.061540  ...   14.970000   25.410000   97.660000
75%              0.066120  ...   18.790000   29.720000  125.400000
max              0.097440  ...   36.040000   49.540000  251.200000

              area3  smoothness3  compactness3  concavity3  concave_points3  \
count   569.000000   569.000000    569.000000  569.000000       569.000000
mean    880.583128     0.132369      0.254265    0.272188         0.114606
std     569.356993     0.022832      0.157336    0.208624         0.065732
min     185.200000     0.071170      0.027290    0.000000         0.000000
25%     515.300000     0.116600      0.147200    0.114500         0.064930
50%     686.500000     0.131300      0.211900    0.226700         0.099930
75%    1084.000000     0.146000      0.339100    0.382900         0.161400
max    4254.000000     0.222600      1.058000    1.252000         0.291000

        symmetry3  fractal_dimension3
count  569.000000          569.000000
mean     0.290076            0.083946
std      0.061867            0.018061
min      0.156500            0.055040
25%      0.250400            0.071460
50%      0.282200            0.080040
75%      0.317900            0.092080
max      0.663800            0.207500

[8 rows x 30 columns]
```

Exploratory Data Analysis

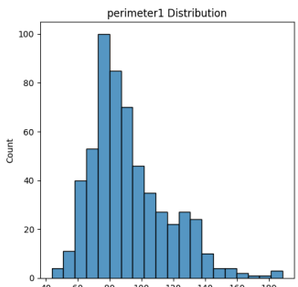
```
# Visualization of each target and features
import math
# Number of features
num_features = len(new_data.columns)

# Calculate the number of rows and columns for subplots
n_cols = 3
n_rows = math.ceil(num_features / n_cols)

# Create subplots
fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, 5 * n_rows))
```

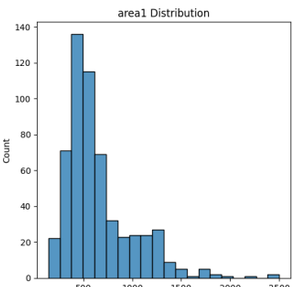
```
fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, 3 * n_rows))

# Flatten axes array for easy iteration
axes = axes.flatten()

# Loop over each column to create histograms
for i, col in enumerate(new_data.columns):
    sns.histplot(data[col], bins=20, ax=axes[i])
    axes[i].set_title(f'{col} Distribution')

# Hide any unused subplots
for j in range(i + 1, n_rows * n_cols):
    fig.delaxes(axes[j])

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

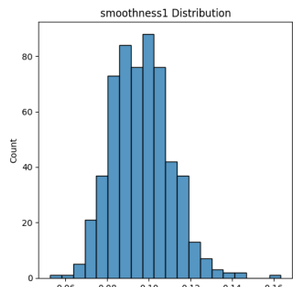

Diagnosis Distribution
Count
Diagnosis
M
B

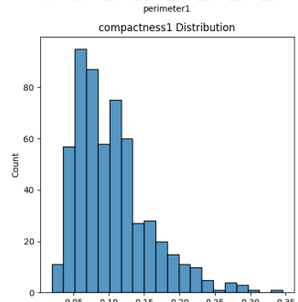
radius1 Distribution
Count
radius1

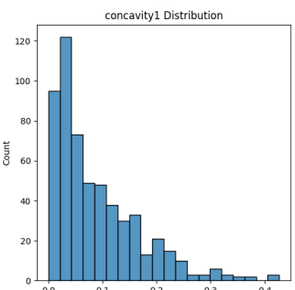
texture1 Distribution
Count
texture1

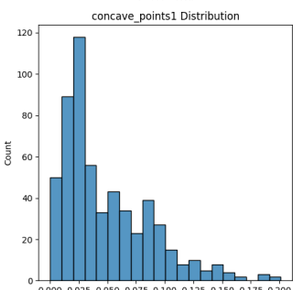

perimeter1 Distribution
Count
perimeter1

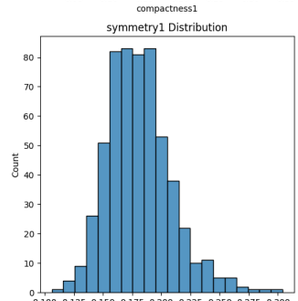

area1 Distribution
Count
area1

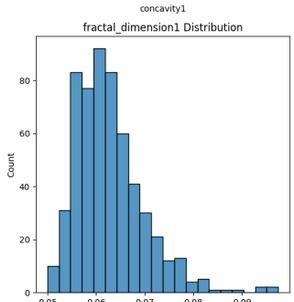

smoothness1 Distribution
Count
smoothness1

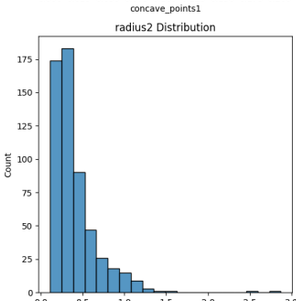

compactness1 Distribution
Count
compactness1

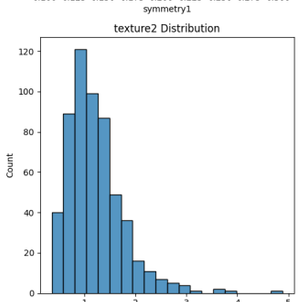

concavity1 Distribution
Count
concavity1

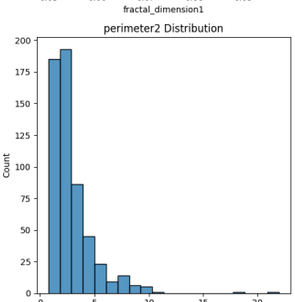

concave_points1 Distribution
Count
concave_points1

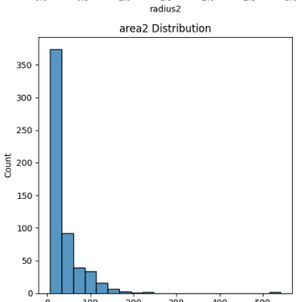

symmetry1 Distribution
Count
symmetry1

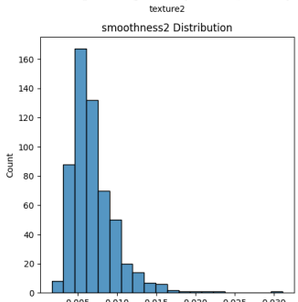

fractal_dimension1 Distribution
Count
fractal_dimension1

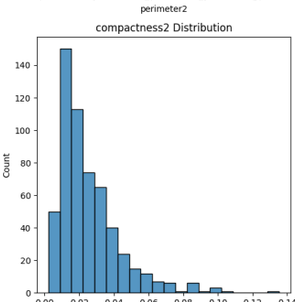

radius2 Distribution
Count
radius2

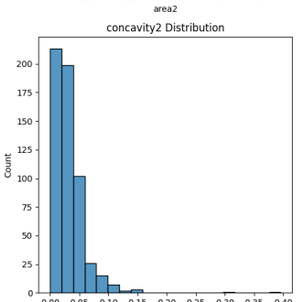

texture2 Distribution
Count
texture2

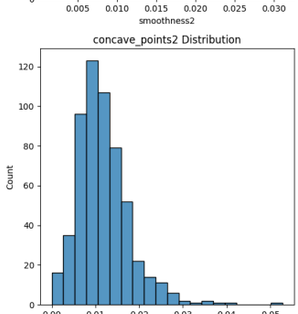

perimeter2 Distribution
Count
perimeter2

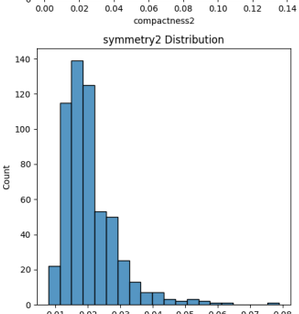

area2 Distribution
Count
area2

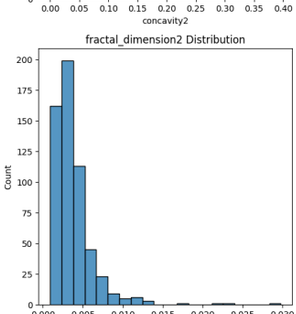

smoothness2 Distribution
Count
smoothness2

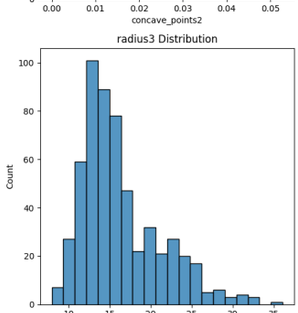

compactness2 Distribution
Count
compactness2

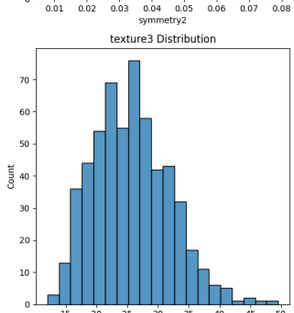

concavity2 Distribution
Count
concavity2

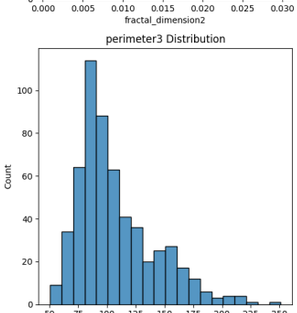

concave_points2 Distribution
Count
concave_points2

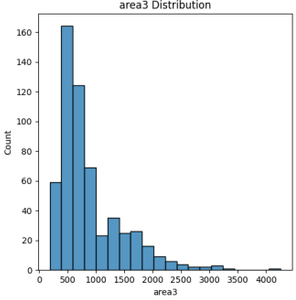

symmetry2 Distribution
Count
symmetry2

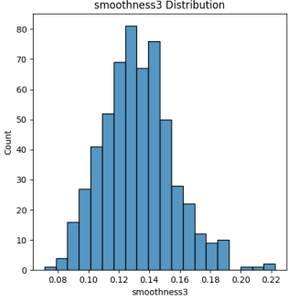

fractal_dimension2 Distribution
Count
fractal_dimension2

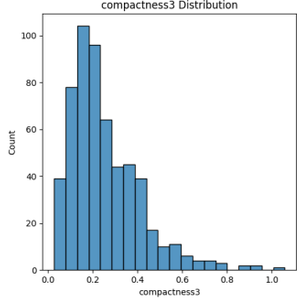

radius3 Distribution
Count
radius3

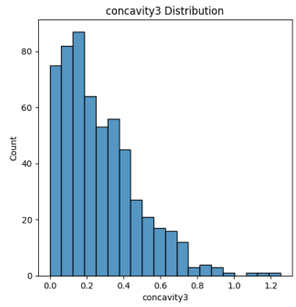

texture3 Distribution
Count
texture3

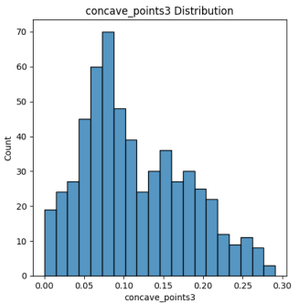

perimeter3 Distribution
Count
perimeter3

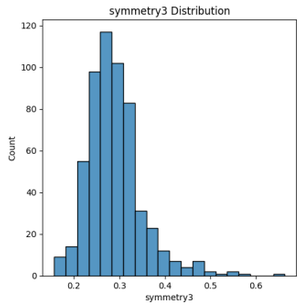

area3 Distribution
Count
area3

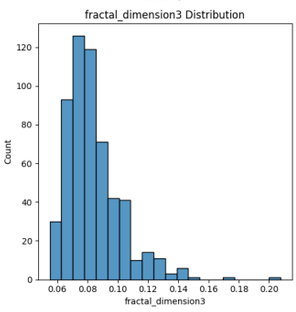

smoothness3 Distribution
Count
smoothness3


compactness3 Distribution
Count
compactness3


concavity3 Distribution
Count
concavity3


concave_points3 Distribution
Count
concave_points3


symmetry3 Distribution
Count
symmetry3


fractal_dimension3 Distribution
Count
fractal_dimension3

```
df = pd.get_dummies(new_data, columns=['Diagnosis'], dtype=int)
```

```
# Checking the count of the instances for each class in the target variable.
class_counts = new_data['Diagnosis'].value_counts()
print(class_counts)
```

```
Diagnosis
B    357
M    212
Name: count, dtype: int64
```

```
# Checking the count of the instances for each class in the target variable.
class_counts = new_data['Diagnosis'].value_counts()
print("Class counts:\n", class_counts)

# Calculate the ratio of the minority class to the majority class
ratio = class_counts.min() / class_counts.max()
print(f"\nRatio of minority to majority class: {ratio:.2f}")

# Determine if oversampling is needed
if ratio < 0.5:
    print("The dataset is imbalanced and may benefit from oversampling.")
else:
    print("The dataset is relatively balanced and may not need oversampling.")
```

```
Class counts:
 Diagnosis
B    357
M    212
Name: count, dtype: int64

Ratio of minority to majority class: 0.59
The dataset is relatively balanced and may not need oversampling.
```

```
X = new_data.drop('Diagnosis', axis=1)
y = new_data['Diagnosis']
```

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=44)
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
```

Model Training and Evaluation

```
import sklearn.metrics as metrics

def print_model_performance(model, X_test, y_test):
    y_pred = model.predict(X_test)
    print('Accuracy score:\n', metrics.accuracy_score(y_test, y_pred))
    print('Confussion matrix:\n',metrics.confusion_matrix(y_test, y_pred))
    print('Classification report:\n', metrics.classification_report(y_test, y_pred, digits=4))
    # Set pos_label to one of your actual labels
    print('Precision:\n',metrics.precision_score(y_test,y_pred, pos_label='M')) # Change 'M' if needed
    print('Recall:\n', metrics.recall_score(y_test, y_pred, pos_label='M'))    # Change 'M' if needed
```

Logistic Regression Classifier & It's ROC Curve

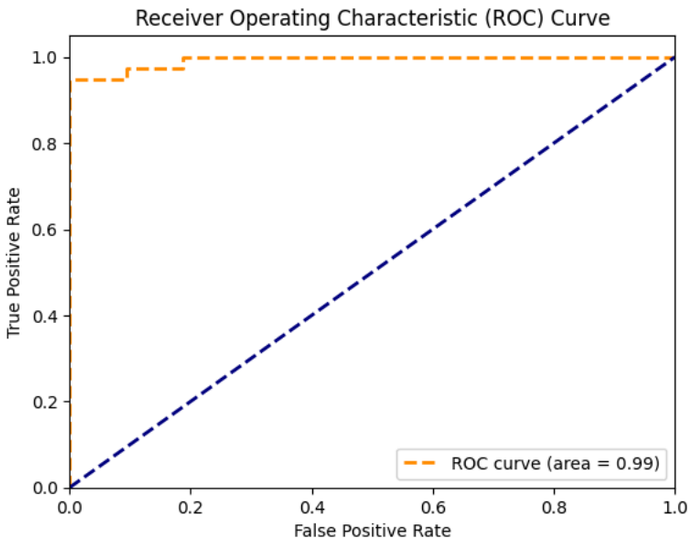
```
import sklearn.metrics as metrics

lr_classifier = LogisticRegression(max_iter=1000)
desc = lr_classifier.fit(X_train , y_train)
print(desc)

y_pred = lr_classifier.predict(X_test)
print(metrics.confusion_matrix(y_test, y_pred))
print(metrics.classification_report(y_test , y_pred))
```

```
LogisticRegression(max_iter=1000)
[[74  1]
 [ 2 37]]
              precision    recall  f1-score   support

           B       0.97      0.99      0.98        75
           M       0.97      0.95      0.96        39

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```

```
from sklearn.utils.class_weight import compute_class_weight

# Find all unique labels in y_train
unique_labels = y_train.unique()

# Calculate class weights using the unique labels
class_weights = compute_class_weight('balanced', classes=unique_labels, y=y_train)

# Create a logistic regression classifier with class weights
lr_classifier = LogisticRegression(class_weight=dict(zip(unique_labels, class_weights)))

# Train and evaluate the model
lr_classifier.fit(X_train, y_train)
y_pred = lr_classifier.predict(X_test)
print_model_performance(lr_classifier, X_test, y_test)
```

```
Accuracy score:
 0.9824561403508771
Confussion matrix:
 [[75  0]
 [ 2 37]]
Classification report:
              precision    recall  f1-score   support

           B     0.9740    1.0000    0.9868        75
           M     1.0000    0.9487    0.9737        39

    accuracy                         0.9825       114
   macro avg     0.9870    0.9744    0.9803       114
weighted avg     0.9829    0.9825    0.9823       114

Precision:
 1.0
Recall:
 0.9487179487179487
```

```
from sklearn.metrics import roc_curve, roc_auc_score
# Generate ROC curve
# Calculate the predicted probabilities for the positive class (e.g., 'M')
y_pred_proba = lr_classifier.predict_proba(X_test)[:, 1]

# Compute ROC curve and ROC AUC score
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba, pos_label='M')
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Plot ROC curve
plt.figure()
plt.plot(fpr, tpr, linestyle='--', color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.savefig('ROC',dpi=300)
plt.show()
```



Logistic Regression Classifier with Hyperparameter Tuning

```
# Define the logistic regression classifier
lr_classifier = LogisticRegression()

# Define the values you want to search for C, penalty, and solver
lr_C = np.array([50])
lr_penalty = ['l1', 'elasticnet']  # Changed '12' to 'l1' and 'elasticnet'
lr_solver = ['lbfgs', 'liblinear', 'sag']  # Added more solver options

grid_values = {'C': lr_C, 'penalty': lr_penalty, 'solver': lr_solver}   # L1 = Lasso L2 = Ridge

# Specify the cross-validation strategy
cross_validation = KFold(n_splits=5, shuffle=False)

# Create the GridSearchCV object
lrc_grid = GridSearchCV(lr_classifier, param_grid=grid_values, cv=cross_validation, n_jobs=-1, scoring='f1_macro')

# Fit the grid search to your training data
desc = lrc_grid.fit(X_train, y_train)

# Print the best parameters and model performance
print("\n The best parameters across all searched params:\n", lrc_grid.best_params_)
print_model_performance(lrc_grid, X_test, y_test)  # You should have a print_model_performance function defined elsewhere
```

```
 The best parameters across all searched params:
 {'C': 50, 'penalty': 'l1', 'solver': 'liblinear'}
Accuracy score:
 0.9912280701754386
Confussion matrix:
 [[75  0]
 [ 1 38]]
Classification report:
              precision    recall  f1-score   support

           B     0.9868    1.0000    0.9934        75
           M     1.0000    0.9744    0.9870        39

    accuracy                         0.9912       114
   macro avg     0.9934    0.9872    0.9902       114
weighted avg     0.9913    0.9912    0.9912       114

Precision:
 1.0
Recall:
 0.9743589743589743
```

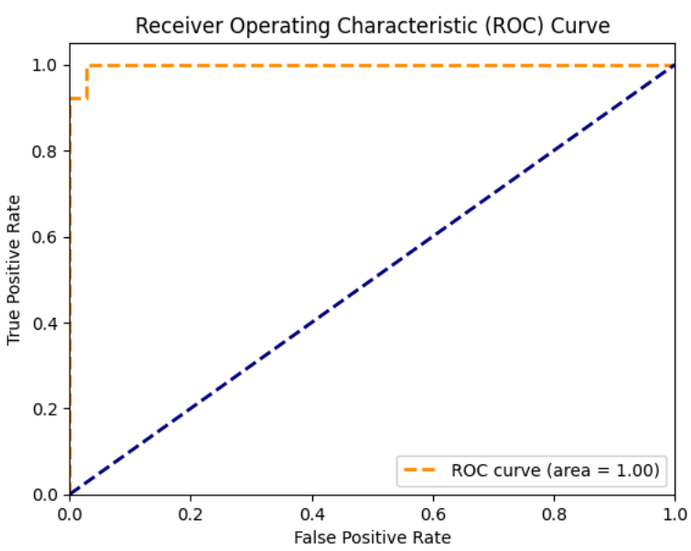
RandomForest Classifier & It's ROC Curve

```
from sklearn.ensemble import RandomForestClassifier

# Define and train a Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=44)
rf_classifier.fit(X_train, y_train)

# Evaluate the model
y_pred = rf_classifier.predict(X_test)
print_model_performance(rf_classifier, X_test, y_test)  # Define a print_model_performance function
```

```
Accuracy score:
 0.9649122807017544
Confussion matrix:
 [[73  2]
 [ 2 37]]
Classification report:
              precision    recall  f1-score   support

           B     0.9733    0.9733    0.9733        75
           M     0.9487    0.9487    0.9487        39

    accuracy                         0.9649       114
   macro avg     0.9610    0.9610    0.9610       114
weighted avg     0.9649    0.9649    0.9649       114

Precision:
 0.9487179487179487
Recall:
```

```
0.9487179487179487
```

```
# Generate the ROC curve
y_pred_proba = rf_classifier.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_proba, pos_label='M') # Specify the positive class
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, linestyle='--', color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.savefig('ROC',dpi=300)
plt.show()
```



Support Vector Machine (SVM) Classifier & It's ROC Curve

```
from sklearn import svm
svm_classifier = svm.SVC() #default kernal is radial basic function (RBF) kernal

desc = svm_classifier.fit(X_train, y_train)
print(desc)
print_model_performance(svm_classifier, X_test, y_test)
```

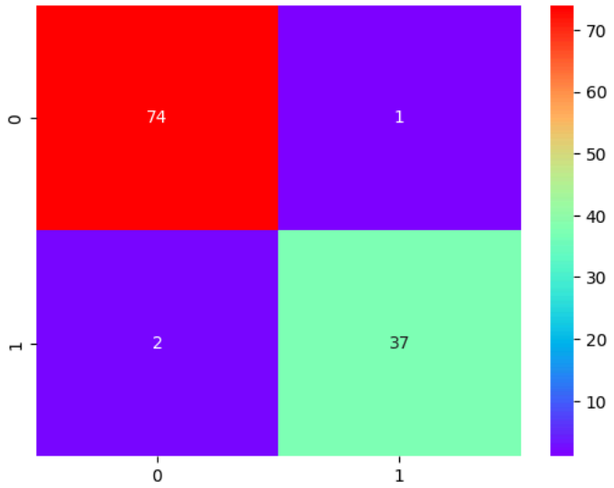
```
SVC()
Accuracy score:
 0.956140350877193
Confussion matrix:
 [[73  2]
 [ 3 36]]
Classification report:
              precision    recall  f1-score   support

           B     0.9605    0.9733    0.9669        75
           M     0.9474    0.9231    0.9351        39

    accuracy                         0.9561       114
   macro avg     0.9539    0.9482    0.9510       114
weighted avg     0.9560    0.9561    0.9560       114

Precision:
 0.9473684210526315
Recall:
 0.9230769230769231
```

```
import sklearn.metrics as metrics

for C in[1,10,100,1000,10000,100000,1000000]:
    for kernel in ['rbf','poly']:
        svm_classifier = svm.SVC(C=C, kernel=kernel) #similarly.gamma=0.01, 0.5
        svm_classifier.fit(X_train, y_train)
        y_pred = svm_classifier.predict(X_test)
        scores = metrics.accuracy_score(y_test, y_pred)
        print(f'C={C:<10} kernel={kernel:<10} accuracy score={scores: .3%}')
```

```
C=1          kernel=rbf        accuracy score= 95.614%
C=1          kernel=poly       accuracy score= 94.737%
C=10         kernel=rbf        accuracy score= 97.368%
C=10         kernel=poly       accuracy score= 96.491%
C=100        kernel=rbf        accuracy score= 97.368%
C=100        kernel=poly       accuracy score= 96.491%
C=1000       kernel=rbf        accuracy score= 97.368%
C=1000       kernel=poly       accuracy score= 96.491%
C=10000      kernel=rbf        accuracy score= 97.368%
C=10000      kernel=poly       accuracy score= 98.246%
C=100000     kernel=rbf        accuracy score= 98.246%
C=100000     kernel=poly       accuracy score= 98.246%
C=1000000    kernel=rbf        accuracy score= 96.491%
C=1000000    kernel=poly       accuracy score= 97.368%
```

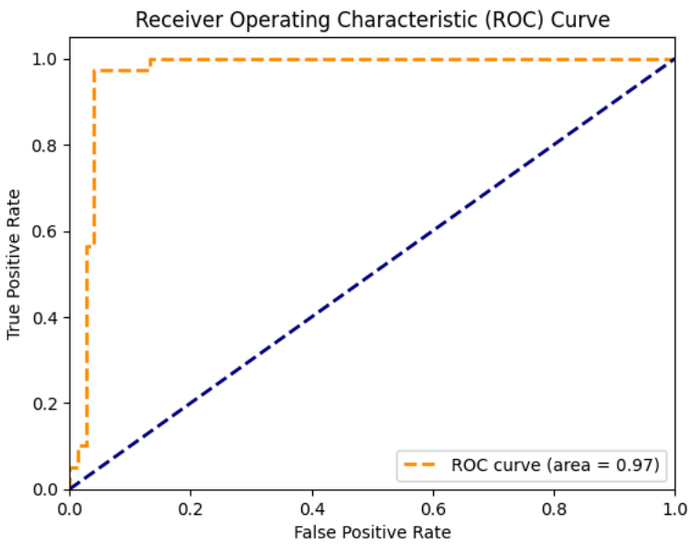
```
sns.heatmap(metrics.confusion_matrix(y_test, y_pred),annot=True, fmt='d', cmap='rainbow')
```

<Axes: >



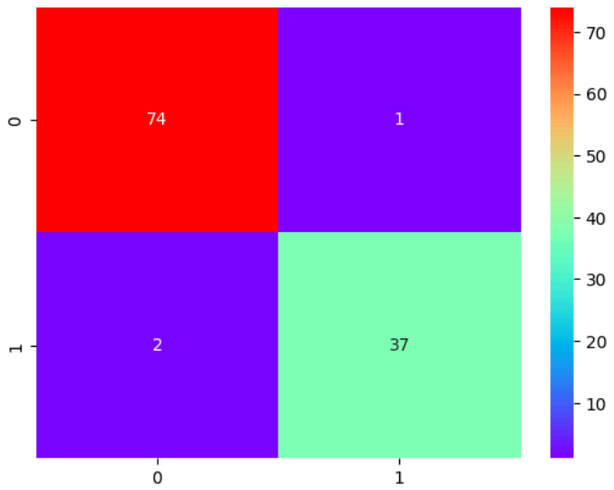

```
# Define the SVM classifier
svm_classifier = svm.SVC(probability=True)  # Set probability=True to enable predict_proba method

# Define the parameter grid
param_grid = {
    'C': [0.1, 1, 10, 100],
    'gamma': [1, 0.1, 0.01, 0.001],
    'kernel': ['rbf']
}

# Initialize GridSearchCV with SVM classifier and the parameter grid
grid = GridSearchCV(svm_classifier, param_grid, refit=True, verbose=2, cv=3)

# Fit the GridSearchCV to the data
grid.fit(X_train, y_train.values.ravel())

# Print the best parameters and estimator
print(f"Best parameters: {grid.best_params_}")
print(f"Best estimator: {grid.best_estimator_}")

# Evaluate the best model found by GridSearchCV
best_model = grid.best_estimator_
print_model_performance(best_model, X_test, y_test)

# Generate the ROC curve for the best model
y_pred_proba = best_model.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_proba, pos_label='M') # Specify 'M' as the positive class
roc_auc = roc_auc_score(y_test, y_pred_proba)
# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr,linestyle='--', color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
[CV] END .....................C=0.1, gamma=1, kernel=rbf; total time=   0.0s
[CV] END .....................C=0.1, gamma=1, kernel=rbf; total time=   0.0s
[CV] END .....................C=0.1, gamma=1, kernel=rbf; total time=   0.0s
[CV] END ....................C=0.1, gamma=0.1, kernel=rbf; total time=   0.0s
[CV] END ....................C=0.1, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ....................C=0.1, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ...................C=0.1, gamma=0.01, kernel=rbf; total time=   0.0s
[CV] END ...................C=0.1, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ...................C=0.1, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ..................C=0.1, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ..................C=0.1, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ..................C=0.1, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END .......................C=1, gamma=1, kernel=rbf; total time=   0.0s
[CV] END .......................C=1, gamma=1, kernel=rbf; total time=   0.1s
[CV] END .......................C=1, gamma=1, kernel=rbf; total time=   0.0s
[CV] END ......................C=1, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ......................C=1, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ......................C=1, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END .....................C=1, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END .....................C=1, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END .....................C=1, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ....................C=1, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ....................C=1, gamma=0.001, kernel=rbf; total time=   0.1s
[CV] END ....................C=1, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ......................C=10, gamma=1, kernel=rbf; total time=   0.1s
[CV] END ......................C=10, gamma=1, kernel=rbf; total time=   0.1s
[CV] END ......................C=10, gamma=1, kernel=rbf; total time=   0.1s
[CV] END .....................C=10, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END .....................C=10, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END .....................C=10, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ....................C=10, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ....................C=10, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ....................C=10, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ...................C=10, gamma=0.001, kernel=rbf; total time=   0.1s
[CV] END ...................C=10, gamma=0.001, kernel=rbf; total time=   0.1s
[CV] END ...................C=10, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END .....................C=100, gamma=1, kernel=rbf; total time=   0.1s
[CV] END .....................C=100, gamma=1, kernel=rbf; total time=   0.1s
[CV] END .....................C=100, gamma=1, kernel=rbf; total time=   0.1s
[CV] END ....................C=100, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ....................C=100, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ....................C=100, gamma=0.1, kernel=rbf; total time=   0.1s
[CV] END ...................C=100, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ...................C=100, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ...................C=100, gamma=0.01, kernel=rbf; total time=   0.1s
[CV] END ..................C=100, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ..................C=100, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ..................C=100, gamma=0.001, kernel=rbf; total time=   0.1s
Best parameters: {'C': 10, 'gamma': 0.001, 'kernel': 'rbf'}
Best estimator: SVC(C=10, gamma=0.001, probability=True)
Accuracy score:
 0.9210526315789473
Confussion matrix:
 [[67  8]
 [ 1 38]]
Classification report:
              precision    recall  f1-score   support

           B     0.9853    0.8933    0.9371        75
           M     0.8261    0.9744    0.8941        39

    accuracy                         0.9211       114
   macro avg     0.9057    0.9338    0.9156       114
weighted avg     0.9308    0.9211    0.9224       114

Precision:
 0.8260869565217391
Recall:
 0.9743589743589743
```




```
sns.heatmap(metrics.confusion_matrix(y_test, y_pred),annot=True, fmt='d', cmap='rainbow')
```

```
<Axes: >
```

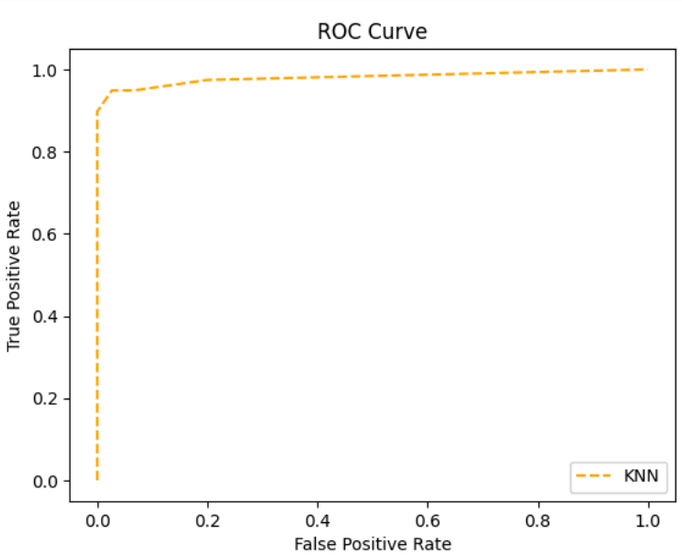


K-Nearest Neighbors Classifier & It's ROC Curve

```
knn_classifier = KNeighborsClassifier(n_neighbors=4)
knn_classifier.fit(X_train, y_train)

desc = knn_classifier.fit(X_train, y_train)
print(desc)
print_model_performance(knn_classifier, X_test, y_test)
```

```
KNeighborsClassifier(n_neighbors=4)
Accuracy score:
 0.9649122807017544
Confussion matrix:
 [[73  2]
 [ 2 37]]
Classification report:
              precision    recall  f1-score   support

           B     0.9733    0.9733    0.9733        75
           M     0.9487    0.9487    0.9487        39

    accuracy                         0.9649       114
   macro avg     0.9610    0.9610    0.9610       114
weighted avg     0.9649    0.9649    0.9649       114

Precision:
 0.9487179487179487
Recall:
 0.9487179487179487
```

```
# Predict probabilities
y_pred_proba = knn_classifier.predict_proba(X_test)[:, 1]

# Calculate ROC curve
fpr, tpr, _ = roc_curve(y_test, y_pred_proba, pos_label='M') # Specify 'M' as the positive class

# Plot ROC curve
plt.plot(fpr, tpr, linestyle='--', color='orange', label='KNN')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='best')
plt.savefig('ROC', dpi=300)
plt.show()
```



Decision Tree Classifier & It's ROC Curve

```
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier(criterion= "entropy" ,max_depth=10, random_state=44)
dt_classifier.fit(X_train,y_train)

print(dt_classifier)
print_model_performance(dt_classifier, X_test, y_test)
```

```
DecisionTreeClassifier(criterion='entropy', max_depth=10, random_state=44)
Accuracy score:
 0.956140350877193
Confussion matrix:
 [[72  3]
 [ 2 37]]
Classification report:
              precision    recall  f1-score   support

           B     0.9730    0.9600    0.9664        75
           M     0.9250    0.9487    0.9367        39

    accuracy                         0.9561       114
   macro avg     0.9490    0.9544    0.9516       114
weighted avg     0.9566    0.9561    0.9563       114
```

Hypermparameter tuning with Desision Tree

```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, roc_curve, roc_auc_score, classification_report, confusion_matrix, precision_score, recall_score
from sklearn.tree import DecisionTreeClassifier
# Set up the parameter grid for the Decision Tree
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize a Decision Tree classifier
dt_classifier = DecisionTreeClassifier(random_state=44)
```