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Machine Learning Mini Project

Aim:

Choose a dataset of your preference.

Perform the EDA

Apply a variety of classification algorithms, including Logistic Regression (LR), Naive Bayes (NB), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and K-means.

Assess their performance using classification metrics.

Compare the performance of the entire classification algorithm.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_sc
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv('Heart Attack Data Set.csv')
```

In [3]:
```
df.head()
```

Out[3]:

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

In [4]:
```
df.tail()
```

Out[4]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	tl
298	57	0	0	140	241	0	1	123	1	0.2	1	0	
299	45	1	3	110	264	0	1	132	0	1.2	1	0	
300	68	1	0	144	193	1	1	141	0	3.4	1	2	
301	57	1	0	130	131	0	1	115	1	1.2	1	1	
302	57	0	1	130	236	0	0	174	0	0.0	1	1	

In [5]:
```
df.describe()
```

Out[5]:

	age	sex	cp	trestbps	chol	fbs	reste
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000(
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528(
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525ł
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000(
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000(
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000(
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000(
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000(

In [6]:
```
df.shape
```

Out[6]:
```
(303, 14)
```

In [7]:
```
missing_values = df.isnull().sum()
missing_values
```

Out[7]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

In [8]:
```
print("Duplicates:\n", df.duplicated().sum())
```

```
Duplicates:
 1
```

In [9]:
```
df.drop_duplicates(inplace=True)
```

In [10]:
```
print("Duplicates:\n", df.duplicated().sum())
```

```
Duplicates:
 0
```

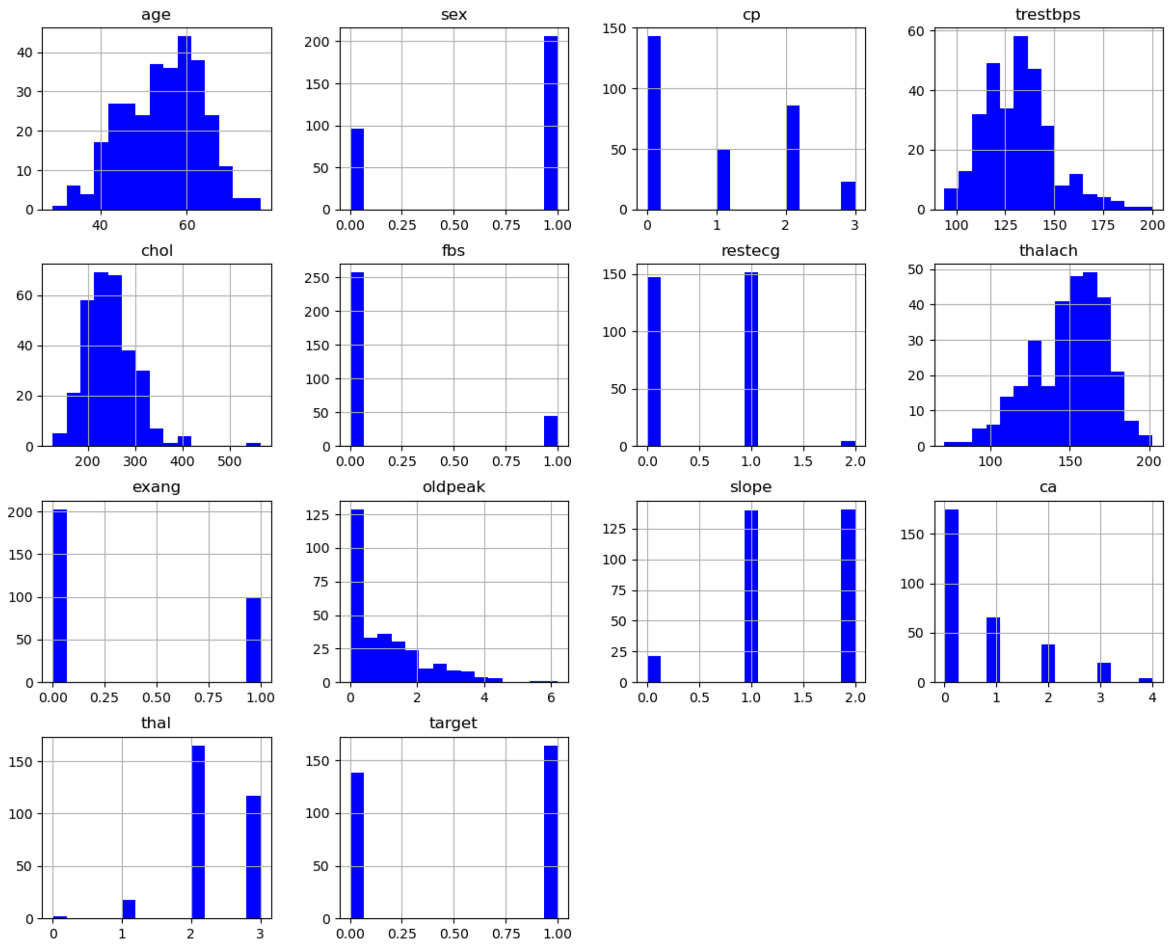
In [11]:
```
df.columns
```

Out[11]:
```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

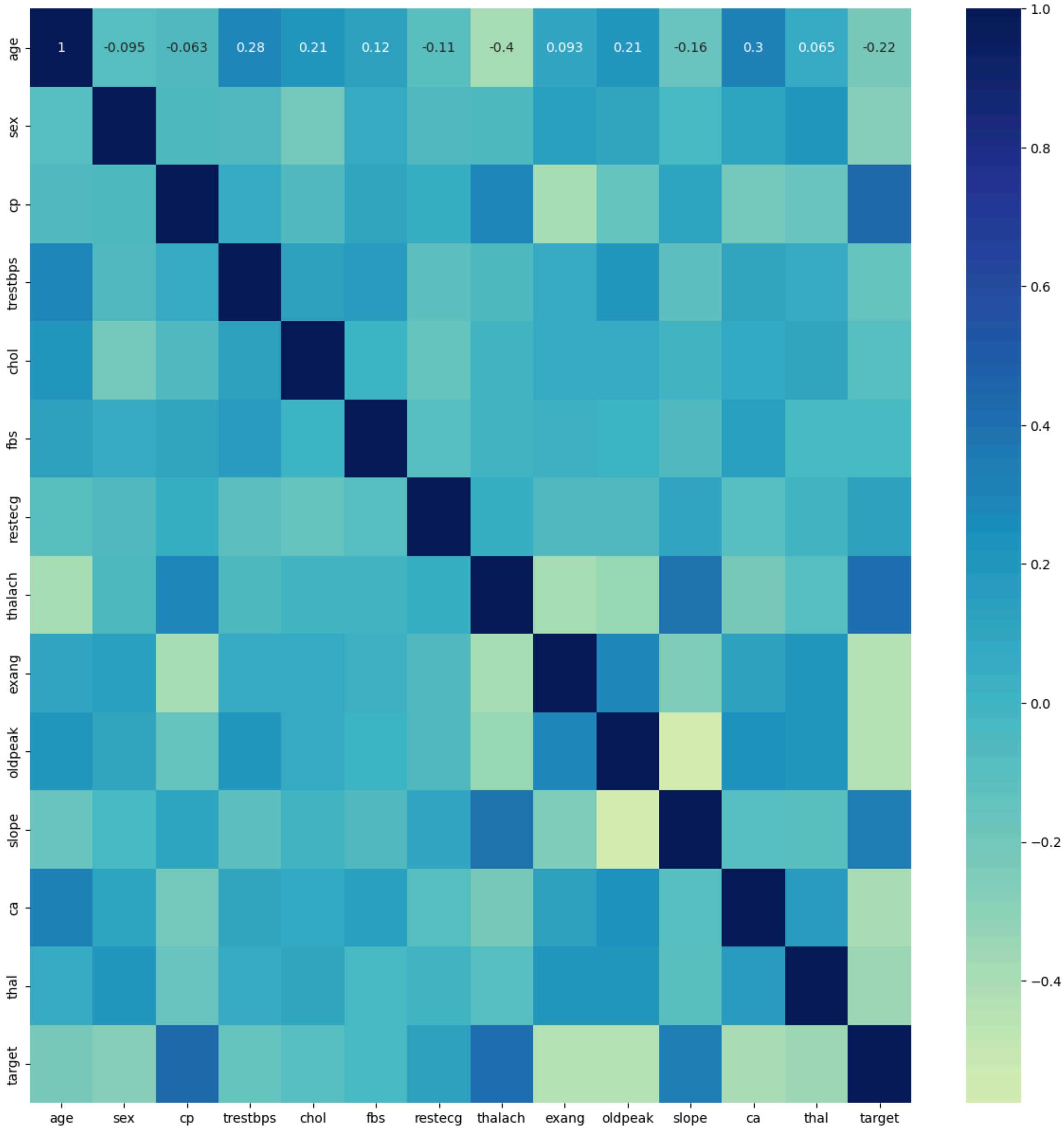
In [12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 302 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       302 non-null    int64  
 1   sex       302 non-null    int64  
 2   cp        302 non-null    int64  
 3   trestbps  302 non-null    int64  
 4   chol      302 non-null    int64  
 5   fbs       302 non-null    int64  
 6   restecg   302 non-null    int64  
 7   thalach   302 non-null    int64  
 8   exang     302 non-null    int64  
 9   oldpeak   302 non-null    float64
 10  slope     302 non-null    int64  
 11  ca        302 non-null    int64  
 12  thal      302 non-null    int64  
 13  target    302 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 35.4 KB
```

In [13]:
```
df.hist(figsize=(15,12),bins = 15, color = "blue")
plt.title("Features Distribution")
plt.show()
```



In [14]:
```
plt.figure(figsize=(15,15))
p=sns.heatmap(df.corr(), annot=True,cmap='YlGnBu',center=0)
```



In [15]:
```
X = df.drop('target', axis=1)  # Features
y = df['target']  # Target (whether an individual defaults)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [16]:
```
X_train.shape, X_test.shape
```

Out[16]:
```
((241, 13), (61, 13))
```

In [17]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)
```

Logistic Regression

In [18]:
```
from sklearn.linear_model import LogisticRegression

log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
```

Out[18]:

```
▾ LogisticRegression
LogisticRegression()
```

In [19]:

```
y_pred_log = log_reg.predict(X_test)

accuracy_log = accuracy_score(y_test, y_pred_log)
precision_log = precision_score(y_test, y_pred_log)
recall_log = recall_score(y_test, y_pred_log)
f1_log = f1_score(y_test, y_pred_log)

print("Logistic Regression Performance:")
print("Accuracy:", accuracy_log)
print("Precision:", precision_log)
print("Recall:", recall_log)
print("F1 Score:", f1_log)
```

```
Logistic Regression Performance:
Accuracy: 0.8688524590163934
Precision: 0.8529411764705882
Recall: 0.90625
F1 Score: 0.8787878787878788
```

In [20]:

```
print(classification_report(y_test,y_pred_log))
```

```
              precision    recall  f1-score   support

           0       0.89      0.83      0.86        29
           1       0.85      0.91      0.88        32

    accuracy                           0.87        61
   macro avg       0.87      0.87      0.87        61
weighted avg       0.87      0.87      0.87        61
```

In [21]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_log)
print('Confusion Matrix:\n', cm)
```

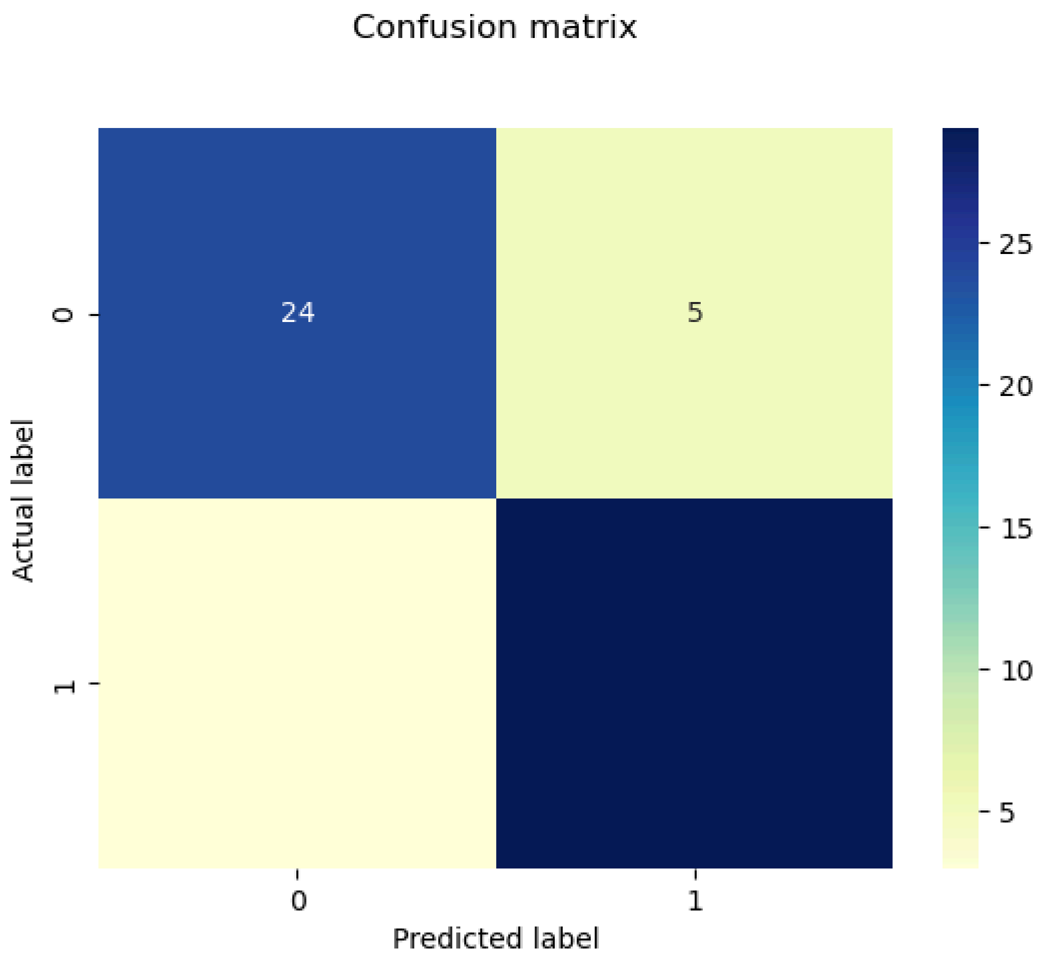
```
Confusion Matrix:
 [[24  5]
 [ 3 29]]
```

In [22]:

```
p = sns.heatmap(pd.DataFrame(cm), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[22]:

```
Text(0.5, 23.52222222222222, 'Predicted label')
```



Naive Bayes Classifier

In [23]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(X_train, y_train)
```

Out[23]:
```
GaussianNB
GaussianNB()
```

In [24]:
```
y_pred_nb = gnb.predict(X_test)

accuracy_nb = accuracy_score(y_test, y_pred_nb)
precision_nb = precision_score(y_test, y_pred_nb)
recall_nb = recall_score(y_test, y_pred_nb)
f1_nb = f1_score(y_test, y_pred_nb)

print("Accuracy: ",accuracy_nb)
print("Precision: ",precision_nb)
print("Recall: ",recall_nb)
print("F1 Score: ",f1_nb)
```

```
Accuracy:  0.8852459016393442
Precision:  0.9032258064516129
Recall:  0.875
F1 Score:  0.8888888888888888
```

In [25]:
```
print(classification_report(y_test,y_pred_nb))
```

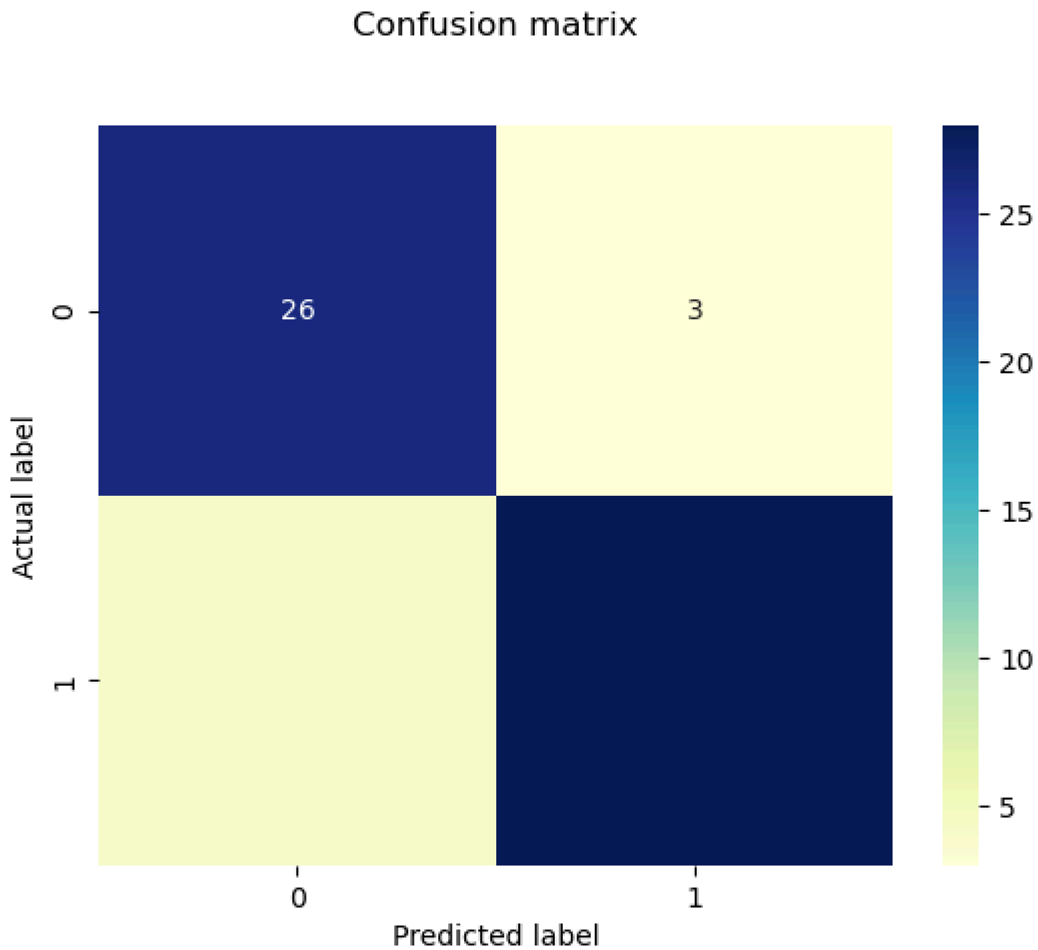
```
              precision    recall  f1-score   support

           0       0.87      0.90      0.88        29
           1       0.90      0.88      0.89        32

    accuracy                           0.89        61
   macro avg       0.88      0.89      0.89        61
weighted avg       0.89      0.89      0.89        61
```

In [26]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_nb)
print('Confusion Matrix:\n', cm)
```

```
Confusion Matrix:
 [[26  3]
 [ 4 28]]
```

In [27]:
```
p = sns.heatmap(pd.DataFrame(cm), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[27]:
```
Text(0.5, 23.52222222222222, 'Predicted label')
```



KNN Classifier

In [28]:
```python
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=20)
knn.fit(X_train, y_train)
```

Out[28]:
```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=20)
```

In [29]:
```python
y_pred_knn = knn.predict(X_test)

accuracy_knn = accuracy_score(y_test, y_pred_knn)
precision_knn = precision_score(y_test, y_pred_knn)
recall_knn = recall_score(y_test, y_pred_knn)
f1_knn = f1_score(y_test, y_pred_knn)

print("KNN Performance:")
print("Accuracy:", accuracy_knn)
print("Precision:", precision_knn)
print("Recall:", recall_knn)
print("F1 Score:", f1_knn)
```

```
KNN Performance:
Accuracy: 0.8524590163934426
Precision: 0.8285714285714286
Recall: 0.90625
F1 Score: 0.8656716417910447
```

In [30]:
```python
print(classification_report(y_test,y_pred_knn))
```

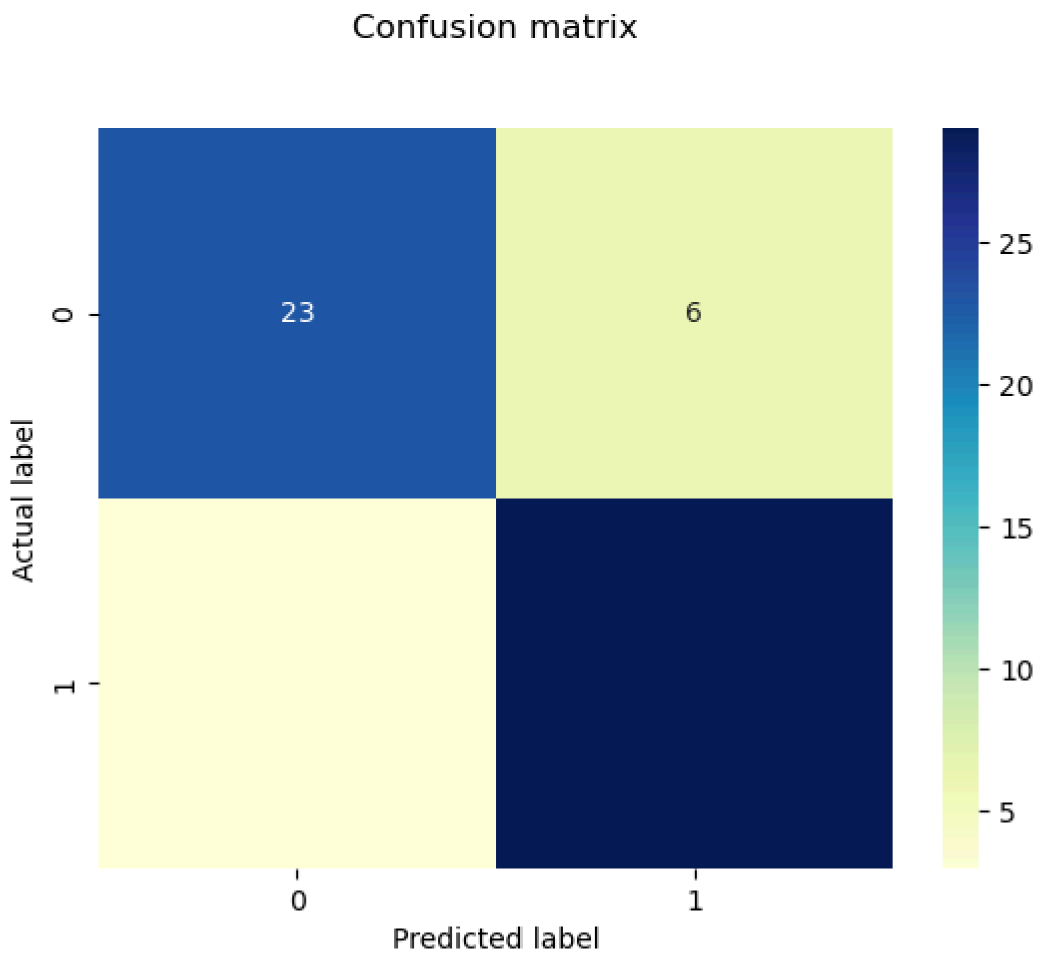
```
              precision    recall  f1-score   support

           0       0.88      0.79      0.84        29
           1       0.83      0.91      0.87        32

    accuracy                           0.85        61
   macro avg       0.86      0.85      0.85        61
weighted avg       0.86      0.85      0.85        61
```

In [31]:
```python
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_knn)
print('Confusion Matrix:\n', cm)
```

```
Confusion Matrix:
 [[23  6]
 [ 3 29]]
```

In [32]:
```python
p = sns.heatmap(pd.DataFrame(cm), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[32]:
```
Text(0.5, 23.52222222222222, 'Predicted label')
```



Decision Tree Classifier

In [33]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier()

dt.fit(X_train, y_train)
```

Out[33]:
```
DecisionTreeClassifier

DecisionTreeClassifier()
```

In [34]:
```
y_pred_dt = dt.predict(X_test)

accuracy_dt = accuracy_score(y_test, y_pred_dt)
precision_dt = precision_score(y_test, y_pred_dt)
recall_dt = recall_score(y_test, y_pred_dt)
f1_dt = f1_score(y_test, y_pred_dt)

print("Decision Tree Performance:")
print("Accuracy:", accuracy_dt)
print("Precision:", precision_dt)
print("Recall:", recall_dt)
print("F1 Score:", f1_dt)
```

```
Decision Tree Performance:
Accuracy: 0.7868852459016393
Precision: 0.8518518518518519
Recall: 0.71875
F1 Score: 0.7796610169491526
```

In [35]:
```
print(classification_report(y_test,y_pred_knn))
```

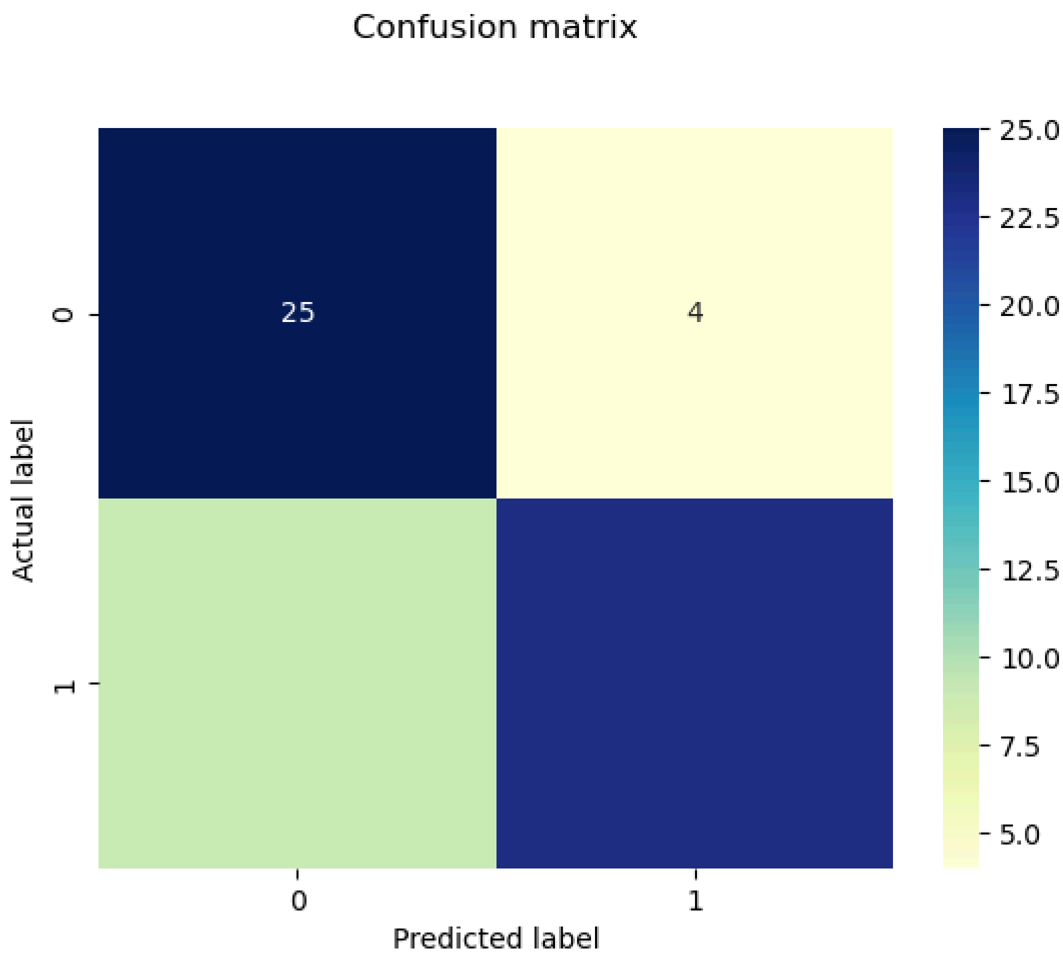
```
              precision    recall  f1-score   support

           0       0.88      0.79      0.84        29
           1       0.83      0.91      0.87        32

    accuracy                           0.85        61
   macro avg       0.86      0.85      0.85        61
weighted avg       0.86      0.85      0.85        61
```

In [36]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_dt)
print('Confusion Matrix:\n', cm)
```

```
Confusion Matrix:
 [[25  4]
 [ 9 23]]
```

In [37]:
```
p = sns.heatmap(pd.DataFrame(cm), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[37]:
```
Text(0.5, 23.52222222222222, 'Predicted label')
```



Random Forest Classifier

In [38]:
```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(random_state=42)

rf_model.fit(X_train, y_train)
```

Out[38]:
```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In [39]:
```
y_pred_rf = rf_model.predict(X_test)

accuracy_rf = accuracy_score(y_test, y_pred_rf)
precision_rf = precision_score(y_test, y_pred_rf)
recall_rf = recall_score(y_test, y_pred_rf)
f1_rf = f1_score(y_test, y_pred_rf)

print("Accuracy: ",accuracy_rf)
print("Precision: ",precision_rf)
print("Recall: ",recall_rf)
print("F1 Score: ",f1_rf)
```

```
Accuracy:  0.8688524590163934
Precision:  0.9
Recall:  0.84375
F1 Score:  0.8709677419354839
```

In [40]:
```
print(classification_report(y_test,y_pred_rf))
```

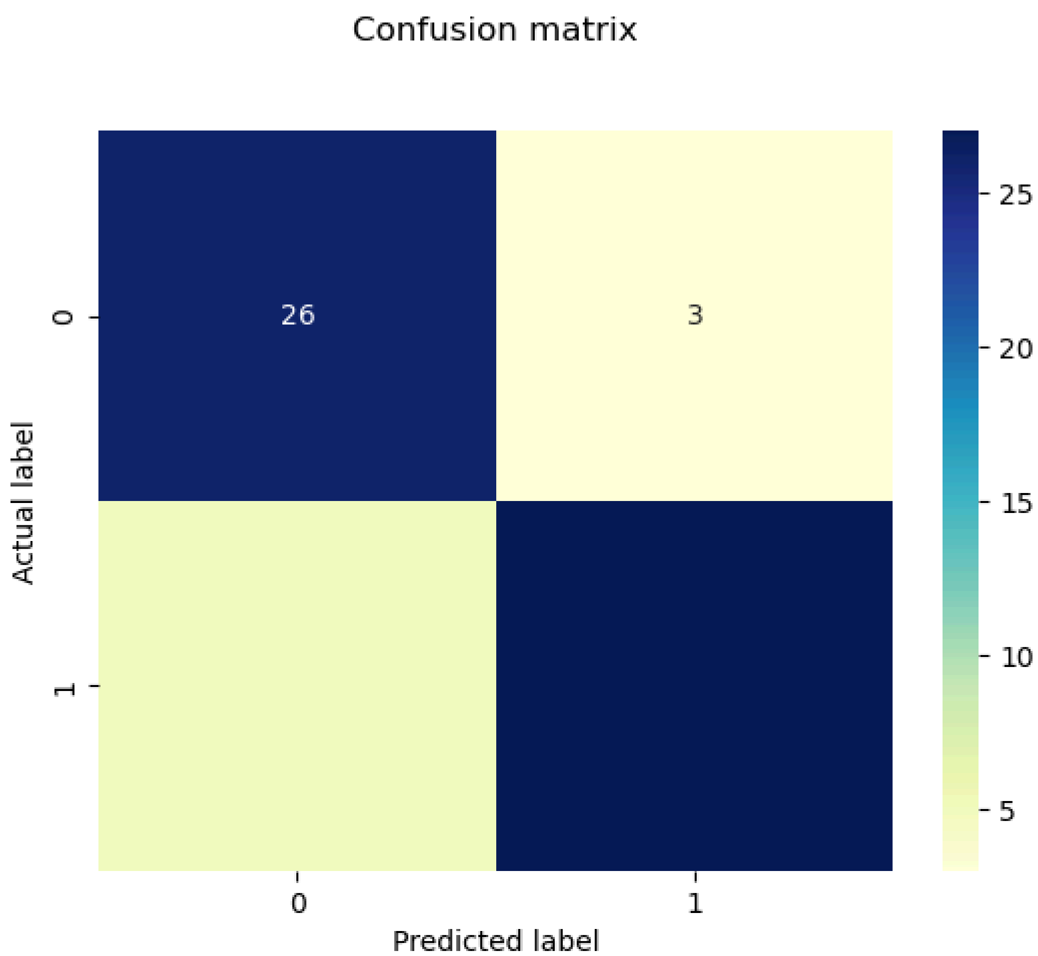
```
              precision    recall  f1-score   support

           0       0.84      0.90      0.87        29
           1       0.90      0.84      0.87        32

    accuracy                           0.87        61
   macro avg       0.87      0.87      0.87        61
weighted avg       0.87      0.87      0.87        61
```

In [41]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_rf)
print('Confusion Matrix:\n', cm)
```

```
Confusion Matrix:
 [[26  3]
 [ 5 27]]
```

In [42]:
```
p = sns.heatmap(pd.DataFrame(cm), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[42]:
```
Text(0.5, 23.52222222222222, 'Predicted label')
```



Kmeans Clustering

In [43]:
```
XY = df[['trestbps', 'thalach']]
XY
```

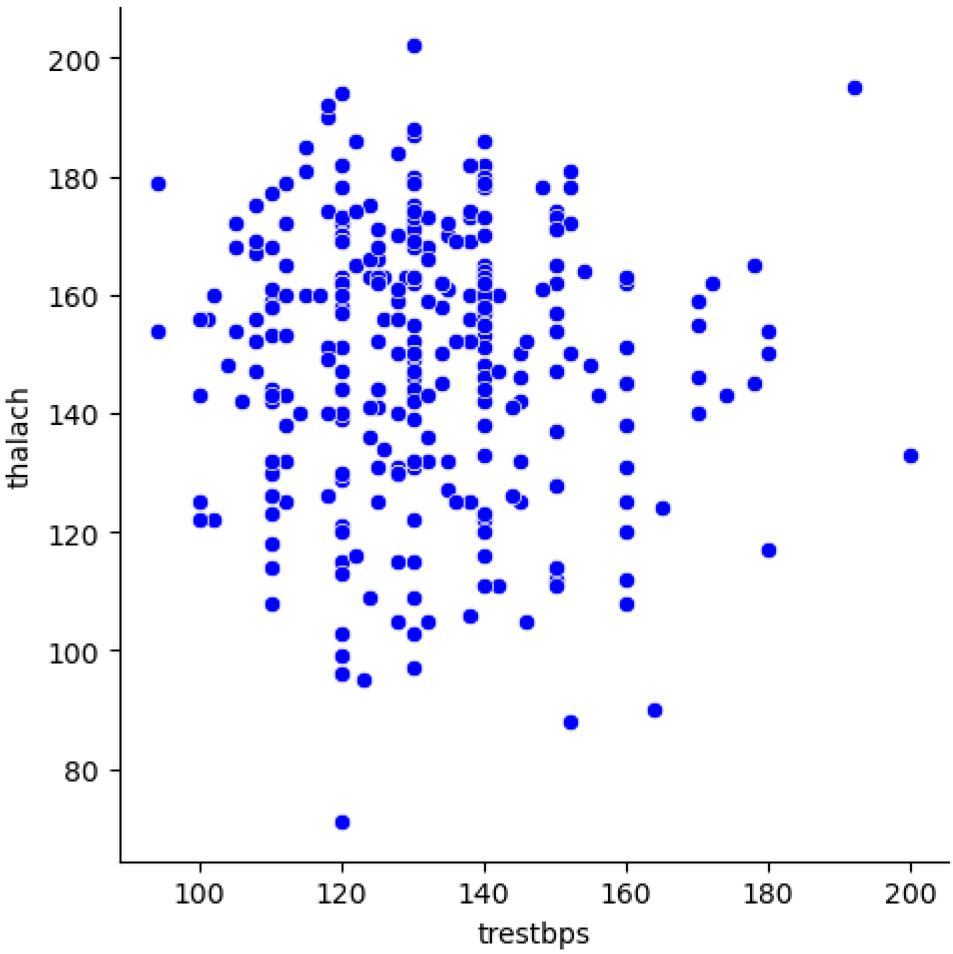
Out[43]:

	trestbps	thalach
0	145	150
1	130	187
2	130	172
3	120	178
4	120	163
...	...	...
298	140	123
299	110	132
300	144	141
301	130	115
302	130	174

302 rows × 2 columns

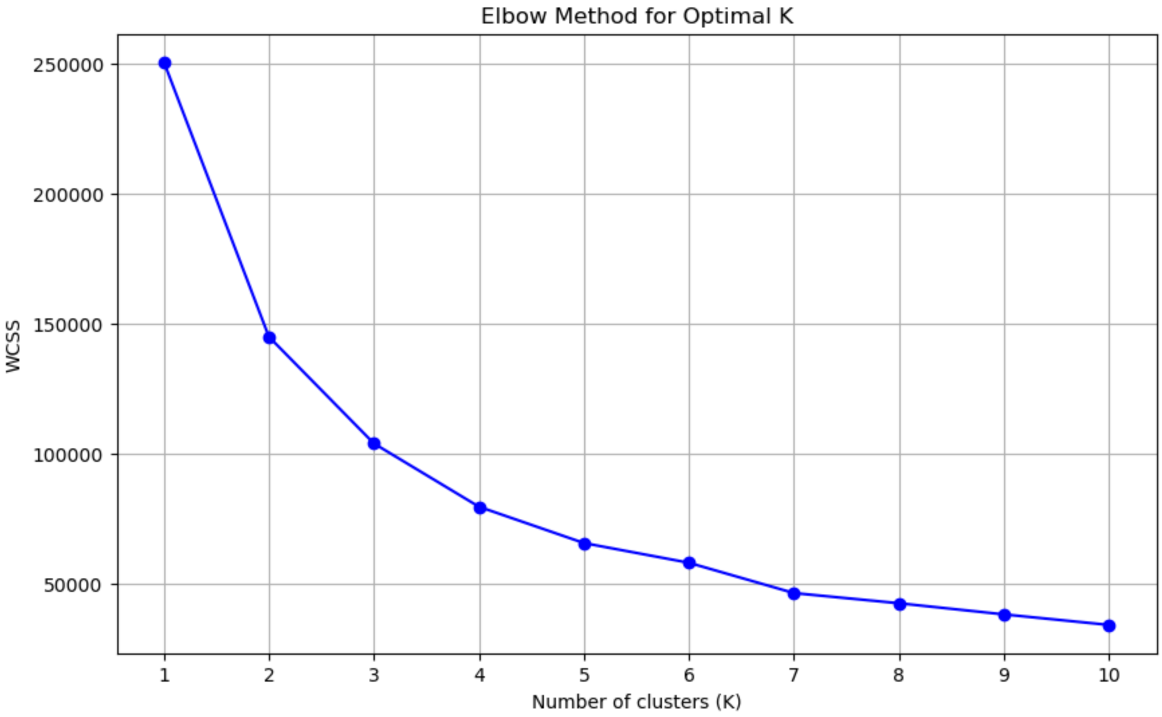
In [44]:
```
sns.relplot( x="trestbps", y="thalach", data=df, color="blue")
```

Out[44]:
```
<seaborn.axisgrid.FacetGrid at 0x25f9f68f090>
```



In [45]:

```
from sklearn.cluster import KMeans
# Generate the elbow curve
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(XY)
    wcss.append(kmeans.inertia_)

# Plot the elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), wcss, marker='o', color='blue')
plt.title('Elbow Method for Optimal K')
plt.xlabel('Number of clusters (K)')
plt.ylabel('WCSS')
plt.xticks(range(1, 11))
plt.grid()
plt.show()
```



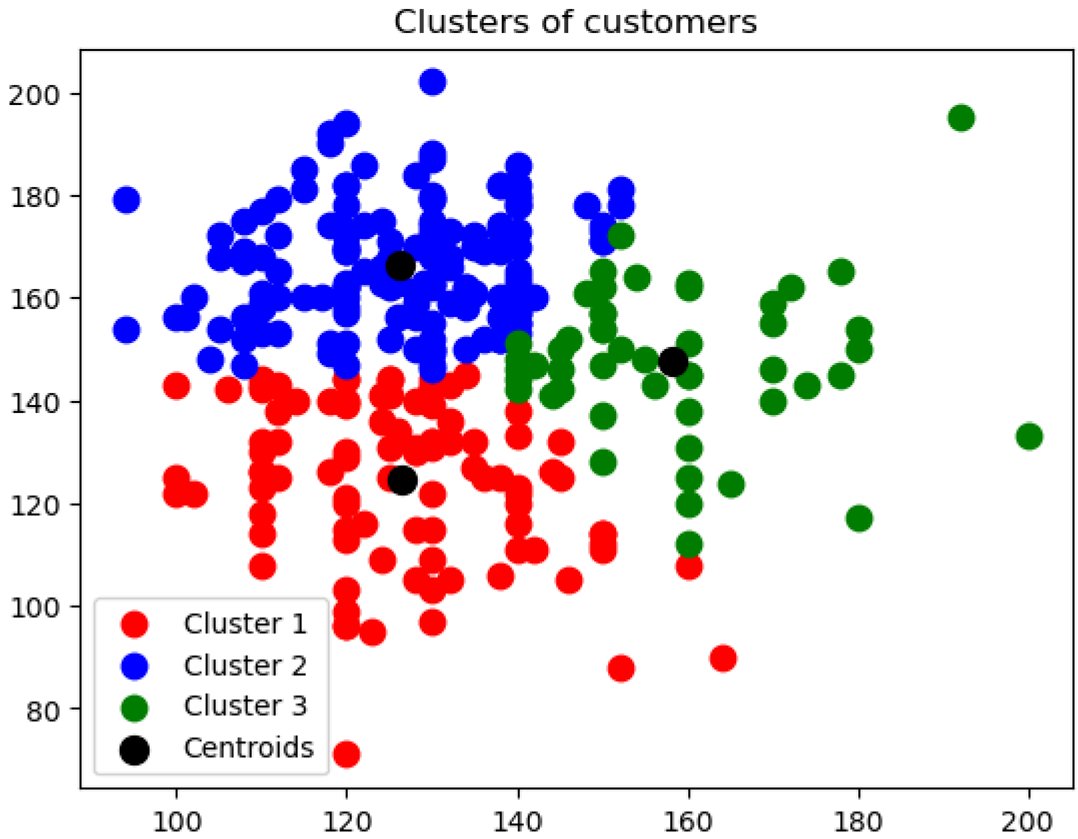
In [46]:
```
kmeans = KMeans(n_clusters=3, random_state=0)
label = kmeans.fit_predict(XY)
print(label)
```

```
[2 1 1 1 1 2 1 1 2 1 1 0 1 0 2 1 1 0 1 2 1 1 1 2 1 2 2 0 1 1 1 0 1 1 0 1 1
 2 2 2 2 1 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 0 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 0 0 1 1 1 1 1 2 1 1 1 0 2 1 1 1 2
 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 0 2 1 0 2 1 1 1 1 1 0 0 0 0 1 1 1 0 0 2 1 1
 1 1 2 0 2 2 1 0 1 1 0 1 1 1 1 1 0 0 1 1 1 0 1 1 1 0 0 1 1 0 0 0 0 1 1 2 1
 0 0 1 1 0 0 0 2 1 2 2 1 0 1 1 0 0 2 2 1 0 2 0 1 1 0 0 2 0 0 0 0 0 1 2 0 1
 2 0 0 0 0 2 0 1 2 2 0 0 1 1 1 1 1 2 2 0 0 0 1 1 2 2 2 0 0 0 0 2 2 0 0 2 1
 2 1 0 1 0 0 2 0 0 0 0 0 0 1 0 1 0 0 1 0 0 1 0 1 0 0 1 2 0 0 2 0 2 2 0 2 0
 0 0 0 2 0 1]
```

In [47]:
```
print(kmeans.cluster_centers_)
```

```
[[126.36734694 124.45918367]
 [126.27922078 166.13636364]
 [158.26       147.76      ]]
```

In [48]:
```
import matplotlib.pyplot as plt

plt.scatter(XY.loc[label == 0, 'trestbps'], XY.loc[label == 0,
                   'thalach'],
            s=80, c='red', label='Cluster 1')

plt.scatter(XY.loc[label == 1, 'trestbps'], XY.loc[label == 1, 'thalach'], s=80,
plt.scatter(XY.loc[label == 2, 'trestbps'], XY.loc[label == 2, 'thalach'], s=80,

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=100,
            c='black', label='Centroids')

plt.title('Clusters of customers')
plt.legend()
plt.show()
```



In [49]:
```
true_labels = df['target']

accuracy_kmeans = accuracy_score(true_labels, label)
precision_kmeans = precision_score(true_labels, label, average='weighted')
recall_kmeans = recall_score(true_labels, label, average='weighted')
f1_kmeans = f1_score(true_labels, label, average='weighted')
print("Accuracy: ",accuracy_kmeans)
print("Precision: ",precision_kmeans)
print("Recall: ",recall_kmeans)
print("F1 Score: ",f1_kmeans)
```

```
Accuracy:  0.6059602649006622
Precision:  0.7237280222143042
Recall:  0.6059602649006622
F1 Score:  0.6565556983927636
```

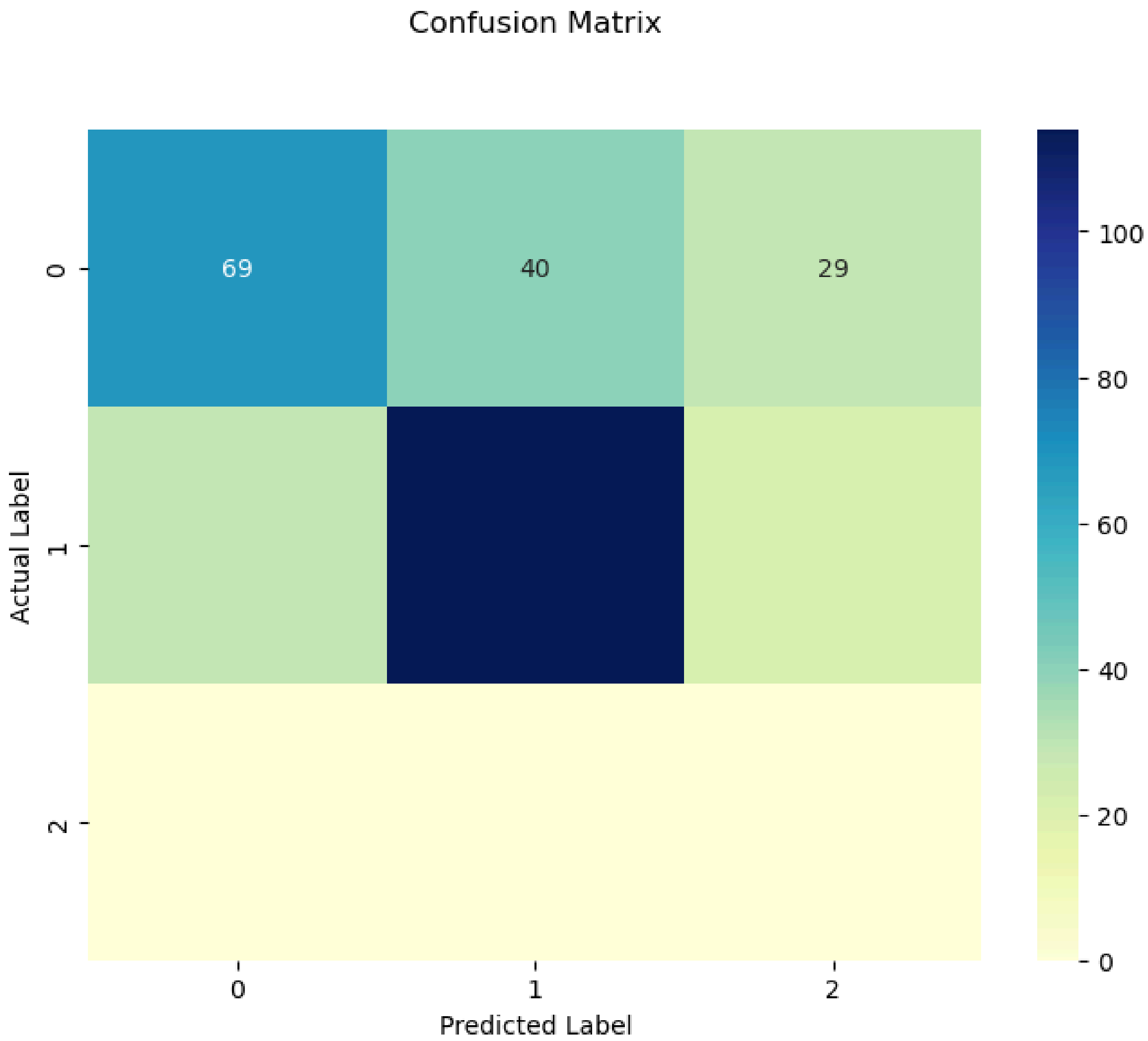
In [50]:
```
report = classification_report(true_labels, label)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.70      0.50      0.58       138
           1       0.74      0.70      0.72       164
           2       0.00      0.00      0.00         0

    accuracy                           0.61       302
   macro avg       0.48      0.40      0.43       302
weighted avg       0.72      0.61      0.66       302
```

In [51]:
```
from sklearn.metrics import confusion_matrix

confusion_mat = confusion_matrix(true_labels, label)
print('Confusion Matrix:\n', confusion_mat)
```

```
Confusion Matrix:
 [[ 69  40  29]
 [ 29 114  21]
 [  0   0   0]]
```

In [52]:
```
confusion_mat = confusion_matrix(true_labels, label)
plt.figure(figsize=(8, 6))
p = sns.heatmap(pd.DataFrame(confusion_mat), annot=True, cmap="YlGnBu", fmt='g')
plt.title('Confusion Matrix', y=1.1)
plt.ylabel('Actual Label')
plt.xlabel('Predicted Label')
plt.show()
```



Comparision Between Models

In [53]:
```
# Compare performance across models
models = ['Logistic Regression', 'Naive Bayes', 'K-Nearest Neighbors', 'Decision
accuracies = [accuracy_log, accuracy_nb, accuracy_knn, accuracy_dt, accuracy_rf,
precisions = [precision_log, precision_nb, precision_knn, precision_dt, precisic
recalls = [recall_log, recall_nb, recall_knn, recall_dt, recall_rf, recall_kmean
f1_scores = [f1_log, f1_nb, f1_knn, f1_dt, f1_rf, f1_kmeans]

performance_df = pd.DataFrame({
    'Model': models,
    'Accuracy': accuracies,
    'Precision': precisions,
    'Recall': recalls,
```

```
    'F1 Score': f1_scores
})

print(performance_df)
```

```
                 Model  Accuracy  Precision   Recall  F1 Score
0  Logistic Regression  0.868852   0.852941  0.90625  0.878788
1          Naive Bayes  0.885246   0.903226  0.87500  0.888889
2  K-Nearest Neighbors  0.852459   0.828571  0.90625  0.865672
3   Decision Tree (DT)  0.786885   0.851852  0.71875  0.779661
4        Random Forest  0.868852   0.900000  0.84375  0.870968
5               Kmeans  0.605960   0.723728  0.60596  0.656556
```