```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import scikitplot as skplt

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split, cross_val_score

heart = pd.read_csv(r"C:\Users\Ayesha\Downloads\heart (ML 5215).csv")

# Display the first 5 rows of the data to understand the nature of the
values
heart.head()
```

```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak
slope  \
0   63    1   3       145   233    1        0      150      0      2.3
0
1   37    1   2       130   250    0        1      187      0      3.5
0
2   41    0   1       130   204    0        0      172      0      1.4
2
3   56    1   1       120   236    0        1      178      0      0.8
2
4   57    0   0       120   354    0        1      163      1      0.6
2

   ca  thal  target
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

```
#generating a concise summary of features
#helps understand the structure of the DataFrame + identifying missing
or null values
heart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
```

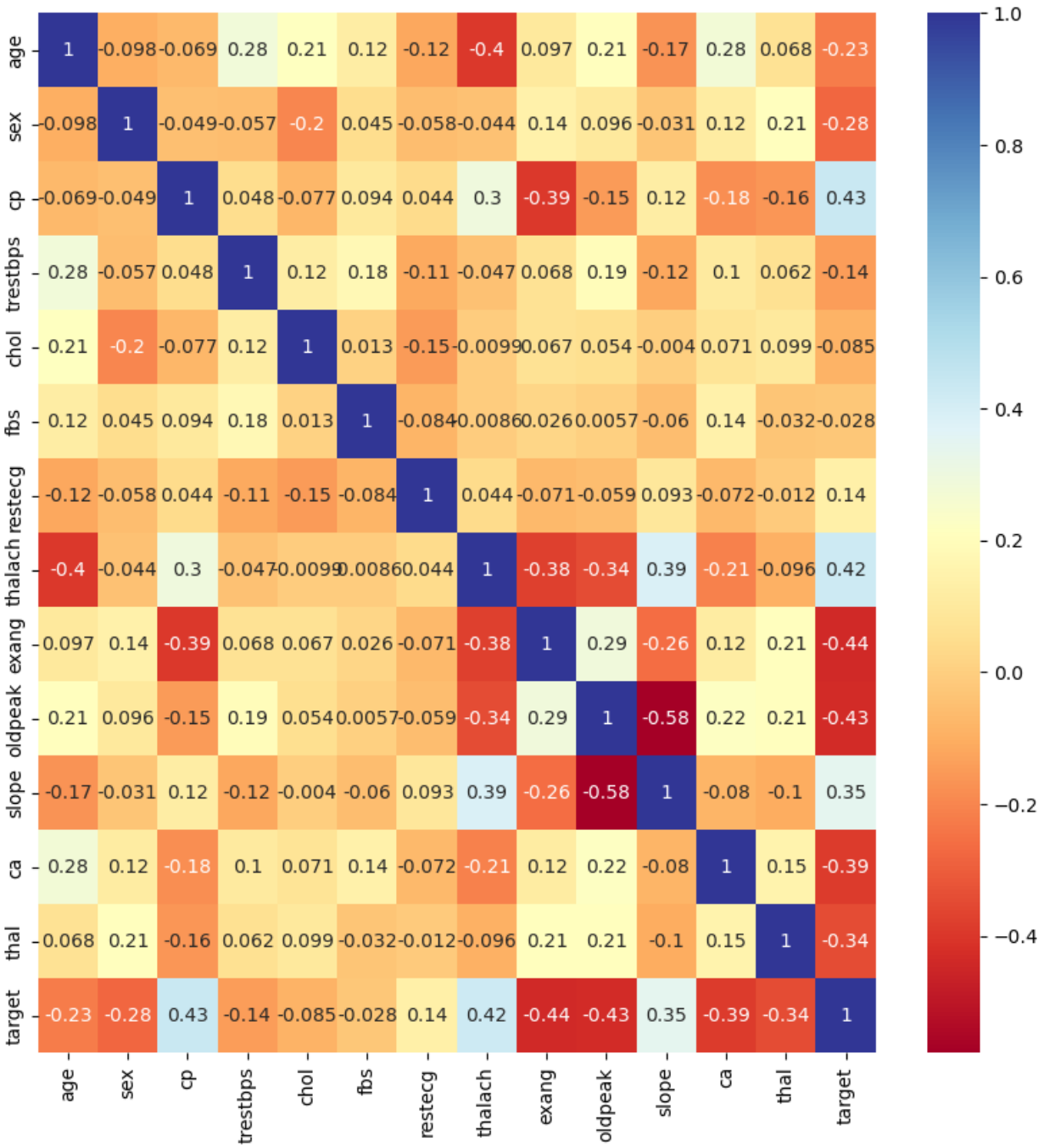
```
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

```
#generating a quick overview of the distribution and range for each
feature
#can help identify potential outliers or issues with the data
heart.describe()
```

```
              age         sex          cp    trestbps        chol
fbs  \
count  303.000000  303.000000  303.000000  303.000000  303.000000
303.000000
mean    54.366337    0.683168    0.966997  131.623762  246.264026
0.148515
std      9.082101    0.466011    1.032052   17.538143   51.830751
0.356198
min     29.000000    0.000000    0.000000   94.000000  126.000000
0.000000
25%     47.500000    0.000000    0.000000  120.000000  211.000000
0.000000
50%     55.000000    1.000000    1.000000  130.000000  240.000000
0.000000
75%     61.000000    1.000000    2.000000  140.000000  274.500000
0.000000
max     77.000000    1.000000    3.000000  200.000000  564.000000
1.000000

          restecg     thalach       exang     oldpeak       slope
ca  \
count  303.000000  303.000000  303.000000  303.000000  303.000000
303.000000
mean     0.528053  149.646865    0.326733    1.039604    1.399340
0.729373
std      0.525860   22.905161    0.469794    1.161075    0.616226
1.022606
min      0.000000   71.000000    0.000000    0.000000    0.000000
0.000000
25%      0.000000  133.500000    0.000000    0.000000    1.000000
0.000000
50%      1.000000  153.000000    0.000000    0.800000    1.000000
0.000000
```

```
75%      1.000000  166.000000    1.000000    1.600000    2.000000
1.000000
max      2.000000  202.000000    1.000000    6.200000    2.000000
4.000000

              thal      target
count  303.000000  303.000000
mean     2.313531    0.544554
std      0.612277    0.498835
min      0.000000    0.000000
25%      2.000000    0.000000
50%      2.000000    1.000000
75%      3.000000    1.000000
max      3.000000    1.000000
```

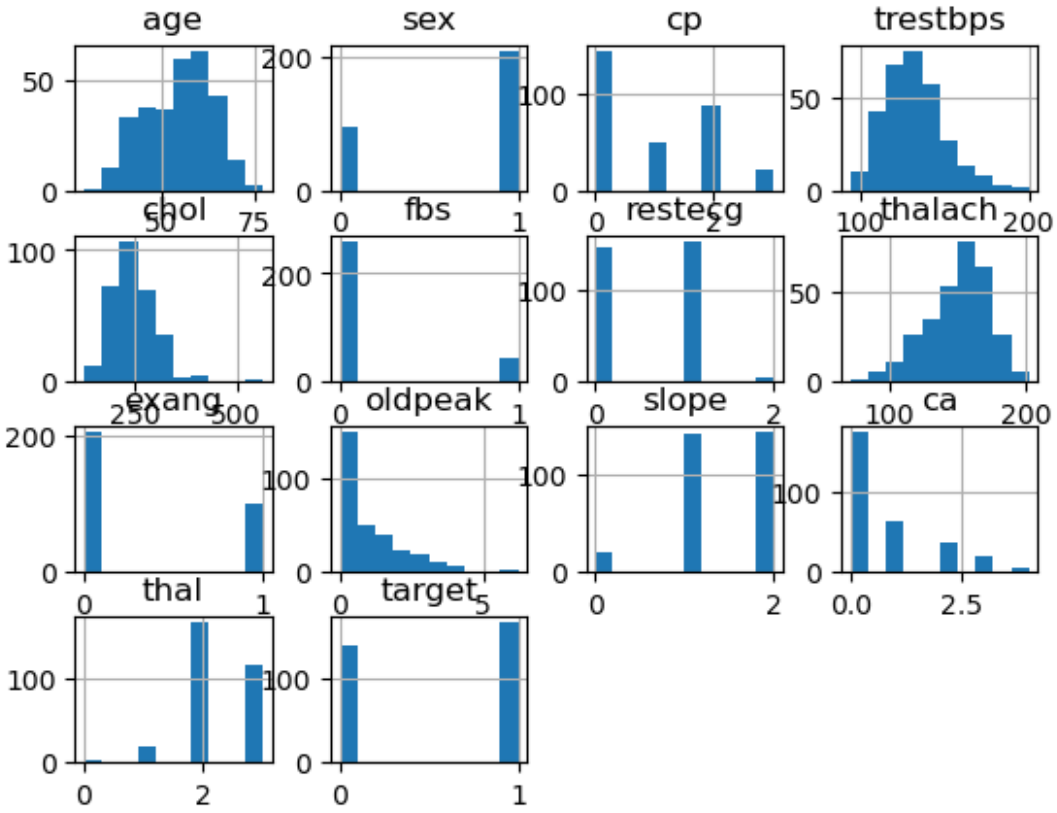
```python
#Performing feature selection and understanding the correlation btw
different features and the target values
import seaborn as sns
corr_matrix = heart.corr()

#idenfying features with higest correlation
#helps understand which features are most relevant for predicting
target variable
significant_features = corr_matrix.index
plt.figure(figsize = (10,10))

#plotting a heatmap
# Plot heatmap
heatmap = sns.heatmap(corr_matrix.loc[significant_features,
significant_features], cmap="RdYlBu", annot=True)
```



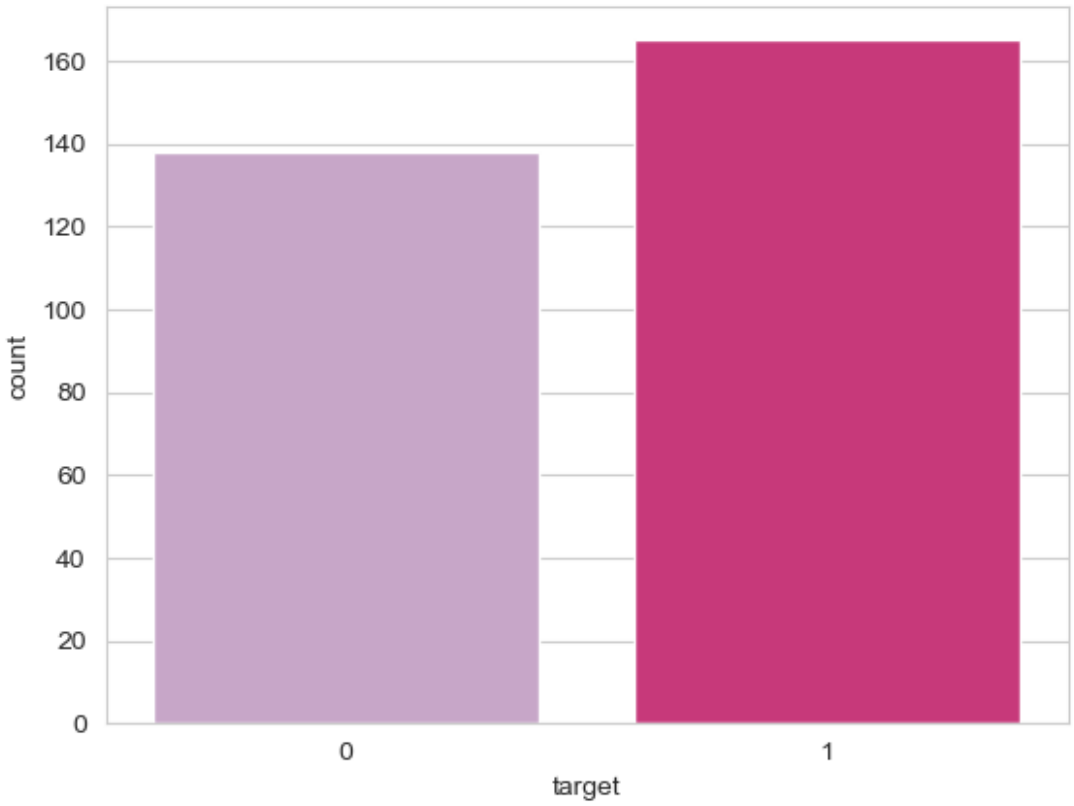

```
#generating distograms to visualise the distribution of data
heart.hist()
```

```
array([[<Axes: title={'center': 'age'}>, <Axes: title={'center':
'sex'}>,
        <Axes: title={'center': 'cp'}>,
        <Axes: title={'center': 'trestbps'}>],
       [<Axes: title={'center': 'chol'}>,
        <Axes: title={'center': 'fbs'}>,
```

```
       <Axes: title={'center': 'restecg'}>,
       <Axes: title={'center': 'thalach'}>],
      [<Axes: title={'center': 'exang'}>,
       <Axes: title={'center': 'oldpeak'}>,
       <Axes: title={'center': 'slope'}>,
       <Axes: title={'center': 'ca'}>],
      [<Axes: title={'center': 'thal'}>,
       <Axes: title={'center': 'target'}>, <Axes: >, <Axes: >]],
     dtype=object)
```




```
#identifying whether that DataFrame is balanced or imbalanced
sns.set_style('whitegrid')
sns.countplot(x = 'target',data = heart, palette = "PuRd")

<Axes: xlabel='target', ylabel='count'>
```




```
#converting categorical variables into dummy variables

categorical_cols = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope',
'ca', 'thal']
dummy = pd.get_dummies(heart, columns=categorical_cols,
drop_first=True)

#performing standard scaling
#helps bring the features to a standard normal distribution and helps
in dealing with features in different units


from sklearn.preprocessing import StandardScaler

# create a StandardScaler object
scaler = StandardScaler()

# select the columns to be scaled - select non-catergorical variables
excluding target
cols_to_scale = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']

# fit and transform the selected columns
dummy[cols_to_scale] = scaler.fit_transform(dummy[cols_to_scale])
```

```
#observing changes in the dataframe
dummy.head()
```

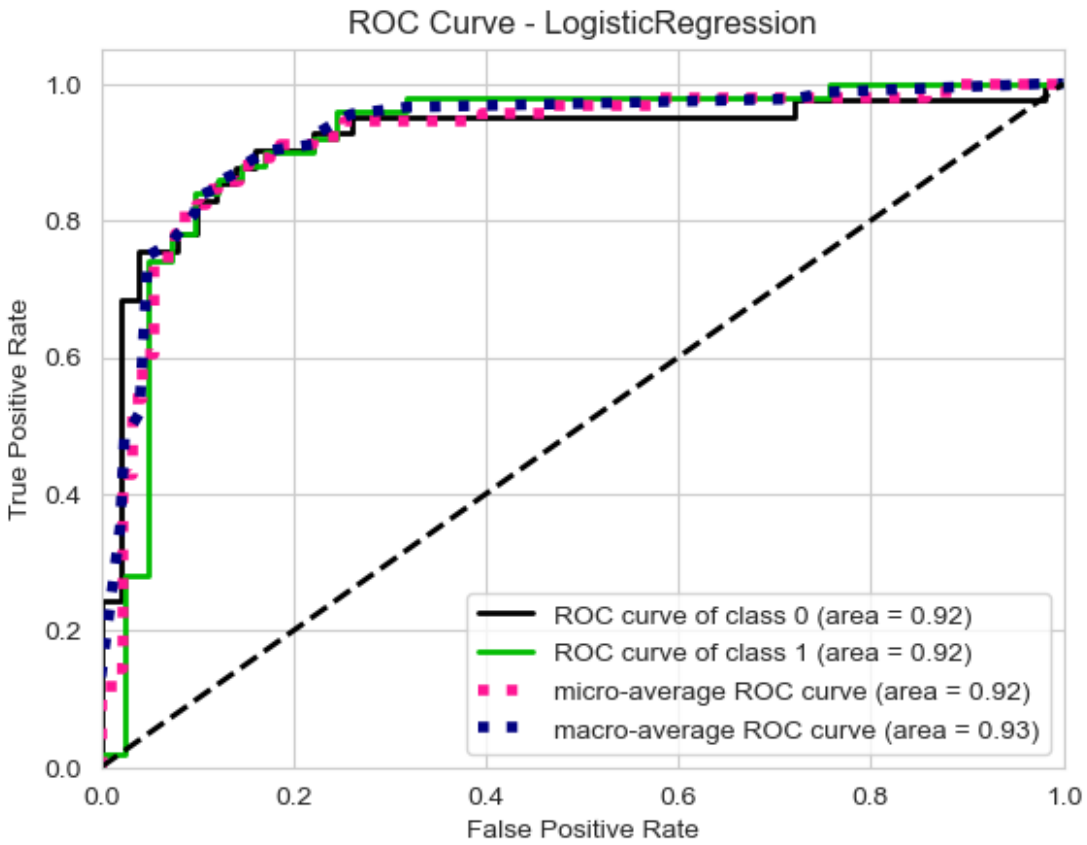
```
        age  trestbps      chol   thalach   oldpeak  target  sex_1
cp_1  \
0  0.952197  0.763956 -0.256334  0.015443  1.087338       1      1
0
1 -1.915313 -0.092738  0.072199  1.633471  2.122573       1      1
0
2 -1.474158 -0.092738 -0.816773  0.977514  0.310912       1      0
1
3  0.180175 -0.663867 -0.198357  1.239897 -0.206705       1      1
1
4  0.290464 -0.663867  2.082050  0.583939 -0.379244       1      0
0

   cp_2  cp_3  ...  exang_1  slope_1  slope_2  ca_1  ca_2  ca_3  ca_4
thal_1  \
0     0     1  ...        0        0        0     0     0     0     0
1
1     1     0  ...        0        0        0     0     0     0     0
0
2     0     0  ...        0        0        1     0     0     0     0
0
3     0     0  ...        0        0        1     0     0     0     0
0
4     0     0  ...        1        0        1     0     0     0     0
0

   thal_2  thal_3
0       0       0
1       1       0
2       1       0
3       1       0
4       1       0

[5 rows x 23 columns]
```

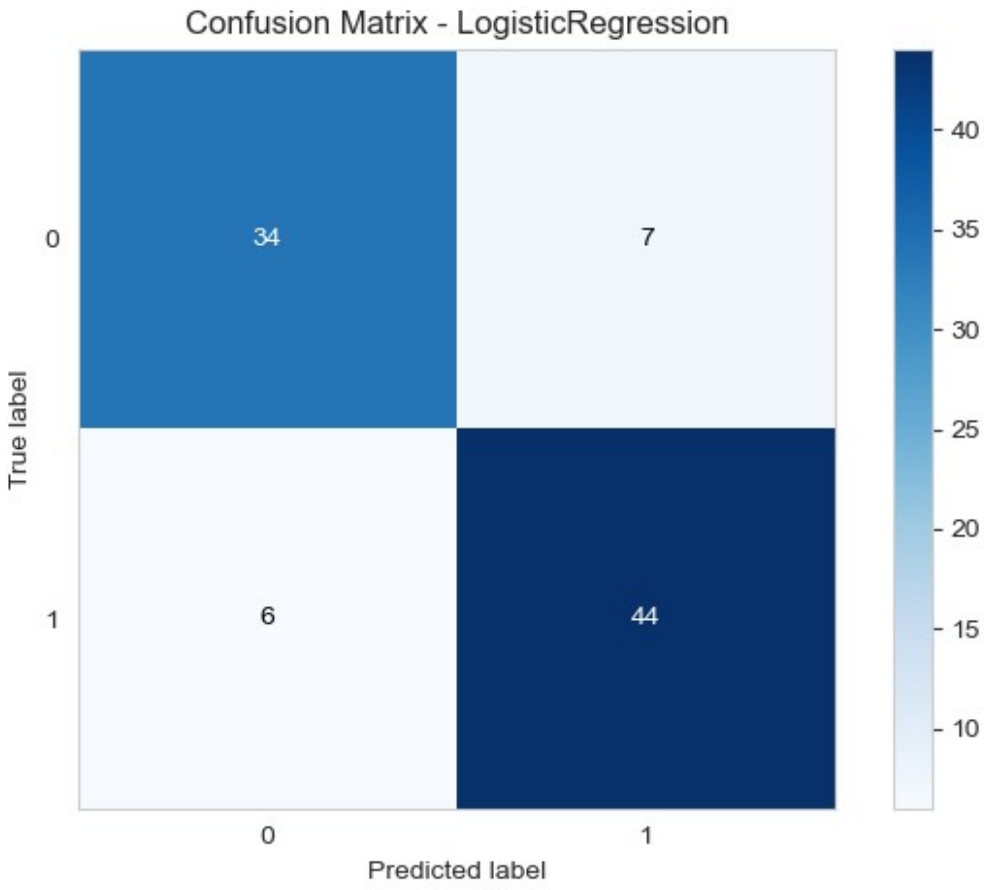
```
# Split data into train and test sets
X_train, X_test, y_train, y_test =
train_test_split(dummy.drop('target', axis=1), dummy['target'],
test_size=0.3, random_state=42)

from sklearn.model_selection import GridSearchCV

models = [
    {'name': 'LogisticRegression',
                'model': LogisticRegression(random_state=1),
                'params': {
                    'C': [0.1, 0.4, 0.7, 1],
```

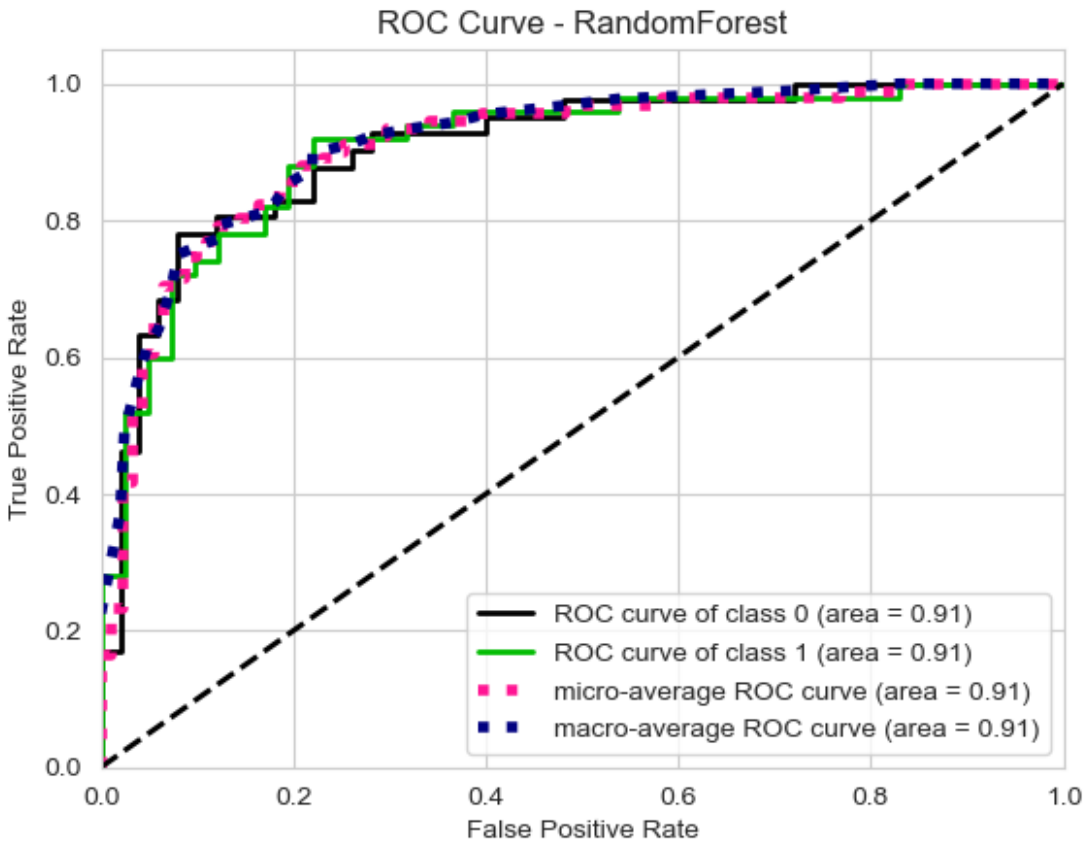
```
                    'multi_class': ['auto', 'ovr', 'multinomial'],
                    'solver': ['newton-cg']
        }
    },
    {'name': 'RandomForest',
     'model': RandomForestClassifier(random_state=1),
     'params': {
            'n_estimators': [10, 50, 100, 200],
            'criterion': ['gini', 'entropy'],
            'max_features': ['sqrt', 'log2'],
            'max_depth': [2, 3, 4, 5]
        }
    },
    {
    'name': 'KNN',
    'model': KNeighborsClassifier(),
    'params': {
            'n_neighbors': [3, 4, 5, 6, 7],
            'weights': ['uniform', 'distance']
        }
    }
]
#Iterating over the models, performing grid search cv to find the best
hyperparameters and displaying their scores

best_models = []
for model in models:
    clf = GridSearchCV(model['model'], model['params'], cv=5)
    clf.fit(X_train, y_train)
    best_score = clf.best_score_
    best_estimator = clf.best_estimator_
    accuracy = best_estimator.score(X_test, y_test)
    print(f"Mean Cross-Validated score of best {model['name']}:
{clf.best_score_:.16f}")
    print(f"Accuracy of {model['name']} on test data:
{accuracy:.16f}")
    best_models.append({
        'name': model['name'],
        'model': best_estimator,
        'accuracy': accuracy
    })
```

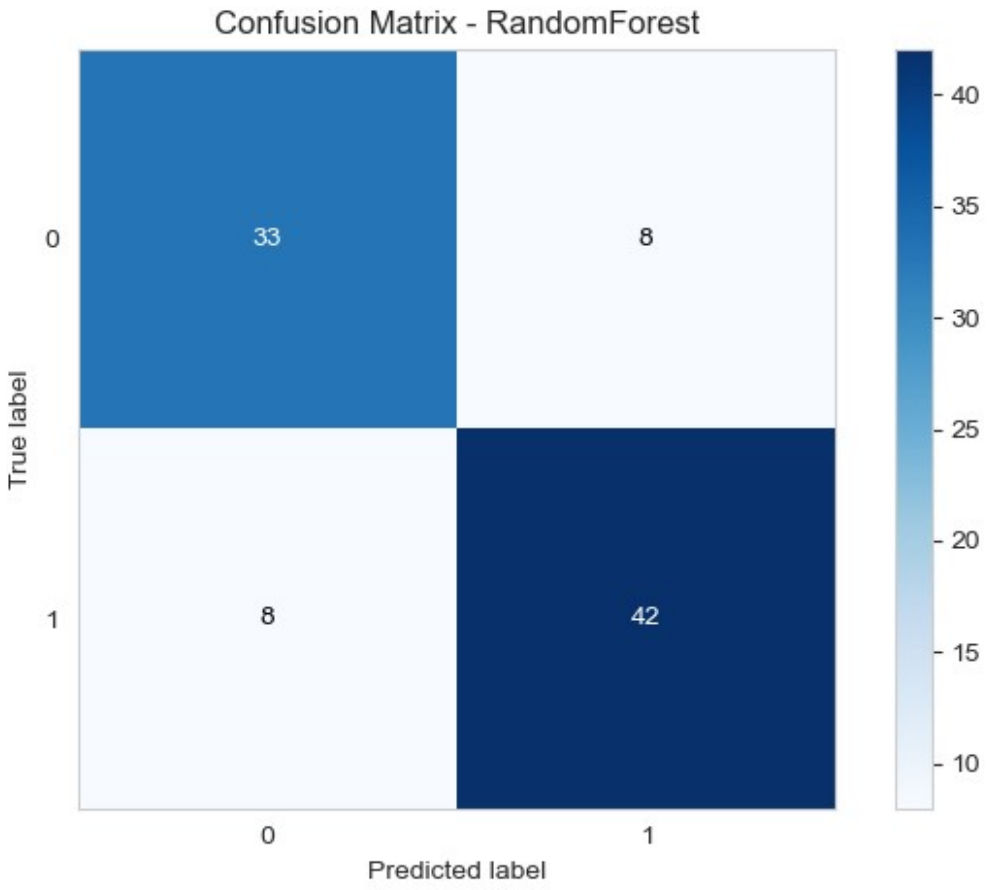
```
Mean Cross-Validated score of best LogisticRegression:
0.8156146179401993
Accuracy of LogisticRegression on test data: 0.8571428571428571
Mean Cross-Validated score of best RandomForest: 0.8156146179401993
Accuracy of RandomForest on test data: 0.8241758241758241
Mean Cross-Validated score of best KNN: 0.7971207087486156
Accuracy of KNN on test data: 0.7582417582417582
```

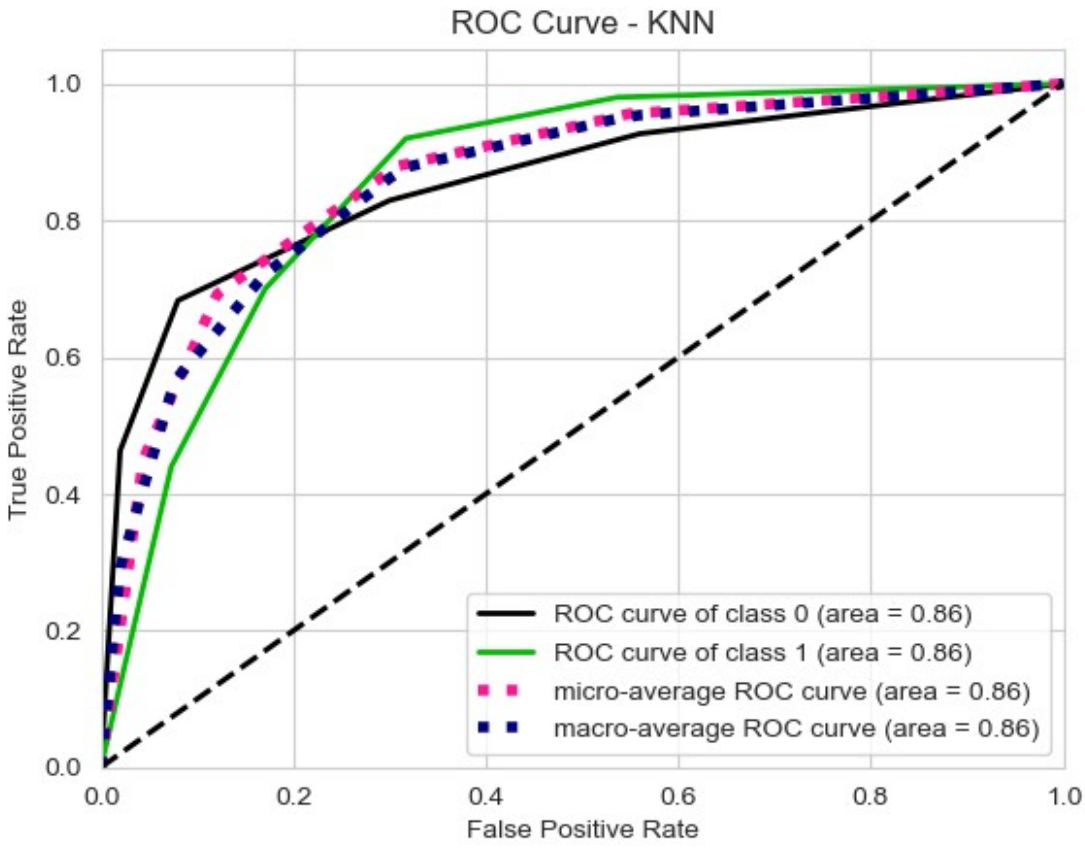
```
import scikitplot as skplt

# Iterate over the best models obtained from GridSearchCV
for best_model in best_models:
    # Generate predicted probabilities and predicted labels for the
test set
    y_probas = best_model['model'].predict_proba(X_test)
    y_pred = best_model['model'].predict(X_test)

    # Plot ROC curve
    skplt.metrics.plot_roc(y_test, y_probas)
    plt.title(f"ROC Curve - {best_model['name']}")
    plt.show()

    # Plot confusion matrix
    skplt.metrics.plot_confusion_matrix(y_test, y_pred)
    plt.title(f"Confusion Matrix - {best_model['name']}")
    plt.tight_layout()
    plt.show()
```

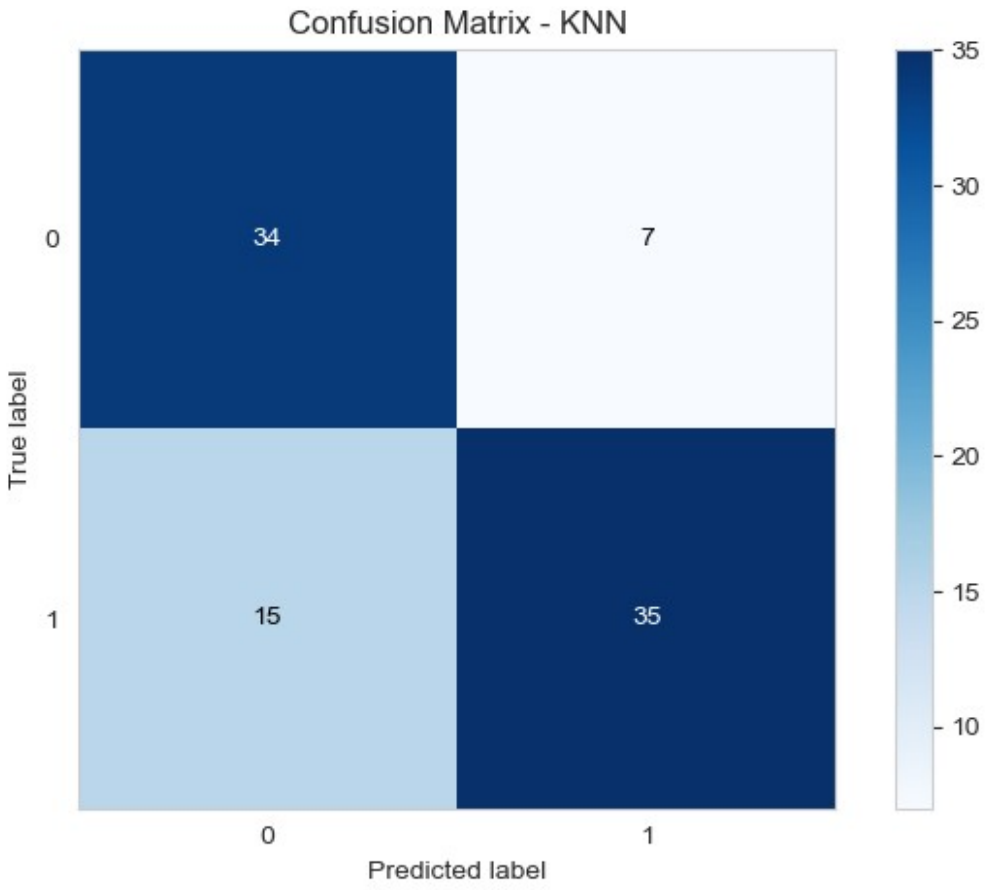



Confusion Matrix - LogisticRegression
34
7
6
44
0
1
True label
0
1
Predicted label
40
35
30
25
20
15
10


ROC Curve - RandomForest
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.91)
ROC curve of class 1 (area = 0.91)
micro-average ROC curve (area = 0.91)
macro-average ROC curve (area = 0.91)


Confusion Matrix - RandomForest
33
8
8
42
0
1
True label
0
1
Predicted label
40
35
30
25
20
15
10


ROC Curve - KNN
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.86)
ROC curve of class 1 (area = 0.86)
micro-average ROC curve (area = 0.86)
macro-average ROC curve (area = 0.86)


Confusion Matrix - KNN
34
7
15
35
0
1
True label
0
1
Predicted label
35
30
25
20
15
10