```
In [1]:
          import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn
          from sklearn import preprocessing,svm,datasets,neighbors
In [2]:
          df = pd.read_csv('C:/Users/Megha Patel/Downloads/heart.csv')
          print(df)
                              trestbps
                                         chol
                                                fbs
                                                      restecg
                                                                thalach
                                                                          exang
                                                                                  oldpeak \
               age
                    sex
                          ср
         0
                63
                      1
                           3
                                    145
                                           233
                                                  1
                                                            0
                                                                    150
                                                                              0
                                                                                      2.3
                           2
         1
                37
                      1
                                    130
                                           250
                                                  0
                                                            1
                                                                    187
                                                                              0
                                                                                      3.5
         2
                41
                      0
                           1
                                    130
                                           204
                                                  0
                                                            0
                                                                    172
                                                                              0
                                                                                      1.4
         3
                56
                      1
                           1
                                    120
                                           236
                                                  0
                                                            1
                                                                    178
                                                                              0
                                                                                      0.8
         4
                57
                      0
                           0
                                    120
                                           354
                                                  0
                                                            1
                                                                    163
                                                                              1
                                                                                      0.6
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                                                                                      . . .
         298
                57
                           0
                                    140
                                           241
                                                  0
                                                                    123
                                                                                      0.2
                      0
                                                            1
                                                                              1
         299
                45
                      1
                           3
                                    110
                                           264
                                                  0
                                                            1
                                                                    132
                                                                              0
                                                                                      1.2
         300
                68
                      1
                           0
                                    144
                                           193
                                                            1
                                                                    141
                                                                              0
                                                                                      3.4
                                                  1
         301
                57
                      1
                           0
                                    130
                                           131
                                                  0
                                                            1
                                                                    115
                                                                              1
                                                                                      1.2
         302
                57
                           1
                                    130
                                           236
                                                  0
                                                                    174
                                                                              0
                                                                                      0.0
                           thal
                                 target
               slope
                      ca
         0
                       0
                   0
                              1
                                       1
         1
                   0
                       0
                              2
                                       1
         2
                   2
                       0
                              2
                                       1
         3
                   2
                        0
                              2
                                       1
         4
                   2
                        0
                              2
                                       1
         . .
                 . . .
                       . .
                            . . .
                                     . . .
                       0
         298
                   1
                              3
                                       0
         299
                   1
                        0
                              3
                                       0
         300
                   1
                        2
                              3
                                       0
         301
                   1
                              3
                                       0
                        1
         302
                   1
                              2
         [303 rows x 14 columns]
In [3]:
          df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 303 entries, 0 to 302
         Data columns (total 14 columns):
               Column
                          Non-Null Count Dtype
          #
          0
                          303 non-null
                                            int64
               age
          1
                          303 non-null
               sex
                                            int64
          2
                          303 non-null
                                            int64
               ср
          3
                          303 non-null
               trestbps
                                            int64
          4
                          303 non-null
               chol
                                            int64
          5
                          303 non-null
               fbs
                                            int64
          6
                          303 non-null
               restecg
                                           int64
          7
                          303 non-null
               thalach
                                           int64
               exang
          8
                          303 non-null
                                            int64
          9
                          303 non-null
                                           float64
               oldpeak
          10
                          303 non-null
               slope
                                            int64
                          303 non-null
          11
                                            int64
              ca
          12
              thal
                          303 non-null
                                            int64
          13
              target
                          303 non-null
                                            int64
         dtypes: float64(1), int64(13)
         memory usage: 33.3 KB
In [4]:
          df['sex'].value_counts()
```

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```
Untitled36
Out[4]: 1
               207
                96
         Name: sex, dtype: int64
In [5]:
          pd.crosstab(df.sex,df.target).plot(kind="bar",figsize=(15,6),color=['#1CA53B','#AA11
          plt.title('Heart Disease Frequency for Sex')
          plt.xlabel('Sex (0 = Female, 1 = Male)')
          plt.xticks(rotation=0)
          plt.legend(["Haven't Disease", "Have Disease"])
          plt.ylabel('count')
          plt.show()
                                                Heart Disease Frequency for Sex
                                                                                              Haven't Disease
                                                                                              Have Disease
           100
           80
           60
           40
           20
                                                   Sex (0 = Female, 1 = Male)
In [6]:
          df['target'].value_counts()
               165
Out[6]:
               138
         Name: target, dtype: int64
In [7]:
          plt.scatter(x=df.age[df.target==1], y=df.thalach[(df.target==1)], c="red")
          plt.scatter(x=df.age[df.target==0], y=df.thalach[(df.target==0)])
          plt.legend(["Disease", "Not Disease"])
          plt.xlabel("Age")
          plt.ylabel("Maximum Heart Rate")
          plt.show()
            200
                                                          Disease
                                                          Not Disease
            180
         Maximum Heart Rate
            160
           140
            120
            100
             80
```

```
In [8]:
         # extracting the x and y from the dataset
         x = df.iloc[:,:-1].values
```

60

70

30

40

50

Age

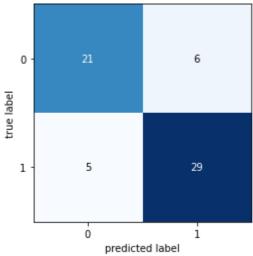
```
y = df.iloc[:,-1].values
       print(x)
       print(y)
       [[63.
           1. 3. ... 0. 0. 1.]
       [37. 1. 2. ... 0. 0. 2.]
       [41.
           0. 1. ... 2. 0.
                         2.]
       [68.
           1. 0. ... 1. 2.
                          3.]
       [57. 1. 0. ... 1. 1. 3.]
           0. 1. ... 1. 1. 2.]]
       0 0 0 0 0 0 0 0
In [9]:
       # feature Scaling
       from sklearn.preprocessing import StandardScaler
       sc = StandardScaler()
       x = sc.fit_transform(x)
       print(x)
       [[ 0.9521966
                 0.68100522 1.97312292 ... -2.27457861 -0.71442887
        -2.14887271]
       [-1.91531289 0.68100522 1.00257707 ... -2.27457861 -0.71442887
        -0.51292188]
       [-1.47415758 -1.46841752 0.03203122 ... 0.97635214 -0.71442887
        -0.51292188]
       [ \ 1.50364073 \ \ 0.68100522 \ -0.93851463 \ \dots \ -0.64911323 \ \ 1.24459328
         1.12302895]
       [ \ 0.29046364 \ \ 0.68100522 \ -0.93851463 \ \dots \ -0.64911323 \ \ 0.26508221
         1.12302895]
       -0.51292188]]
In [10]:
       # splitting x and y into training and test data
       from sklearn.model selection import train test split
       x_tr,x_te,y_tr,y_te = train_test_split(x,y,test_size = 0.2,random_state = 0)
       print(x_te)
       [ 1.72421839 0.68100522 -0.93851463 0.76395577 -1.39653716 -0.41763453
         0.89896224 -1.07781984 1.43548113 1.34614673 -2.27457861 -0.71442887
         1.12302895]
       [ 1.06248543  0.68100522  1.97312292  2.19177836  -0.3722866  -0.41763453
        -1.00583187 0.23409531 -0.69663055 -0.37924438 -0.64911323 -0.71442887
         1.12302895]
       -1.00583187 0.40901733 -0.69663055 -0.7243226 -0.64911323 -0.71442887
         1.12302895]
       [ 0.62133012  0.68100522  -0.93851463  -0.3783023
                                            0.22680335 -0.41763453
        -1.00583187 -0.37813176 1.43548113 1.51868584 -0.64911323 0.26508221
         1.123028951
       [ 0.84190778  0.68100522  1.00257707  -0.09273778  -0.29498467  -0.41763453
         0.89896224 -0.15947923 -0.69663055 0.65599028 -0.64911323 2.22410436
         1.123028951
                0.68100522 -0.93851463 -0.43541521 0.53601107 -0.41763453
       [-0.7021358]
        -1.00583187 0.71513086 -0.69663055 -0.46551394 -0.64911323 -0.71442887
         1.123028951
       [-1.58444641 0.68100522 -0.93851463 -1.23499586 -1.53181554 -0.41763453
        -1.00583187 -1.55885539 1.43548113 0.82852939 -0.64911323 -0.71442887
```

```
1.12302895]
-1.00583187 -0.11574873 -0.69663055 0.31091206 -0.64911323 0.26508221
 1.12302895]
-1.00583187 -0.7279758 1.43548113 2.55392051 -2.27457861 1.24459328
 1.12302895]
-1.00583187 - 0.7717063 1.43548113 0.65599028 0.97635214 2.22410436
 1.12302895]
0.89896224 1.0212444 -0.69663055 -0.7243226 0.97635214 0.26508221
 1.12302895]
[-0.59184697 -1.46841752 -0.93851463 -0.09273778 0.43938366 -0.41763453
 -0.51292188]
[ 1.17277425  0.68100522 -0.93851463  0.19282673  0.14950142 -0.41763453
-1.00583187 -0.99035883 -0.69663055 1.51868584 -0.64911323 0.26508221
 1.12302895]
[-0.59184697 \quad 0.68100522 \quad 0.03203122 \quad -0.09273778 \quad 0.38140721 \quad -0.41763453
 -0.51292188]
[-0.48155814 -1.46841752 1.00257707 -0.66386682 -0.52689046 -0.41763453
 -0.51292188]
[-0.37126932  0.68100522  1.00257707  -1.80612489  -0.46891401  -0.41763453
 0.89896224 -0.29067075 1.43548113 0.13837295 -0.64911323 -0.71442887
-0.51292188]
[-0.26098049 0.68100522 -0.93851463 -1.34922166 -0.25633371 2.394438
 0.89896224 -0.11574873 -0.69663055 -0.81059216 0.97635214 2.22410436
 1.12302895]
0.89896224 1.10870541 -0.69663055 -0.89686172 0.97635214 1.24459328
-0.51292188]
0.89896224 -2.21481297 1.43548113 0.65599028 -0.64911323 1.24459328
 1.12302895]
[-1.36386876  0.68100522  1.00257707  -0.66386682  -0.12105533  2.394438
 0.89896224 1.939585 -0.69663055 -0.20670527 -2.27457861 -0.71442887
 1.12302895]
0.89896224 1.23989692 -0.69663055 -0.89686172 0.97635214 -0.71442887
-0.51292188]
0.89896224 -0.42186226 -0.69663055 0.13837295 -0.64911323 -0.71442887
 1.123028951
-1.00583187 \ -2.03989095 \ -0.69663055 \ \ 0.31091206 \ -0.64911323 \ \ 0.26508221
 1.12302895]
-1.00583187 -1.82123842 1.43548113 -0.89686172 -0.64911323 0.26508221
-0.51292188]
0.89896224  0.1466343  -0.69663055  -0.89686172  0.97635214  -0.71442887
-0.51292188]
0.89896224 -2.30227398 -0.69663055 0.13837295 -0.64911323 0.26508221
 1.12302895]
0.89896224  0.80259187  -0.69663055  -0.03416616  0.97635214  1.24459328
 1.12302895]
-1.00583187 -0.24694024 -0.69663055 -0.20670527 0.97635214 -0.71442887
 1.123028951
[-1.69473524 -1.46841752 1.00257707 0.36416545 -0.50756498 -0.41763453
 -0.512921881
[-0.26098049 0.68100522 0.03203122 0.13571383 -0.87474914 -0.41763453
```

```
-0.51292188]
[ 0.62133012  0.68100522  1.00257707  0.47839125  -1.18395686  -0.41763453
-1.00583187 0.23409531 -0.69663055 1.69122495 -0.64911323 -0.71442887
-0.51292188]
 \begin{bmatrix} -1.03300228 & 0.68100522 & -0.93851463 & 0.59261706 & 1.21240295 & -0.41763453 \end{bmatrix} 
-1.00583187 \ -0.11574873 \ 1.43548113 \ -0.89686172 \ -0.64911323 \ 2.22410436
 1.12302895]
[-1.47415758 -1.46841752 0.03203122 -0.3211894 1.1544265 -0.41763453]
 -0.51292188]
 \hbox{$\left[-0.26098049\  \  \, 0.68100522\  \  \, 1.00257707\  \  \, 2.30600417\  \, -0.91340011\  \  \, 2.394438\  \  \, \right] }
 1.12302895]
 \begin{bmatrix} -2.13589054 & 0.68100522 & 0.03203122 & -0.54964101 & -1.04867848 & -0.41763453 \\ \end{bmatrix} 
 0.89896224 1.0649749 -0.69663055 -0.89686172 0.97635214 -0.71442887
-0.51292188]
0.89896224 -0.29067075 1.43548113 -0.89686172 -0.64911323 -0.71442887
-0.51292188]
[ 1.72421839  0.68100522  1.00257707  1.62064933  0.43938366  -0.41763453
 1.12302895]
[-1.03300228  0.68100522  0.03203122  -0.20696359  1.19307747  -0.41763453
-1.00583187 0.89005288 -0.69663055 -0.89686172 0.97635214 -0.71442887
-0.51292188]
[ 0.18017482  0.68100522  -0.93851463  -0.3783023  0.05287401  2.394438
-1.00583187 -0.24694024 1.43548113 0.13837295 -0.64911323 0.26508221
-0.51292188]
-0.51292188]
[ 0.29046364  0.68100522 -0.93851463  0.47839125 -1.04867848 -0.41763453
 0.89896224 -0.07201822 -0.69663055 -0.55178349 -0.64911323 -0.71442887
-2.14887271]
[ 0.29046364 -1.46841752 -0.93851463 -0.20696359 1.09645005 -0.41763453
-0.51292188]
[-0.26098049   0.68100522   1.00257707   0.36416545   -0.44958853   -0.41763453
 -0.51292188]
[-0.81242462 \quad 0.68100522 \quad -0.93851463 \quad -1.23499586 \quad 0.55533655 \quad -0.41763453
-1.00583187 -1.38393337 1.43548113 -0.03416616 -0.64911323 0.26508221
 \begin{bmatrix} -0.37126932 & 0.68100522 & 1.97312292 & -0.3783023 & -0.64284335 & -0.41763453 \end{bmatrix} 
-1.00583187 -1.07781984 1.43548113 0.31091206 0.97635214 0.26508221
-0.51292188]
[ 1.72421839  0.68100522  0.03203122  1.39219771  -0.02442792  -0.41763453
-1.00583187 \ -0.29067075 \ -0.69663055 \ -0.89686172 \ \ 0.97635214 \ -0.71442887
-0.51292188]
[-1.47415758 0.68100522 1.00257707 -0.09273778 -0.62351787 -0.41763453
-0.51292188]
1.12302895]
[ 0.18017482 -1.46841752 -0.93851463  0.13571383  3.14495118 -0.41763453
-1.00583187 0.01544279 1.43548113 0.74225984 -0.64911323 1.24459328
 1.12302895]
[-1.1432911    0.68100522    0.03203122    -0.66386682    0.32343076    -0.41763453
 0.89896224 1.0212444 -0.69663055 -0.89686172 0.97635214 -0.71442887
 1.12302895]
[-0.26098049 0.68100522 0.03203122 -0.66386682 1.52161066 -0.41763453
 -0.512921881
[ 2.16537369 -1.46841752  0.03203122 -0.66386682  0.43938366 -0.41763453
-1.00583187 -1.25274186 1.43548113 -0.7243226 0.97635214 0.26508221
-0.512921881
[-1.47415758 -1.46841752 1.00257707 -1.12077005 0.42005817 -0.41763453
-1.00583187 0.97751389 1.43548113 -0.89686172 0.97635214 -0.71442887
```

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-0.51292188]
         [-1.47415758 \quad 0.68100522 \quad 0.03203122 \quad 0.19282673 \quad -0.83609818 \quad -0.41763453
          0.89896224 -0.7717063 -0.69663055 -0.89686172 -0.64911323 -0.71442887
          -2.14887271]
         [-1.69473524 -1.46841752 \ 1.00257707 -2.14880232 -0.91340011 -0.41763453
          0.89896224 1.28362743 -0.69663055 -0.89686172 0.97635214 -0.71442887
          -0.51292188]
          \hbox{ $[-2.13589054$ } \quad 0.68100522 \ -0.93851463 \ -0.66386682 \ -0.93272559 \ -0.41763453 \\
          0.89896224 -0.85916731 1.43548113 0.48345117 -0.64911323 -0.71442887
          1.12302895]
         0.89896224 \ -0.02828772 \ -0.69663055 \ -0.63805305 \ -0.64911323 \ \ 0.26508221
          -0.51292188]
         -1.00583187 1.0649749 -0.69663055 -0.89686172 -0.64911323 0.26508221
         -0.51292188]
         -0.51292188]
         [-0.48155814 \ -1.46841752 \ \ 0.03203122 \ -0.66386682 \ -0.0437534 \ \ -0.41763453
          -0.51292188]
          [ \ 0.40075247 \ -1.46841752 \ -0.93851463 \ -1.80612489 \ \ 0.03354853 \ -0.41763453 
          -1.00583187 -1.20901135 -0.69663055 -0.03416616 -0.64911323 -0.71442887
          -0.51292188]]
In [11]:
        # creating and training the KNN algorithm
        from sklearn.neighbors import KNeighborsClassifier
         classifier = KNeighborsClassifier(n neighbors=5,metric='minkowski',p=2)
         classifier.fit(x_tr,y_tr)
Out[11]: KNeighborsClassifier()
In [12]:
        # predciting the output and printing
        y_pred = classifier.predict(x_te)
         z = np.append(arr=y_pred.reshape(61,1),values=y_te.reshape(61,1),axis=1)
         print(z)
        [[0 0]
         [0 1]
         [0 0]
         [0 0]
         [0 1]
         [1 0]
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[1 1]
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           [1 1]
           [1\ 1]
           [1 1]]
In [13]:
          # printing the accuracy score and the confusion matrix
          from sklearn.metrics import accuracy_score,confusion_matrix
          acc = accuracy_score(y_te,y_pred)
          cm = confusion_matrix(y_te,y_pred)
          print(acc)
          print(cm)
          0.819672131147541
          [[21 6]
          [ 5 29]]
In [14]:
          # plotting the confusion matrix and the decision regions
          from mlxtend.plotting import plot_confusion_matrix,plot_decision_regions
          plot_confusion_matrix(cm,cmap = 'Blues')
          plt.show()
```



```
In [16]:
         from sklearn.svm import SVC
         classifier = SVC(kernel='linear', random_state=0)
         classifier.fit(x_tr,y_tr)
Out[16]: SVC(kernel='linear', random_state=0)
In [17]:
         y_pred = classifier.predict(x_te)
         print(y_pred)
        1001100011101111111111111
In [18]:
         z = np.append(arr=y_pred.reshape(61,1),values=y_te.reshape(61,1),axis=1)
         print(z)
        [[0 0]
         [1 1]
         [1 0]
         [0 0]
         [0 1]
         [1 0]
         [0 0]
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[1 1] [1 0]

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[1 1]]
```

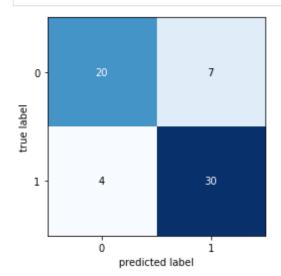
```
from skle acc= accu
```

```
from sklearn.metrics import accuracy_score,confusion_matrix
acc= accuracy_score(y_te,y_pred)
cm = confusion_matrix(y_te,y_pred)
print(acc)
print(cm)
```

0.819672131147541 [[20 7] [4 30]]

In [20]:

from mlxtend.plotting import plot_confusion_matrix,plot_decision_regions
plot_confusion_matrix(cm)
plt.show()

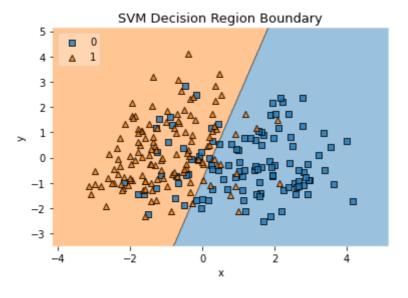


```
from sklearn.decomposition import PCA
from mlxtend.plotting import plot_decision_regions
```

```
clf = SVC(C=100,gamma=0.0001)
pca = PCA(n_components = 2)
X_train2 = pca.fit_transform(x_tr)
clf.fit(X_train2, y_tr)
plot_decision_regions(X_train2, y_tr, clf=clf, legend=2)

plt.xlabel('x')
plt.ylabel('y')
plt.title('SVM Decision Region Boundary', size=13)
```

Out[21]: Text(0.5, 1.0, 'SVM Decision Region Boundary')



In [22]:

```
from sklearn.decomposition import PCA

# the PCA class take n_components as the input values, since in the starting

# we do not have any information about the eigen values or the explained variance

# we do not use the n_components parameter

pca = PCA(n_components=2)

x = pca.fit_transform(x)

# to know the explained variance we have explained_variance_ration function

# of the PCA class

PVE = pca.explained_variance_ratio_

print(PVE)

# now as we know the explained valriance aof all the features we can select any

# number of features we want. for this dataset i am choosing first 2 components

print(x)
```

```
[0.21254053 0.11820708]
[[ 6.24110729e-01 2.32127028e+00]
 [-4.55987975e-01 -9.57350982e-01]
 [-1.82880491e+00 4.28847737e-02]
 [-1.71600605e+00 -4.95337323e-01]
 [-3.71356421e-01 3.01156175e-01]
 [-6.48867460e-01 -3.82882350e-01]
 [-7.26534041e-02 1.46021954e+00]
 [-1.90592574e+00 -1.15199470e+00]
 [-9.05732769e-01 1.17802505e+00]
 [-1.42452084e+00 6.00440468e-02]
 [-8.29249247e-01 -4.31111662e-01]
 [-1.76837052e+00 6.66082010e-01]
 [-1.73039364e+00 -3.62122452e-01]
 [ 4.78579542e-01 -3.66100880e-01]
 [-1.13904999e+00 3.31505033e+00]
 [-1.15305728e+00 3.38842792e-02]
 [-2.05289635e+00 1.44304375e+00]
[ 1.24660567e+00 1.56563220e+00]
```

[-1.17898795e+00 -5.93288357e-01] [-3.87798996e-01 2.04509682e+00] [-1.09484581e-02 -7.39533549e-01] [-1.69288377e+00 -1.05478211e+00] [-2.03684479e+00 -9.44816640e-01] [9.35559575e-01 9.21609753e-01] [-1.32664177e+00 -1.31154957e+00] [-1.39644919e-01 2.60255695e+00] [-7.38694870e-01 1.29433620e+00] [-1.46985273e+00 -1.28905546e+00] [-1.44718583e-01 4.11799172e+00] [2.33446358e-01 6.83863299e-01] [-2.51462707e+00 -9.04060838e-01] [-3.60909832e-01 -1.23607299e+00] [-2.29381971e+00 -4.11500959e-01] [1.95138723e-01 3.70030395e-01] [4.17978771e-02 -4.34762882e-01] [3.66186582e-01 -9.36466989e-02] [-1.87209672e+00 2.27149641e+00] [-6.12868482e-01 4.38220805e-01] [-8.76984260e-01 2.01456281e+00] [-4.29390862e-01 3.21168571e+00] [-5.57570271e-01 1.74775482e+00] [-1.26081093e+00 -1.64062709e-01] [9.11469357e-01 -2.29447547e+00] [-2.26867255e-01 5.82251192e-01] [-2.28791024e+00 6.01398620e-01] [-1.76066724e+00 -4.09448669e-02] [-2.27329407e+00 2.12736619e-01] [-1.70331203e+00 3.70308829e-01] [-1.86836572e+00 1.42913226e+00] [-1.28263071e+00 7.25685018e-01] [-1.53774483e+00 1.10788521e+00] [2.54315975e-01 3.97205643e-01] [1.04746686e+00 -7.42857672e-03] [-2.33560884e+00 -9.81680314e-01] [-1.67838555e+00 1.84323020e+00] [-1.15501432e+00 -5.46593725e-01] [-1.92948984e+00 -7.06723512e-01] [-2.00256825e+00 -7.52005344e-01] [-3.12837567e+00 -8.91051335e-01] [-8.06669491e-01 1.22947541e+00] [-3.94560324e-01 2.50933383e+00] [-1.27147048e+00 -7.38223238e-01] [-2.53287997e+00 2.47639537e-01] [-1.35079404e+00 -8.95169695e-01] [-1.36230549e+00 1.51234405e+00] [-2.15923721e+00 -8.48789968e-01] [-2.27775319e-01 -1.80679343e+00] [-1.34909390e+00 4.01042008e-01] [-2.31204282e+00 -1.13675227e+00] [-1.47245711e+00 1.91834447e-01] [-3.58290535e-01 -2.15242599e-01] [-9.00657970e-01 -1.98769071e+00] [-3.10263149e+00 -1.14139417e+00] [-7.77727474e-01 -4.08137174e-01] [-2.02255469e+00 -1.84934457e-01] [-3.69141309e-01 1.00307778e+00] [-2.17374162e-01 8.79489279e-01] [-7.00350164e-01 -5.38710651e-01] [-2.03272023e+00 2.56463178e-01] [2.97099388e-01 -1.08443288e+00] [-2.86242797e+00 -9.40849473e-01] [-1.75044772e+00 1.48892731e-01] [-1.73634247e+00 9.78535417e-011 [-5.78469356e-01 1.60771202e+00] [-4.45009018e-01 -6.84698902e-01] 7.36184643e-01 3.19974398e+001 [-2.99639697e-01 2.32348803e-01]

[-1.66919609e+00 -1.16808381e+00] [-1.13082898e+00 -7.24242833e-02] [1.94677672e-01 -1.55839503e-01] [-1.66720309e+00 7.71701262e-01] [-3.28562145e-01 -1.53038550e+00] [-1.01659168e+00 3.47178140e-01] [-1.91812262e-01 1.70969179e+00] [-1.49262806e+00 -1.09040659e+00] [9.62440887e-01 -1.09883802e+00] [5.19560081e-01 2.16304236e+00] [-3.64556302e-02 -5.17554030e-01] [-1.19147000e+00 5.76595678e-03] [-9.03942011e-01 1.58856809e+00] [-1.64330093e+00 8.16829513e-01] [2.21433249e+00 1.57653769e+00] [-1.32410540e+00 1.06586014e+00] [-9.45098926e-01 -3.44255927e-01] [-2.20305006e+00 -5.47149621e-01] [4.42831822e-01 1.06261808e+00] [5.55050959e-01 2.84941902e+00] [5.03643963e-02 -2.94463278e-01] [-1.70100152e+00 3.62769746e-02] [-1.61712759e+00 2.80553463e-02] [3.82396840e-01 1.90838903e+00] [-1.17044214e+00 4.80380395e-01] [-5.50181431e-01 1.55192727e+00] [-1.67849081e+00 -2.14273598e+00] [-1.45734244e+00 -1.48979053e-01] [-3.02772373e+00 -3.84985508e-01] [-9.70018179e-01 -5.29495703e-01] [-4.33119094e-01 -3.11568230e-01] [-2.66826953e+00 -7.16422029e-01] [2.84915902e-02 -1.91342721e-01] [1.49653150e+00 9.69770490e-01] [-1.19623625e+00 5.17978486e-01] [-1.87579331e+00 -1.66117333e-01] [-2.14878334e+00 8.53020352e-01] [-3.43174362e+00 -1.02813770e+00] [-3.04480004e+00 -8.49784825e-01] [-1.53392034e+00 -1.70025940e+00] [-1.28012604e+00 2.29544296e+00] [-1.46794139e+00 8.87683868e-01] [8.89542149e-01 1.14033501e+00] [-1.65505163e+00 1.34730906e+00] [-1.30826680e+00 5.03005648e-01] [-2.06551481e+00 -7.25253420e-01] [-2.17738669e+00 -1.47362290e+00] [-2.22565349e+00 2.73037781e-01] [-1.72382142e+00 1.82338061e-01] [-7.59739493e-01 1.02525927e+00] [-6.34687983e-01 9.96422582e-01] [6.25607126e-01 -1.75577351e+00] [2.10385361e+00 -1.13242627e+00] [-1.66382947e+00 1.15509250e+00] [-1.09304542e+00 -1.10576638e+00] [-2.30540299e+00 -2.71697450e-01] [-4.30092160e-01 1.63349949e-01] [2.48771048e-01 1.00283690e+00] [-2.41139543e-01 1.43371763e+00] [-1.36885327e+00 -2.73621086e-03] [-1.81778359e+00 1.82350637e+00] [-2.54673833e+00 -8.09381006e-01] [-2.26928559e+00 -1.03745572e+00] [4.50718788e-01 1.15403871e+00] [4.65929054e-01 -4.08170719e-01] [1.03307941e-01 1.57236212e+00] [-1.50660602e-01 2.38152957e+001 [-1.81284743e+00 5.03633148e-02] [-1.57907341e-01 -1.36373081e-01]

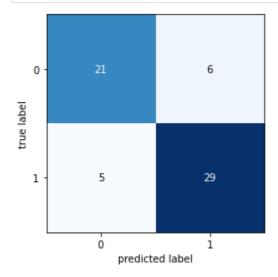
[-2.45862893e+00 -2.00484134e-01] [-2.73927954e+00 -1.67346422e+00] [8.95162473e-01 -5.29213408e-01] [-1.05488497e+00 -2.73396006e-01] [-5.98013045e-01 -6.19006677e-01] [-1.21604215e+00 1.26002507e+00] [-2.77747071e+00 -1.67406427e+00] [-1.68346856e+00 -6.04442562e-01] [-1.68346856e+00 -6.04442562e-01] [3.42750627e+00 8.49963994e-01] [2.98933554e+00 -9.51270294e-01] [2.20059160e+00 1.28327713e+00] [1.21227746e+00 -1.19898712e-01] [2.65181760e+00 -5.65430839e-01] [4.93560075e-01 1.16507761e+00] [-2.61776747e-01 -1.68196011e+00] [1.26485771e-02 1.68105218e-01] [2.87370588e-01 2.50122842e-01] [2.67258979e+00 -1.15735347e+00] [1.32869214e+00 -3.05618567e+00] [1.06495037e+00 -6.22649680e-01] [-1.19599518e+00 1.31739406e+00] [1.63210499e+00 -2.60320608e+00] [1.65603152e+00 2.79448715e-01] [1.90839438e+00 -7.54597839e-01] [2.22220607e+00 1.16804208e+00] [-1.03560367e+00 1.59073877e+00] [3.32834850e-01 -3.74670222e-01] [1.45974253e+00 -4.90202634e-01] [-1.15018365e+00 -6.77304925e-01] [1.07035164e+00 -1.17464142e+00] [2.61659353e+00 -1.31513780e+00] [-5.38173676e-01 -3.53048268e-01] [-1.53832531e+00 -2.09653759e+00] [9.94845520e-01 -5.68084873e-01] [2.81843101e+00 -1.12872025e+00] [1.02161781e+00 -1.77475747e+00] [2.96521759e+00 -2.30563001e-01] [3.26448398e-01 2.78204770e-01] [3.62859705e+00 3.63324103e-01] [1.70317729e-01 -2.49629513e-01] [8.03973390e-01 6.06859830e-01] [2.91576516e+00 -1.39438828e+00] [-5.08161331e-01 3.28011328e-01] [-1.81927484e+00 -1.30075367e+00] [2.45124416e+00 -9.95774976e-01] [1.60916279e+00 -4.00770853e-01] [2.15052545e+00 2.31391554e+00] [4.02011140e+00 6.46738596e-01] [-3.98057583e-02 -1.44794737e+00] [1.61848286e+00 -1.47427040e+00] [1.65217809e+00 1.15863210e+00] [5.94297033e-01 -1.17577198e+00] [1.33672683e-01 -1.38013666e+00] [-2.30574052e-02 1.74943974e-02] [2.50244761e+00 -1.52222713e+00] [-2.80704014e-01 -2.26958995e+00] [1.60151225e+00 7.12705025e-01] [1.50220402e+00 6.50097304e-02] [2.03158524e+00 5.89018929e-01] [1.06473628e+00 7.05765553e-011 [2.69804656e+00 9.41076514e-01] [2.20520701e+00 -3.64042767e-02] 7.63248551e-01 -2.01888579e-01] [2.92325108e+00 2.36151943e+00] [4.00895722e+00 -1.95314675e+00] [-1.83351385e-02 2.54563652e+001 [4.64543392e+00 2.55026802e+001 [2.07257421e+00 -2.24559036e+00]

[3.14268207e+00 -1.27610247e+00] [1.66870959e+00 -8.60889850e-02] [6.51264950e-01 -3.15972941e+00] [-1.49252085e-01 1.80975707e+00] [1.48166051e+00 -3.82242820e-01] [-2.22063581e+00 -9.13453066e-01] [2.46791133e+00 1.75059368e+00] [1.91904872e+00 -2.16699666e-02] [3.36660475e+00 -9.02727928e-01] [2.83534111e+00 1.01099038e+00] [2.44404441e-01 -1.00595328e+00] [-2.02766445e-01 1.70739682e-01] [1.07816964e+00 4.50275681e-01] [1.30334294e+00 8.78937102e-01] [-5.21969910e-01 -1.75780455e+00] [2.97843850e+00 4.58581276e-01] [7.91370382e-01 8.82797166e-01] [1.34086441e+00 6.75245670e-01] [2.80998835e+00 -8.70841338e-01] [1.89414306e+00 -9.55359879e-01] [-2.64717957e-01 -7.88012595e-01] [2.33236000e+00 1.08946575e+00] [1.66749048e+00 8.28025663e-01] [-6.47467855e-01 1.82658564e+00] [1.76295131e+00 1.13012802e+00] [3.53258245e+00 -1.10586565e+00] [1.90690702e+00 -3.61745363e-01] [2.22080478e+00 1.95187504e+00] [2.03223384e+00 -5.67301300e-01] [-7.21984983e-01 1.75405581e+00] [1.63809100e+00 -5.51876851e-01] [2.95613650e+00 -9.57498551e-01] [1.49043380e+00 -1.43444058e+00] [9.38365196e-01 3.55678315e-01] [-1.20144058e-01 -1.84943873e+00] [2.09527012e+00 1.92708014e+00] [-1.37985027e+00 -1.13851558e+00] [2.81468433e+00 -1.63942506e+00] [9.95478319e-01 -2.57026849e-01] [1.19198297e+00 -1.66402855e+00] [6.24205035e-01 -8.78329825e-01] [2.35384370e+00 7.40691621e-01] [-4.50054471e-01 -6.62998751e-01] [2.77991960e+00 -8.24956072e-01] [3.23628081e+00 -2.27227446e-01] [-5.40748692e-01 -1.16363059e+00] [4.72063927e-01 5.54206652e-01] [1.57253846e+00 -7.36114933e-01] [-8.16632677e-01 -1.48838837e+00] [1.28581045e+00 -1.50254445e+00] [-4.36931251e-01 -1.19396153e+00] [1.86431121e+00 -7.87864065e-01] [-7.26512444e-01 -6.06163516e-01] [-3.15969043e-01 2.83672363e+00] [2.63158109e+00 -1.03591185e+00] [7.64330737e-01 -9.90866377e-01] [-2.35336603e-01 -1.62417337e-01] [1.80690338e-01 9.72556211e-01] [-1.67832632e+00 -1.07337582e+00] [1.63929145e+00 -8.25868484e-01] [2.28872040e+00 -1.22909370e+00] [-1.24386827e+00 4.70956394e-01] [-8.56949860e-01 8.73505515e-01] [2.15706459e+00 -1.38606749e+00] [1.41816441e+00 -1.54885040e+00] [-4.06059853e-01 -3.49594568e-01] 2.16927742e+00 -5.31447414e-01] 2.24175970e+00 2.27901051e+00] [4.14157859e-01 8.36052633e-01]

12/13/21, 12:49 PM

```
Untitled36
          [ 9.67660777e-01 -2.38918560e+00]
          [ 2.58185522e+00 -8.59185999e-01]
          [ 4.14314275e-01 -5.79482296e-01]
          [ 1.89555409e+00 1.46786667e+00]
          [ 1.14667187e+00 -5.19529495e-01]
          [-7.08592873e-01 -1.04575189e+00]
          [ 2.45900545e+00 4.78261911e-01]
          [ 1.76275536e+00 -2.33681621e+00]
          [-8.60056772e-01 1.06851556e+00]]
In [23]:
          # splitting the dataset into training and test set for the svm algorithm
          from sklearn.model_selection import train_test_split
          x_tr,x_te,y_tr,y_te = train_test_split(x,y,test_size= 0.2,random_state=0)
In [25]:
          from sklearn.svm import SVC
          classifier = SVC(kernel='linear', random_state=0)
          classifier.fit(x_tr,y_tr)
Out[25]: SVC(kernel='linear', random_state=0)
In [26]:
          y_pred = classifier.predict(x_te)
          from sklearn.metrics import accuracy_score,confusion_matrix
          acc = accuracy_score(y_te,y_pred)
          cm = confusion_matrix(y_te,y_pred)
          print(acc)
          print(cm)
         0.819672131147541
         [[21 6]
          [ 5 29]]
In [27]:
          from mlxtend.plotting import plot_confusion_matrix,plot_decision_regions
          plot_confusion_matrix(cm)
```

plt.show()



In [28]: plot_decision_regions(X=x_te,y=y_te,clf=classifier,colors='blue,black',markers='^x') plt.show()

```
\begin{bmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{x} & \mathbf{1} \end{bmatrix}
```

```
from sklearn.neighbors import KNeighborsClassifier
  classifier = KNeighborsClassifier(n_neighbors=5,metric='minkowski',p=2)
  classifier.fit(x_tr,y_tr)
```

Out[29]: KNeighborsClassifier()

```
In [30]: # predciting the output and printing
y_pred = classifier.predict(x_te)
z = np.append(arr=y_pred.reshape(61,1),values=y_te.reshape(61,1),axis=1)
print(z)
```

```
[[0 0]
[1\ 1]
[1 0]
[0 0]
[0 1]
[1 0]
 [0 0]
 [0 0]
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[0 0]
[1 1]
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[1 0]
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[1 1]
 [1 1]
 [0 0]
[0 0]
[1 1]
[1 1]
```

[1 1] [0 0] [0 0]

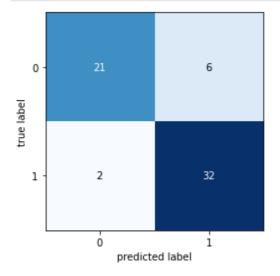
```
[1\ 1]
[0 0]
[0 0]
[1\ 1]
[1\ 1]
[1\ 1]
[0 0]
[1\ 1]
[1\ 1]
[1\ 1]
[1 0]
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[1 1]
[1 1]
[1 1]
[1 1]
[1 1]
[0 0]
[1 1]
[1 0]
[1 1]
[1 1]
[1 1]]
```

```
In [31]: # printing the accuracy score and the confusion matrix
    from sklearn.metrics import accuracy_score,confusion_matrix
    acc = accuracy_score(y_te,y_pred)
    cm = confusion_matrix(y_te,y_pred)
    print(acc)
    print(cm)
```

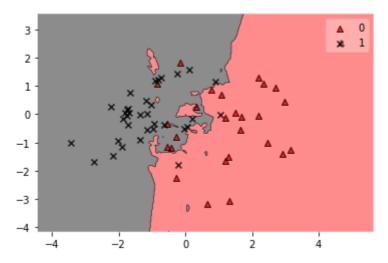
0.8688524590163934 [[21 6] [2 32]]

In [32]:

plotting the confusion matrix and the decision regions
from mlxtend.plotting import plot_confusion_matrix,plot_decision_regions
plot_confusion_matrix(cm,cmap = 'Blues')
plt.show()



```
In [33]: plot_decision_regions(X=x_te,y=y_te,clf=classifier,colors='red,black',markers='^x')
    plt.show()
```



In []: