Classification of two varieties of Raisins

Source: https://www.kaggle.com/datasets/muratkokludataset/raisin-dataset

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In [357]:

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, f1_score, precision_score, recall_scor
e, confusion_matrix

from sklearn.svm import SVC
from sklearn.model_selection import cross_validate
from sklearn.model_selection import KFold
from statistics import mean
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import make_classification
from sklearn.metrics import confusion_matrix, plot_precision_recall_curve
import warnings
warnings.filterwarnings("ignore")
from sklearn import metrics
from sklearn.metrics import roc_curve, roc_auc_score
```

In [205]:

```
#reading the file from the device
df = pd.read_csv('Raisin_Dataset.csv')
#printing the first 5 rows
df.head()
```

Out[205]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class
0	87524	442.246011	253.291155	0.819738	90546	0.758651	1184.040	Kecimen
1	75166	406.690687	243.032436	0.801805	78789	0.684130	1121.786	Kecimen
2	90856	442.267048	266.328318	0.798354	93717	0.637613	1208.575	Kecimen
3	45928	286.540559	208.760042	0.684989	47336	0.699599	844.162	Kecimen
4	79408	352.190770	290.827533	0.564011	81463	0.792772	1073.251	Kecimen

We are classifying two varieties, that is, classes of raisins - Kecimen and Besni.

Checking the rows and columns in the dataframe

In [206]:

```
df.shape
```

Out[206]:

```
(900, 8)
```

There are 900 rows (grains of raisins) and 8 features out of which 1 is the class label.

In [207]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900 entries, 0 to 899
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             900 non-null    int64  
 1   MajorAxisLength  900 non-null    float64
 2   MinorAxisLength  900 non-null    float64
 3   Eccentricity     900 non-null    float64
 4   ConvexArea       900 non-null    int64  
 5   Extent           900 non-null    float64
 6   Perimeter        900 non-null    float64
 7   Class            900 non-null    object 
dtypes: float64(5), int64(2), object(1)
memory usage: 56.4+ KB
```

In [208]:

```
df.describe()
```

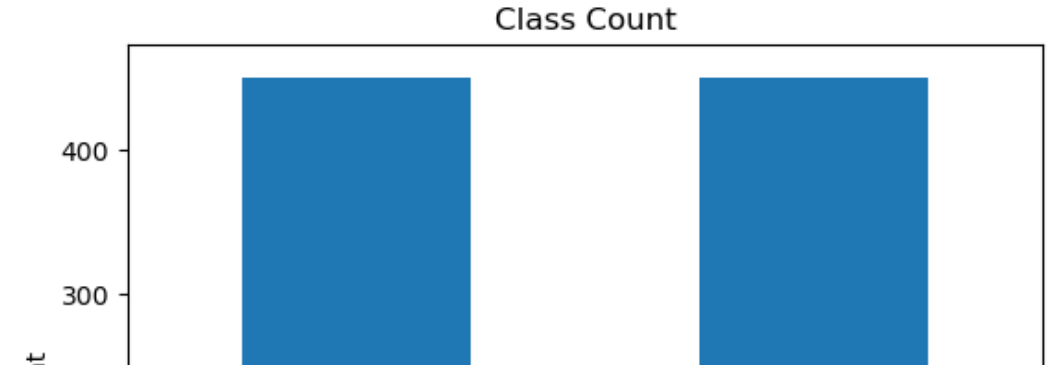
Out[208]:

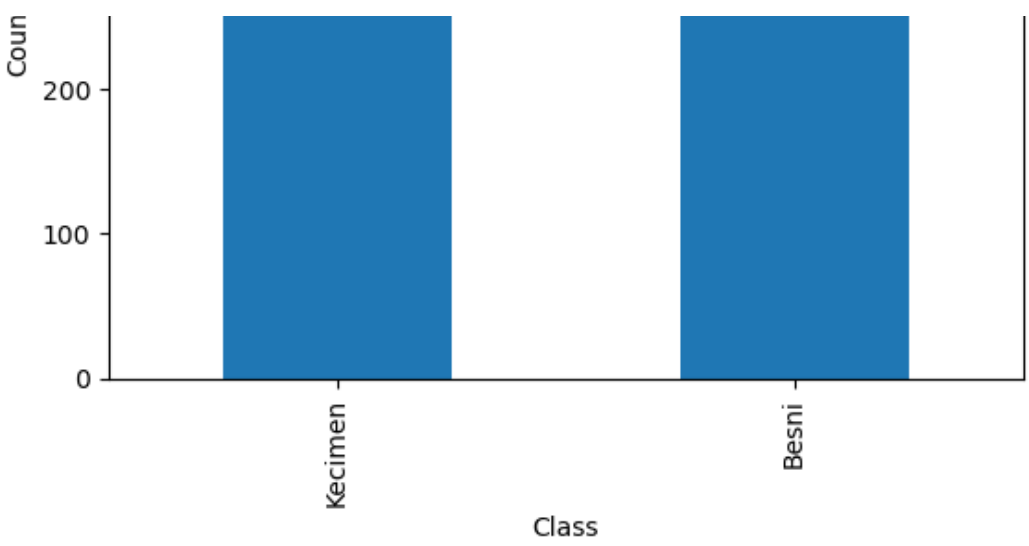
	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter
count	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000
mean	87804.127778	430.929950	254.488133	0.781542	91186.090000	0.699508	1165.906636
std	39002.111390	116.035121	49.988902	0.090318	40769.290132	0.053468	273.764315
min	25387.000000	225.629541	143.710872	0.348730	26139.000000	0.379856	619.074000
25%	59348.000000	345.442898	219.111126	0.741766	61513.250000	0.670869	966.410750
50%	78902.000000	407.803951	247.848409	0.798846	81651.000000	0.707367	1119.509000
75%	105028.250000	494.187014	279.888575	0.842571	108375.750000	0.734991	1308.389750
max	235047.000000	997.291941	492.275279	0.962124	278217.000000	0.835455	2697.753000

Plotting a histogram to see the distribution of the classes

In [209]:

```
class_counts = df['Class'].value_counts()
class_counts.plot(kind='bar')
plt.title('Class Count')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```





The two classes are almost equally distributed from the above graph.

Analyzing the relationship of the features

In [210]:

```
corr = df.corr()
corr
```

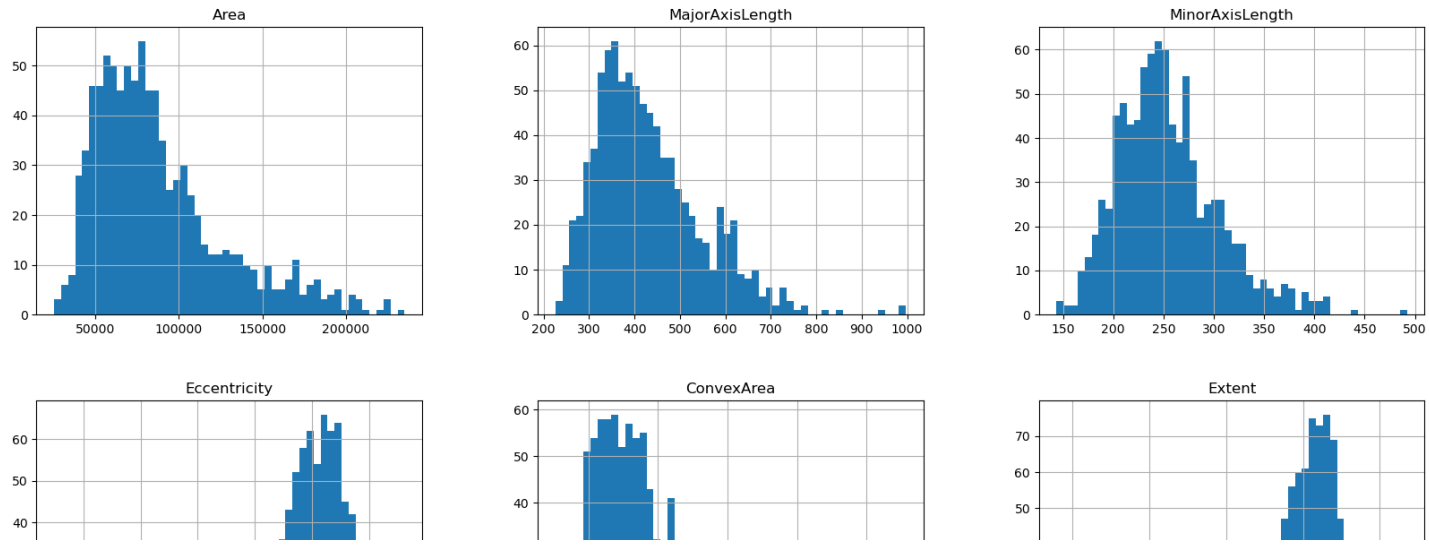
Out[210]:

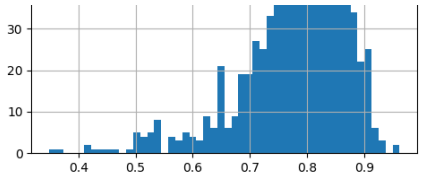
	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter
Area	1.000000	0.932774	0.906650	0.336107	0.995920	-0.013499	0.961352
MajorAxisLength	0.932774	1.000000	0.728030	0.583608	0.945031	-0.203866	0.977978
MinorAxisLength	0.906650	0.728030	1.000000	-0.027683	0.895651	0.145322	0.827417
Eccentricity	0.336107	0.583608	-0.027683	1.000000	0.348210	-0.361061	0.447845
ConvexArea	0.995920	0.945031	0.895651	0.348210	1.000000	-0.054802	0.976612
Extent	-0.013499	-0.203866	0.145322	-0.361061	-0.054802	1.000000	-0.173449
Perimeter	0.961352	0.977978	0.827417	0.447845	0.976612	-0.173449	1.000000

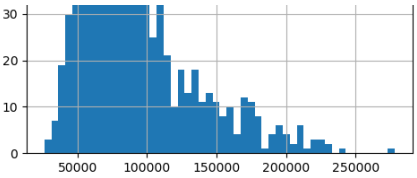
Checking distribution of each variable

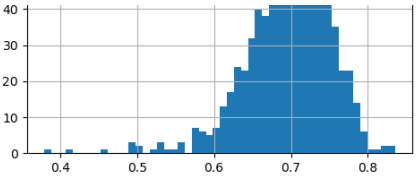
In [211]:

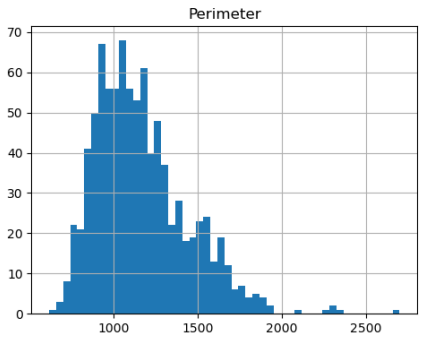
```
df.hist(bins=50, figsize=(20,15))
plt.show()
```











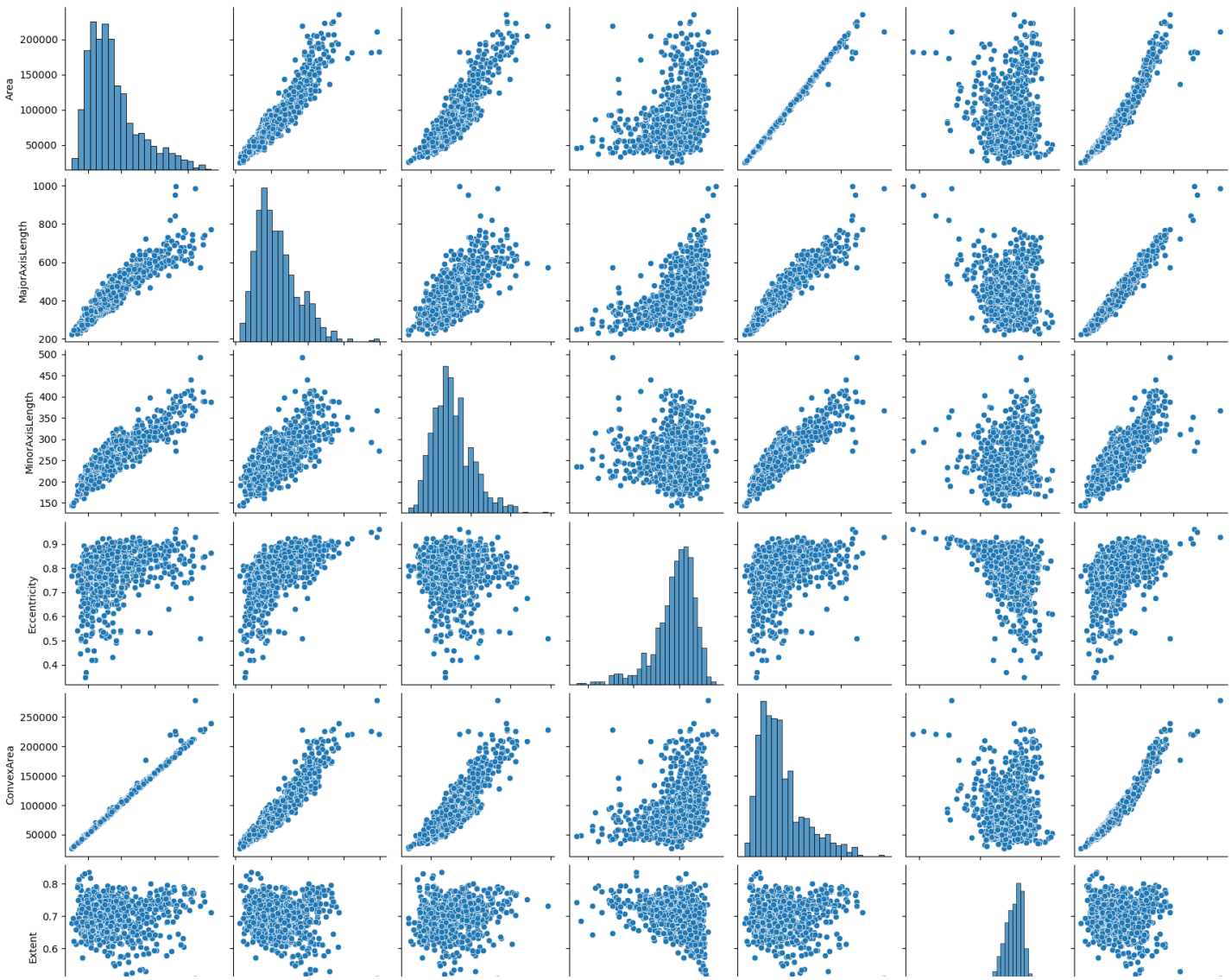
The above histograms show a distribution of each feature in the dataset. The distribution for Area, MajorAxisLength, MinorAxisLength, ConvexArea, Perimeter are positively skewed in distribution. Whereas, Eccentricity and Extent have a negatuvely skewed distribtion.

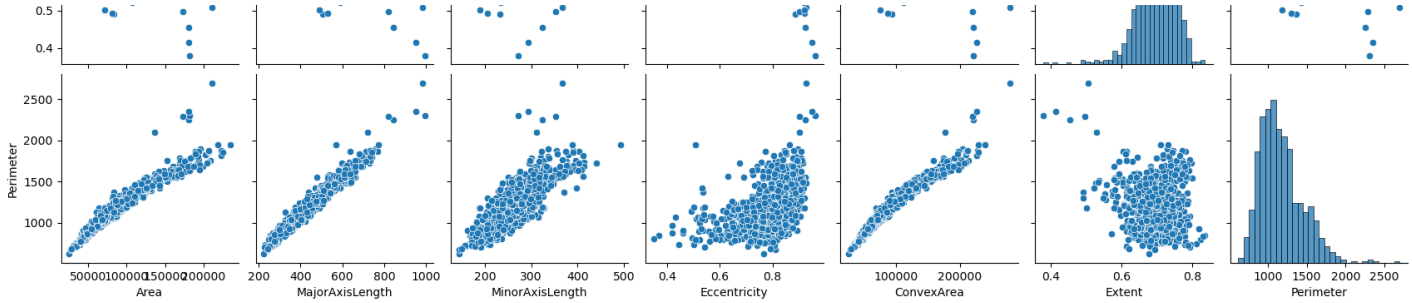
Plotting pairplot to see scatter plots of the features

In [212]:

```
plt.figure(figsize=(15,20))
sns.pairplot(data=df)
plt.show()
```

```
<Figure size 1500x2000 with 0 Axes>
```





Plotting a heatmap to see the correlations

In [213]:

```
corr.style.background_gradient(cmap='coolwarm').set_precision(2)
```

Out[213]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter
Area	1.00	0.93	0.91	0.34	1.00	-0.01	0.96
MajorAxisLength	0.93	1.00	0.73	0.58	0.95	-0.20	0.98
MinorAxisLength	0.91	0.73	1.00	-0.03	0.90	0.15	0.83
Eccentricity	0.34	0.58	-0.03	1.00	0.35	-0.36	0.45
ConvexArea	1.00	0.95	0.90	0.35	1.00	-0.05	0.98
Extent	-0.01	-0.20	0.15	-0.36	-0.05	1.00	-0.17
Perimeter	0.96	0.98	0.83	0.45	0.98	-0.17	1.00

The above correlation matrix shows that Area has positive correlation with MajorAxisLength, MinorAxisLength, Eccentricity, ConvexArea and Perimeter. However, it has negative correaltion with Extent of the raisins.

Checking for null values

In [214]:

```
df.isnull().sum()
```

Out[214]:

```
Area               0
MajorAxisLength    0
MinorAxisLength    0
Eccentricity       0
ConvexArea         0
Extent             0
Perimeter          0
Class              0
dtype: int64
```

No null values were found

Replacing categorical values of Class with 0 and 1

In [215]:

```
df['Class'] = df['Class'].str.replace('Kecimen', '1')
df['Class'] = df['Class'].str.replace('Besni', '0')
df
```

Out[215]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class
0	87524	442.246011	253.291155	0.819738	90546	0.758651	1184.040	1
1	75166	406.690687	243.032436	0.801805	78789	0.684130	1121.786	1
2	90856	442.267048	266.328318	0.798354	93717	0.637613	1208.575	1
3	45928	286.540559	208.760042	0.684989	47336	0.699599	844.162	1
4	79408	352.190770	290.827533	0.564011	81463	0.792772	1073.251	1
...	...	...	...	...	...	...	...	...
895	83248	430.077308	247.838695	0.817263	85839	0.668793	1129.072	0
896	87350	440.735698	259.293149	0.808629	90899	0.636476	1214.252	0
897	99657	431.706981	298.837323	0.721684	106264	0.741099	1292.828	0
898	93523	476.344094	254.176054	0.845739	97653	0.658798	1258.548	0
899	85609	512.081774	215.271976	0.907345	89197	0.632020	1272.862	0

900 rows × 8 columns

In [216]:

```
X = df.drop(['Class'],axis = 1)
y = df['Class']
```

Splitting training and testing data

In [217]:

```
# Split the data into training and testing with test size as 20%
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)
print("Size of X_train: ", X_train.shape)
print("Size of X_test: ", X_test.shape)
print("Size of y_train: ", y_train.shape)
print("Size of y_test: ", y_test.shape)
```

```
Size of X_train:  (720, 7)
Size of X_test:  (180, 7)
Size of y_train:  (720,)
Size of y_test:  (180,)
```

Converting X and y to numpy arrays to perform further operations

In [364]:

```
X_trainn = np.array(X_train, dtype="float32")
y_trainn = np.array(y_train, dtype="float32")
X_testt = np.array(X_test, dtype="float32")
y_testt = np.array(y_test, dtype="float32")
```

Scaling the values of X

In [365]:

```
#scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_trainn)
X_test_scaled = scaler.fit_transform(X_testt)
```

In [220]:

```
X_train_scaled[0]
```

Out[220]:

Out[220]:

```
array([-0.1975479 ,  0.14897284, -0.44638428,  0.81034476, -0.1745895 ,
       -0.45516506,  0.02725015], dtype=float32)
```

Function to plot confusion matrix

In [222]:

```
import itertools
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest
```

Function for evaluating models

In [292]:

```
def evaluate_model(X_train, y_train, model):
    X_neww = X_train
    y_neww = y_train

    # Create a StratifiedKFold object
    kfold = StratifiedKFold(n_splits=4, shuffle=True, random_state=42)

    # Initialize lists to store training and validation accuracies
    train_acc = []
    val_acc = []

    confusion_matrices = []
    classification_reports = []

    # Initialize variables to store best validation accuracy and associated confusion mat
rix
    best_val_acc = 0
    best_cm = None

    # Loop over the folds
    fold_count = 1
    for train, validation in kfold.split(X_neww, y_neww):
        print(f"Fold {fold_count}")
        fold_count = fold_count + 1

        # Split the data into training and validation sets
        X_train, y_train = X_neww[train], y_neww[train]
        X_val, y_val = X_neww[validation], y_neww[validation]

        # Train the model on the training set
        history = model.fit(X_train, y_train)

        # Evaluate the model on the training set
        train_scores = model.score(X_train, y_train)
        train_acc.append(train_scores)

        # Evaluate the model on the validation set
        val_scores = model.score(X_val, y_val)
```

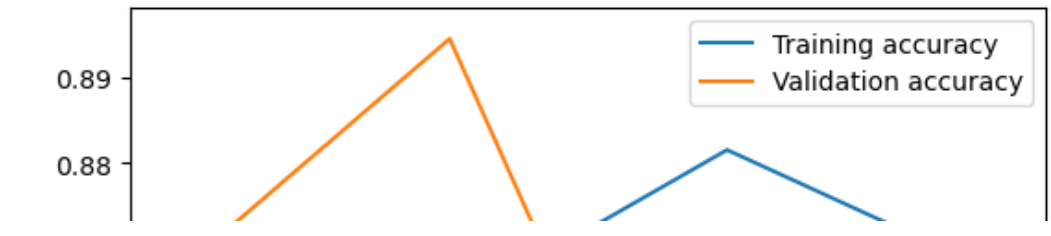
```
        val_acc.append(val_scores)


        # Calculate the confusion matrix and classification report for the validation set
        y_pred = model.predict(X_val)
        cm = confusion_matrix(y_val, y_pred)
        cr = classification_report(y_val, y_pred)

        # Append the confusion matrix and classification report to lists
        confusion_matrices.append(cm)
        classification_reports.append(cr)

        # Check if the current fold has the highest validation accuracy so far
        if val_scores > best_val_acc:
            best_val_acc = val_scores
            best_cm = cm

    # Plot the training and validation accuracies
    print("train_acc:", train_acc)
    print("val_acc:", val_acc)
    mean_train_acc = mean(train_acc)
    mean_val_acc = mean(val_acc)
    train_acc_percent = round(mean_train_acc * 100, 2)
    val_acc_percent = round(mean_val_acc * 100, 2)
    print("Mean train_acc: {:.2f}%".format(train_acc_percent))
    print("Mean val_acc: {:.2f}%".format(val_acc_percent))
    plt.plot(train_acc, label='Training accuracy')
    plt.plot(val_acc, label='Validation accuracy')
    plt.xlabel('Fold')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()

    # Plot the confusion matrix for the fold with the highest validation accuracy
    if best_cm is not None:
        plt.figure(figsize=(6, 4))
        sns.heatmap(best_cm, annot=True, cmap="Blues", fmt="d", cbar=False)
        plt.title("Confusion Matrix (Best Validation Accuracy)")
        plt.xlabel("Predicted label")
        plt.ylabel("True label")
        plt.show()

    # Print the classification report for the last fold
    print("Classification report:")
    print(classification_reports[-1])
```

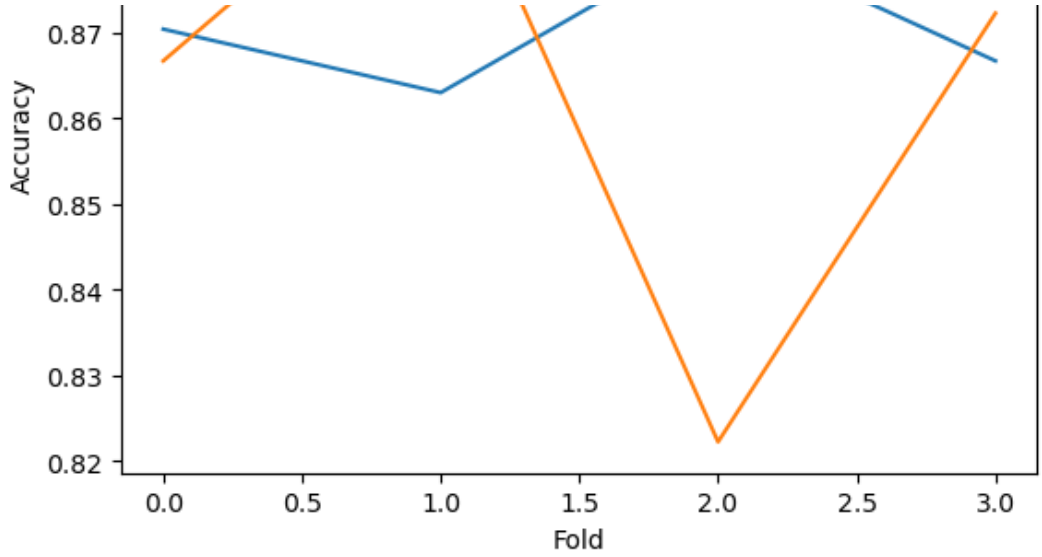
Multinomial Logistic Regression

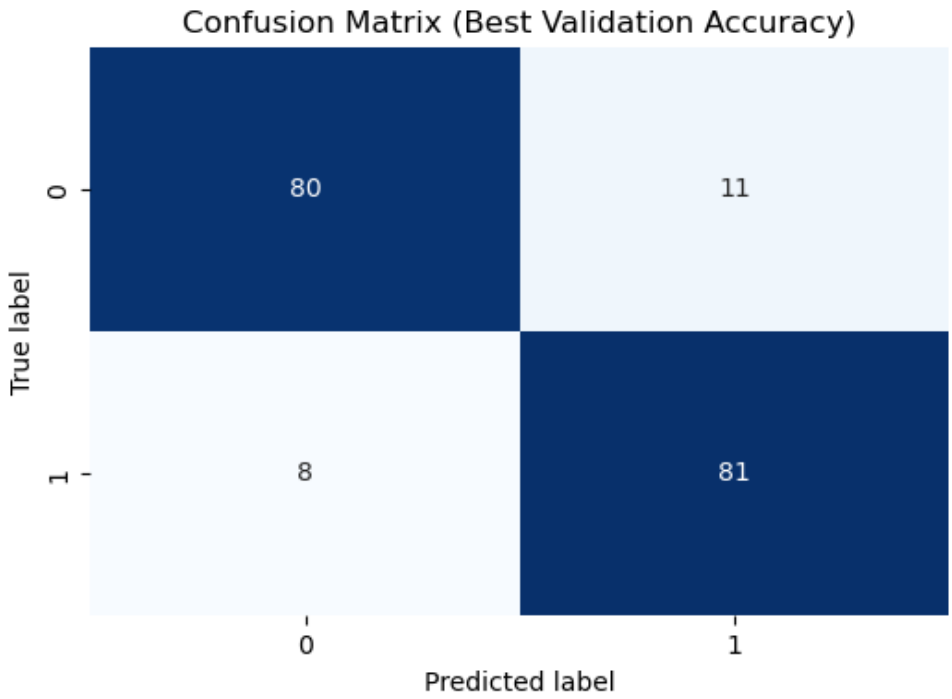
In [293]:

```
evaluate_model(X_train_scaled, y_trainn, model = LogisticRegression(multi_class='multinomial', solver='lbfgs'))
```

```
Fold 1
Fold 2
Fold 3
Fold 4
train_acc: [0.8703703703703703, 0.8629629629629629, 0.8814814814814815, 0.8666666666666667]
val_acc: [0.8666666666666667, 0.8944444444444445, 0.8222222222222222, 0.8722222222222222]
Mean train_acc: 87.04%
Mean val_acc: 86.39%
```








```
Classification report:
              precision    recall  f1-score   support

         0.0       0.88      0.87      0.87        91
         1.0       0.87      0.88      0.87        89

    accuracy                           0.87       180
   macro avg       0.87      0.87      0.87       180
weighted avg       0.87      0.87      0.87       180
```

The above graph shows increasing training and validation accuracies with increasing value of k folds. The mean accuracy is about 86%. Thus, we can say that the Multinomial Logistic Regression has fit well on the data.

The mean accuracy for training and validation has come out to be very close at 86%. From the graph we can say that since both the accuracies are increasing, the model is well fit.

Grid search for logostic regression

In [226]:

```
logistic_regression = LogisticRegression(multi_class='multinomial', solver='lbfgs')

# define the hyperparameter search space
param_grid = {
```

```
    'C': [0.1, 1, 10],
    'penalty': ['l1', 'l2'],
    'max_iter': [100, 500, 1000]
}

# define the grid search
grid_search = GridSearchCV(
    logistic_regression, param_grid=param_grid,
    cv=None, n_jobs=-1, verbose=1
)

# fit the grid search to the data
grid_search.fit(X_train_scaled, y_train)

# print the best hyperparameters and validation accuracy
print("Best hyperparameters: ", grid_search.best_params_)
print("Best validation accuracy: ", grid_search.best_score_)
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
Best hyperparameters:  {'C': 1, 'max_iter': 100, 'penalty': 'l2'}
Best validation accuracy:  0.8625
```

We know that the best parameters using grid search have come out to be c=1, maximum iterations=100, and penalty=12. We will now use it to find the confusion matrix and the classification report.

Function to run the best model with parameters found from grid search

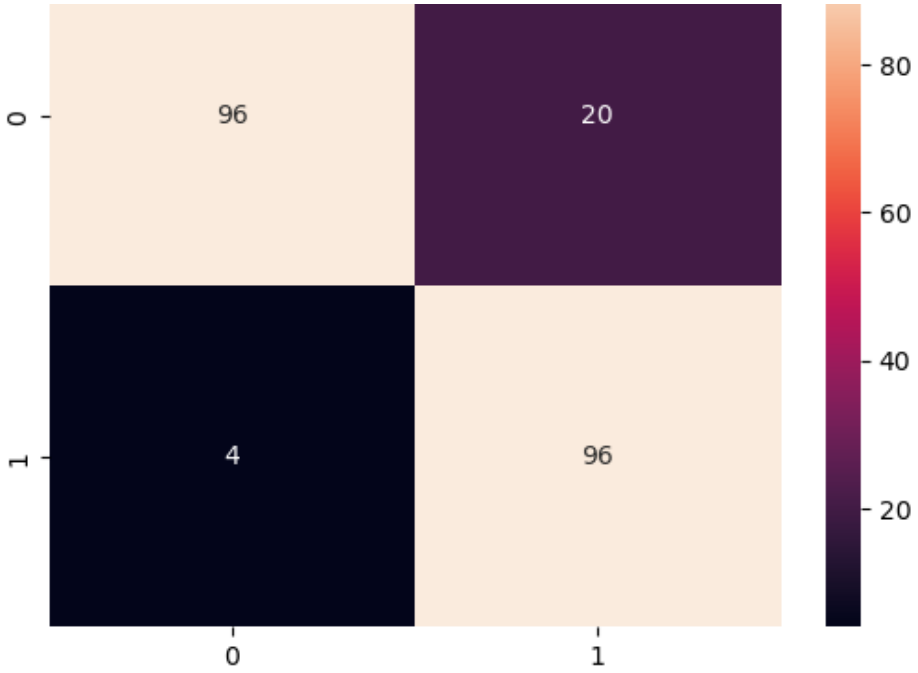
In [300]:

```
def run_the_best_model(X_train, y_train, model):

    X_trainn, X_val, y_trainn, y_val = train_test_split(X_train, y_train, test_size=0.3,
random_state=42)

    model.fit(X_trainn, y_trainn)

    y_pred = model.predict(X_val)

    cm = confusion_matrix(y_val, y_pred)

    sns.heatmap(cm, annot=True)

    report = classification_report(y_val, y_pred)

    print(report)

    val_scores = model.score(X_val, y_val)

    print(val_scores)
```

In [353]:

```
LR = run_the_best_model(X_train_scaled, y_trainn, model = LogisticRegression(C =1, max_i
ter =100, multi_class = 'multinomial', penalty = 'l2', solver= 'lbfgs'))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.83      0.89       116
         1.0       0.83      0.96      0.89       100

    accuracy                           0.89       216
   macro avg       0.89      0.89      0.89       216
weighted avg       0.90      0.89      0.89       216

0.8888888888888888
```



Previously, the mean training and validation accuracy for Logistic regression was about 86%. With the best parameters it has come out to be 88% which is higher. The True Positives are also more in the second confusion matrix (96) than before (86). Thus, this confusion matrix with the best parameters overall has classified better than the previous one.

Testing

In [368]:

```
def run_the_best_model(X_train, y_train,X_test, y_test ,model):


    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)


    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True)
    report = classification_report(y_test, y_pred)
    print(report)

    val_scores = model.score(X_test, y_test)
    print(val_scores)

    return val_scores
```

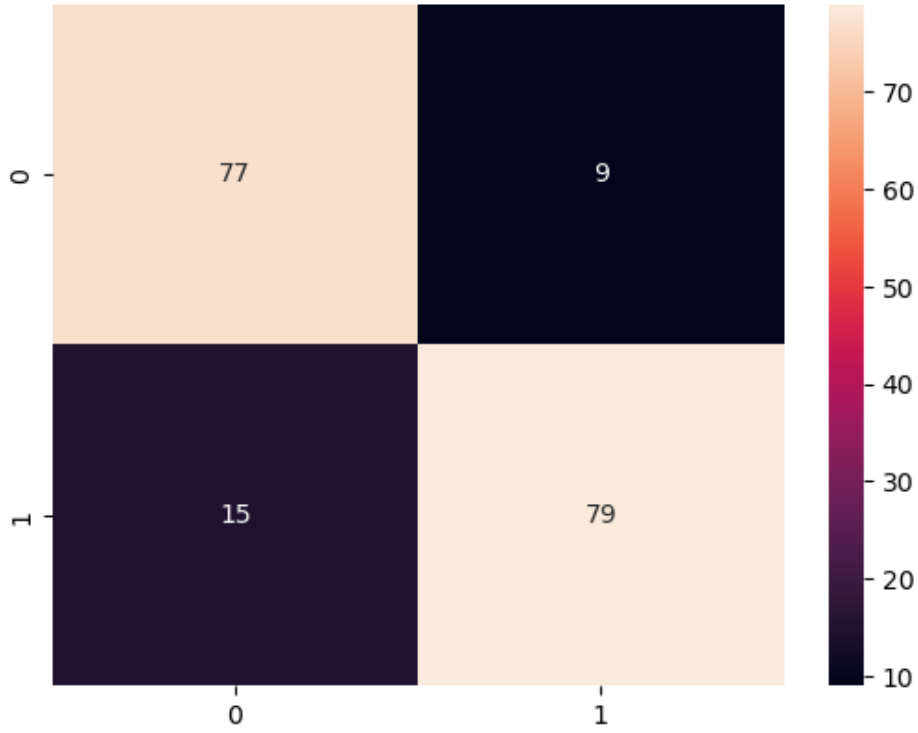
In [372]:

```
run_the_best_model(X_train_scaled, y_trainn, X_test_scaled, y_testt, model=LogisticRegres
sion(C=1, max_iter=100, multi_class='multinomial', penalty='l2', solver='lbfgs'))
```

```
              precision    recall  f1-score   support

         0.0       0.84      0.90      0.87        86
         1.0       0.90      0.84      0.87        94

    accuracy                           0.87       180
   macro avg       0.87      0.87      0.87       180
weighted avg       0.87      0.87      0.87       180

0.8666666666666667
```

Out[372]:

```
0.8666666666666667
```



Function to plot ROC and AUC curve

In [361]:

```
def roc_curve(X_train_scaled, y_train, model):

    # Split the data into training and testing sets

    X_trainb, X_testb, y_trainb, y_testb = train_test_split(X_train_scaled, y_train, tes
t_size=0.3, random_state=42)
    model.fit(X_trainb, y_trainb)

    # Make predictions on the testing data

    y_pred_prob = model.predict_proba(X_testb)[:, 1]

    fpr, tpr, thresholds = roc_curve(y_testb, y_pred_prob)

    # Calculate the AUC score

    auc_score = roc_auc_score(y_testb, y_pred_prob)

    # Plot the ROC curve

    plt.plot(fpr, tpr, label=f'ROC curve (AUC = {auc_score:.2f})')

    plt.plot([0, 1], [0, 1], 'k--', label='Random guess')

    plt.xlabel('False Positive Rate')

    plt.ylabel('True Positive Rate')

    plt.title('ROC Curve')

    plt.legend()

    plt.show()
```

Plotting roc curve for logistic regression with best parameters

In [362]:

```
roc_curve(X_train_scaled, y_trainn, model = LogisticRegression(C =1, max_iter =100, multi
_class = 'multinomial', penalty = 'l2', solver= 'lbfgs', probability = True))
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
/var/folders/zg/9lwlfgpd6q73bcpnyv_ly60r0000gn/T/ipykernel_53874/1311740959.py in <module
>
----> 1 roc_curve(X_train_scaled, y_trainn, model = LogisticRegression(C =1, max_iter =10
0, multi_class = 'multinomial', penalty = 'l2', solver= 'lbfgs', probability = True))

TypeError: __init__() got an unexpected keyword argument 'probability'
```

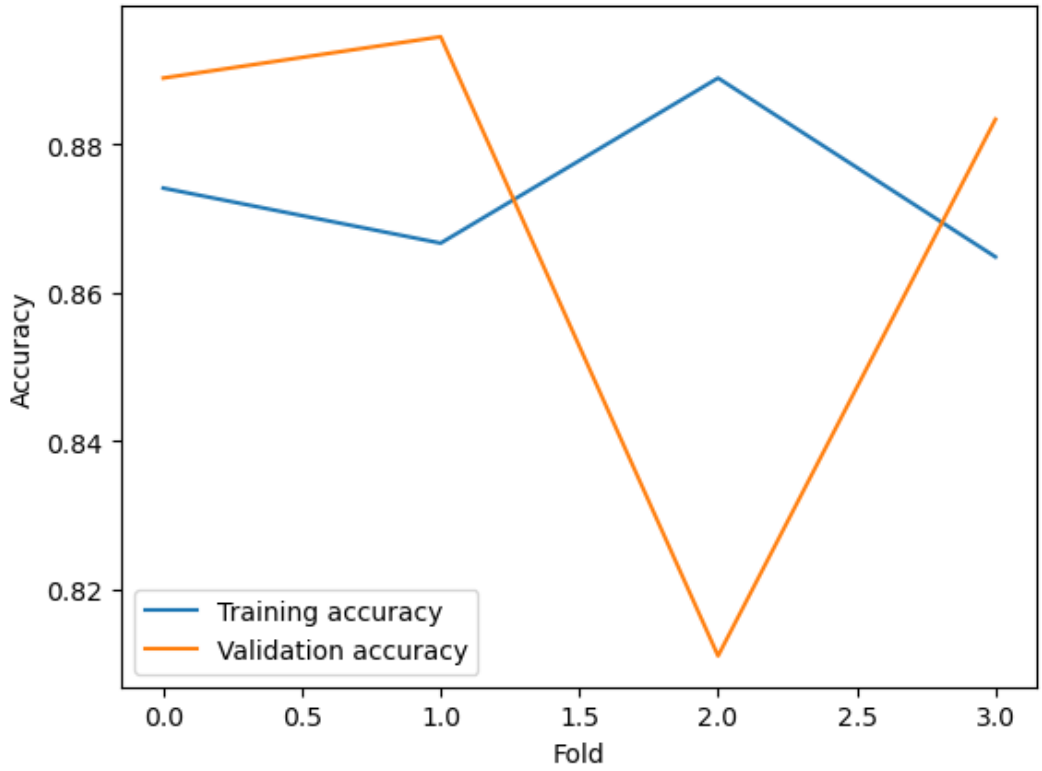
SVM

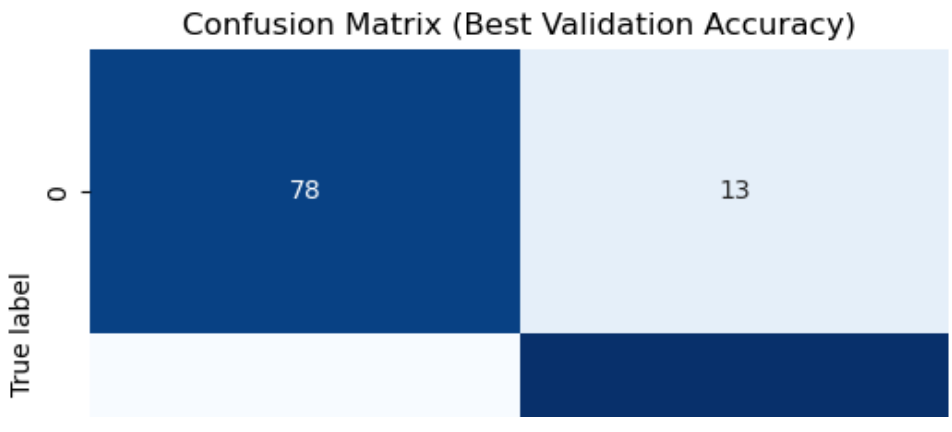
Linear kernel

In [302]:

```
#svm with linear kernel
evaluate_model(X_train_scaled, y_trainn, model = SVC(kernel='linear', C=1))
```

```
Fold 1
Fold 2
Fold 3
Fold 4
train_acc: [0.8740740740740741, 0.8666666666666667, 0.8888888888888888, 0.864814814814814
8]
val_acc: [0.8888888888888888, 0.8944444444444445, 0.8111111111111111, 0.8833333333333333]
Mean train_acc: 87.36%
Mean val_acc: 86.94%
```






```
Classification report:
              precision    recall  f1-score   support

         0.0       0.91      0.86      0.88        91
         1.0       0.86      0.91      0.89        89

    accuracy                           0.88       180
   macro avg       0.88      0.88      0.88       180
weighted avg       0.88      0.88      0.88       180
```

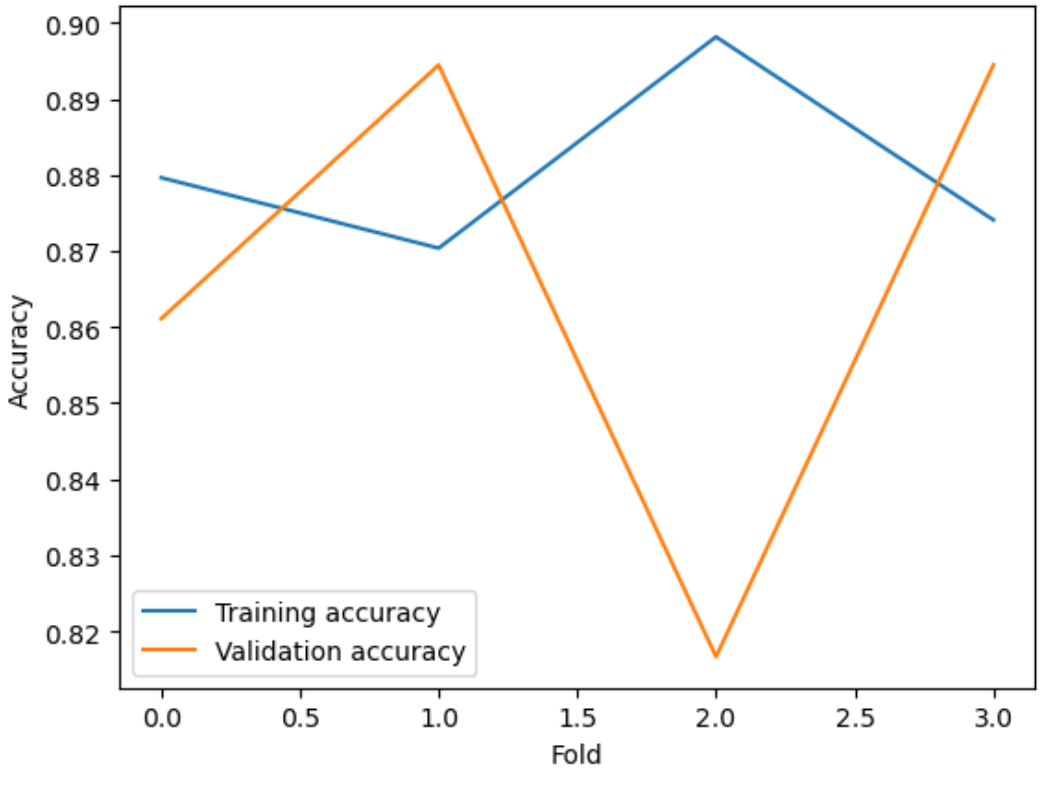
The above graph shows that training accuracy and validation accuracy are very close. The best accuracy for training and validation is about 87% after performing 5 fold cross validation. This tells us that the linear kernel in SVM is well fit.

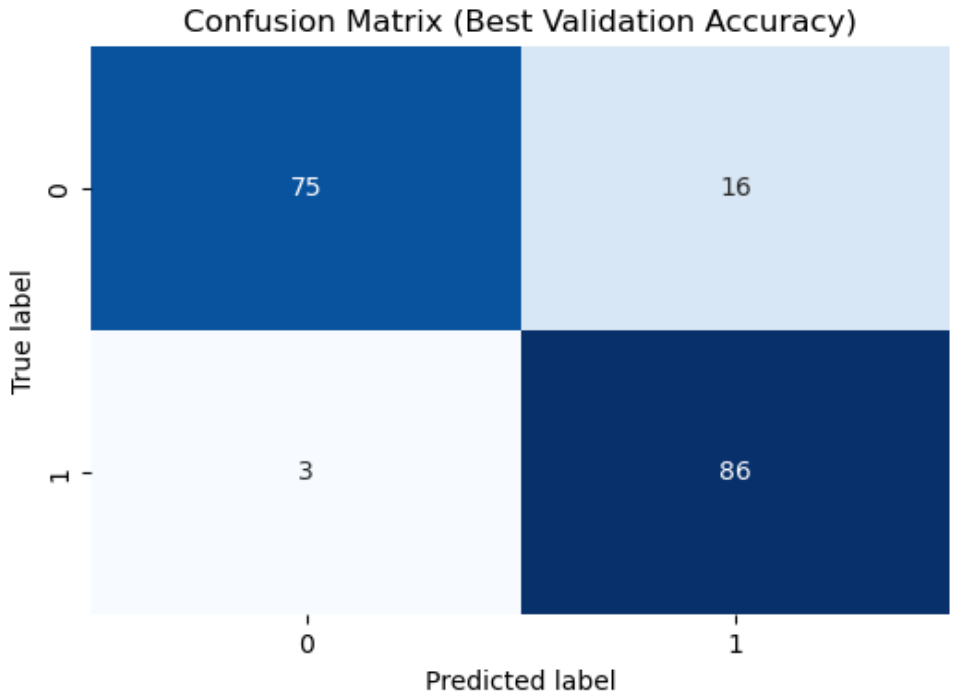
SVM with RBF kernel

In [311]:

```
# svm with rbf kernel
evaluate_model(X_train_scaled, y_trainn, model = SVC(gamma = 'scale', kernel='rbf', C=5)
)
```

```
Fold 1
Fold 2
Fold 3
Fold 4
train_acc: [0.8796296296296297, 0.8703703703703703, 0.8981481481481481, 0.874074074074074
1]
val_acc: [0.8611111111111112, 0.8944444444444445, 0.8166666666666667, 0.8944444444444445]
Mean train_acc: 88.06%
Mean val_acc: 86.67%
```






```
Classification report:
              precision    recall  f1-score   support

         0.0       0.93      0.86      0.89        91
         1.0       0.86      0.93      0.90        89

    accuracy                           0.89       180
   macro avg       0.90      0.89      0.89       180
weighted avg       0.90      0.89      0.89       180
```

The true positives are 75 here and false positives are 16. Let's check these further after grid search.

The above graph shows that training accuracy and validation accuracy are very close. The average accuracy for training and validation is about 87%. This tells us that the rbf kernel is well fit.

Grid search for SVM to check the best parameters

In [310]:

```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

svc = SVC()

# define the hyperparameter search space
param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
    'degree': [2, 3],
    'gamma' :['scale', 'auto', 0.1, 1, 10]
}


# define the grid search
grid_search = GridSearchCV(
    svc, param_grid=param_grid,
    cv=None, n_jobs=-1, verbose=1
)

# fit the grid search to the data
grid_search.fit(X_train_scaled, y_train)

# print the best hyperparameters and validation accuracy
```

```
print("Best hyperparameters: ", grid_search.best_params_)
print("Best validation accuracy: ", grid_search.best_score_)
```

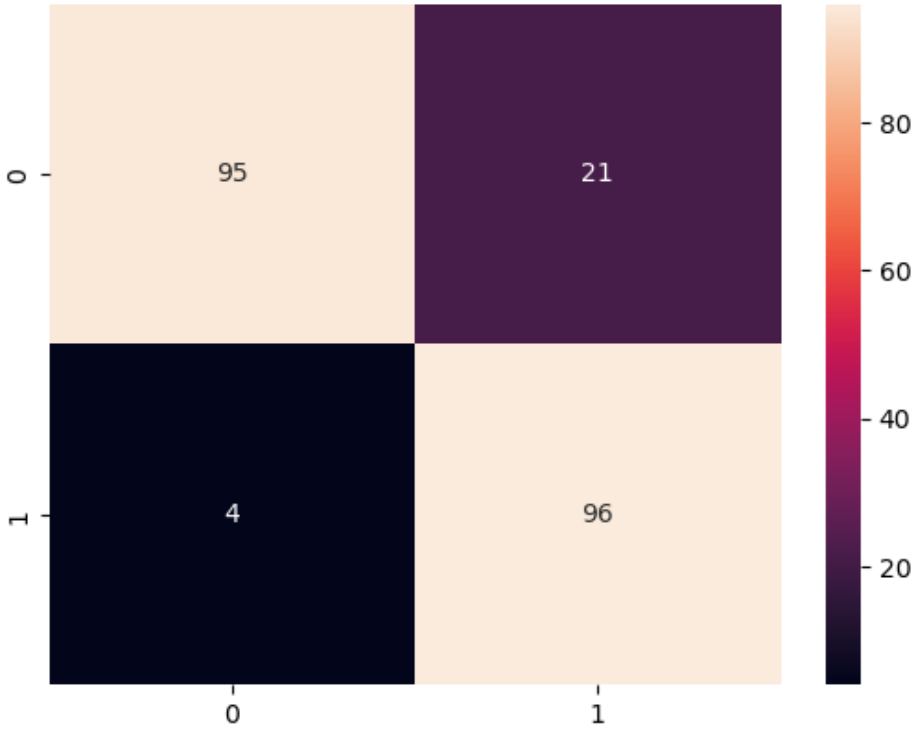
```
Fitting 5 folds for each of 60 candidates, totalling 300 fits
Best hyperparameters:  {'C': 10, 'degree': 2, 'gamma': 1, 'kernel': 'rbf'}
Best validation accuracy:  0.8777777777777779
```

We know that the best parameters using grid search have come out to be rbf kernel, c=10, degree=2 and gamma=1. We will now use it to find the confusion matrix and the classification report.

In [313]:

```
run_the_best_model(X_train_scaled, y_trainn, model=SVC(kernel='rbf', C=10, degree=2, gam
ma=1))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.82      0.88       116
         1.0       0.82      0.96      0.88       100

    accuracy                           0.88       216
   macro avg       0.89      0.89      0.88       216
weighted avg       0.90      0.88      0.88       216

0.8842592592592593
```



Testing on Svm rbf kernel

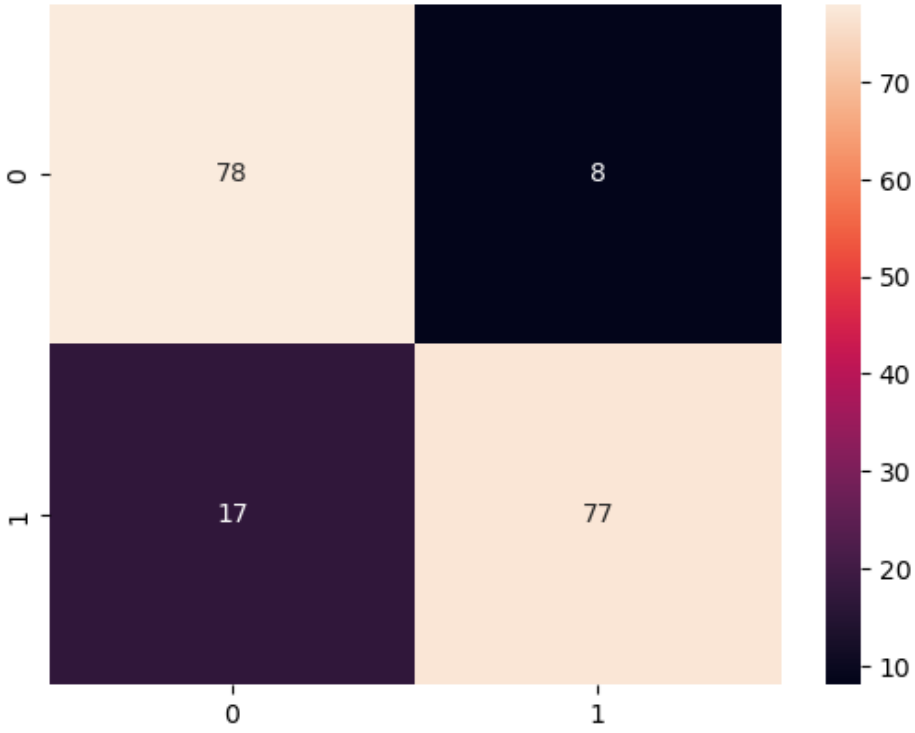
In [373]:

```
run_the_best_model(X_train_scaled, y_trainn, X_test_scaled, y_testt, model=SVC(kernel='rb
f', C=10, degree=2, gamma=1))
```

```
              precision    recall  f1-score   support

         0.0       0.82      0.91      0.86        86
         1.0       0.91      0.82      0.86        94

    accuracy                           0.86       180
   macro avg       0.86      0.86      0.86       180
weighted avg       0.87      0.86      0.86       180

0.8611111111111112
```

Out[373]:

0.8611111111111112



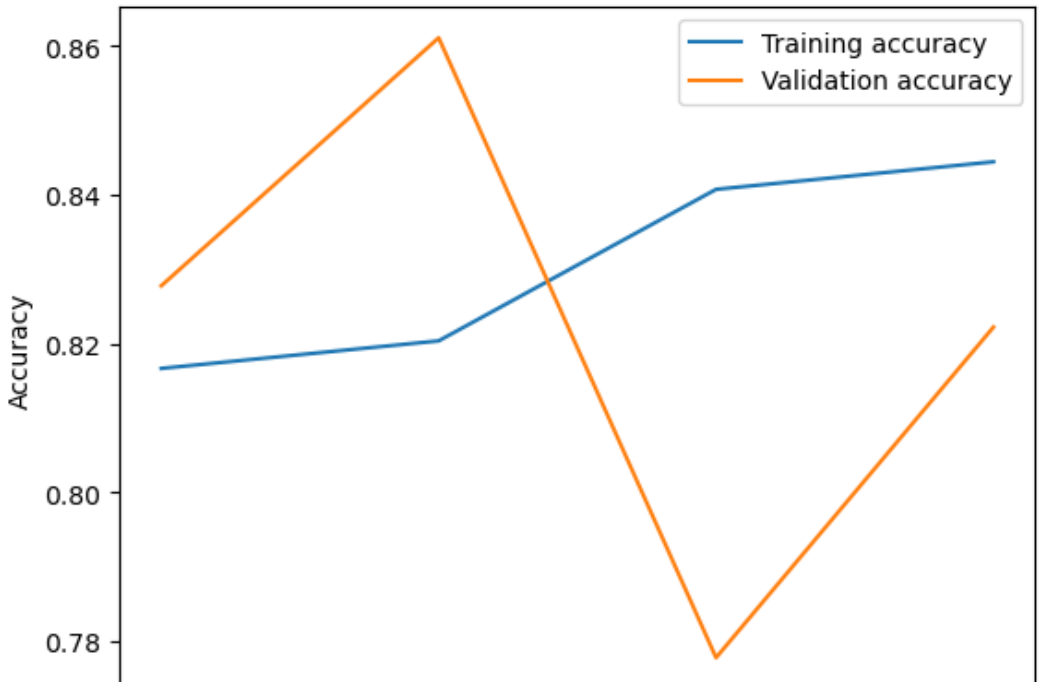
We can see that true positives have increased and are 95 now and false positives are 21.

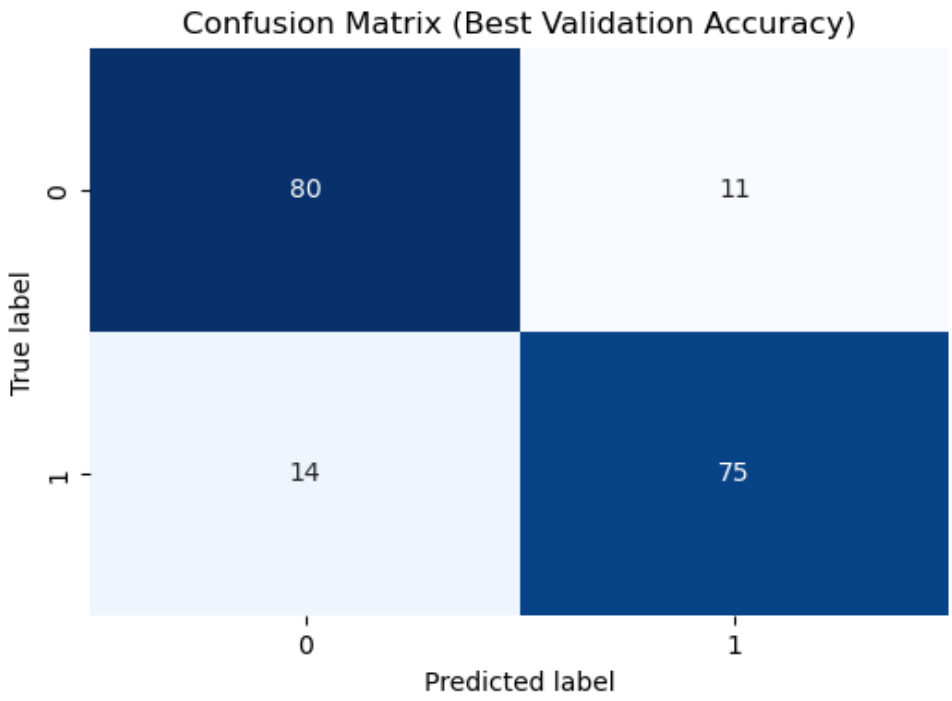
SVM Polynomial kernel

In [305]:

```
# svm with polynomial kernel
evaluate_model(X_train_scaled, y_trainn, model = SVC(kernel='poly', degree=3))
```

```
Fold 1
Fold 2
Fold 3
Fold 4
train_acc: [0.8166666666666667, 0.8203703703703704, 0.8407407407407408, 0.8444444444444444]
val_acc: [0.8277777777777777, 0.8611111111111112, 0.7777777777777778, 0.8222222222222222]
Mean train_acc: 83.06%
Mean val_acc: 82.22%
```






```
Classification report:
              precision    recall  f1-score   support

         0.0       0.82      0.82      0.82        91
         1.0       0.82      0.82      0.82        89

    accuracy                           0.82       180
   macro avg       0.82      0.82      0.82       180
weighted avg       0.82      0.82      0.82       180
```

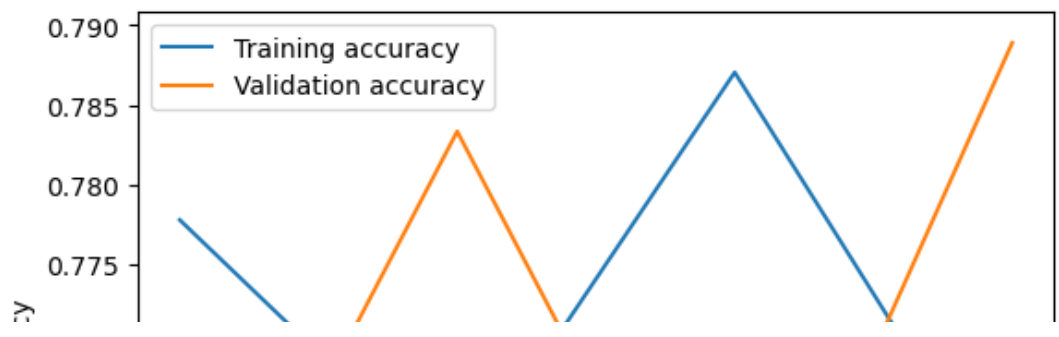
The above graph shows that training accuracy and validation accuracy are very close. The average accuracy for training and validation is about 82%. This tells us that the polynomial kernel is well fit but not as good as rbf.

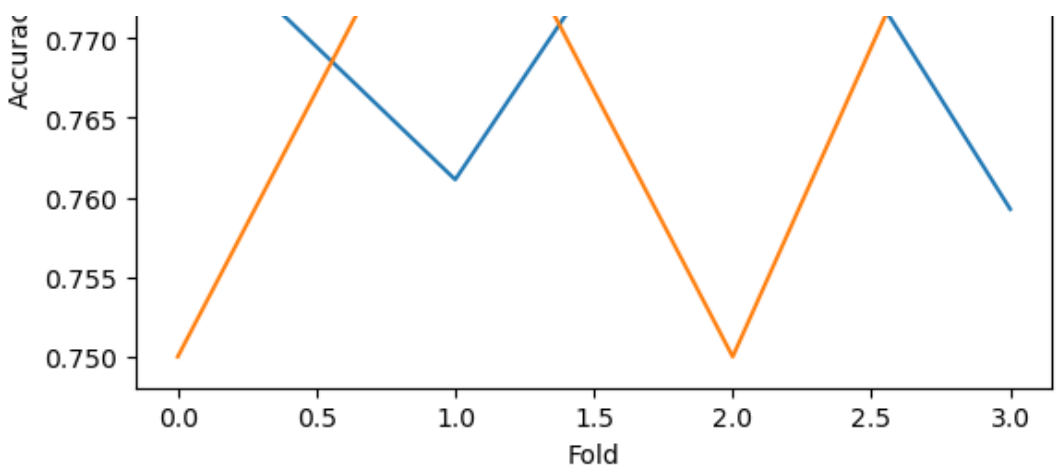
SVM with Sigmoid kernel

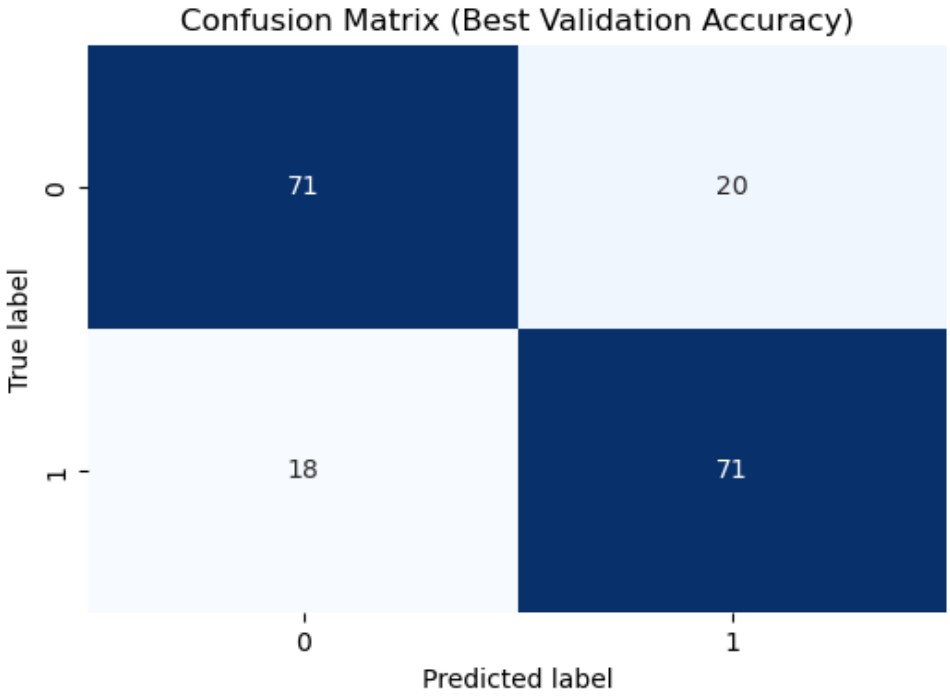
In [303]:

```
#svm with sigmoid kernel
evaluate_model(X_train_scaled, y_trainn, model = SVC(kernel='sigmoid'))
```

```
Fold 1
Fold 2
Fold 3
Fold 4
train_acc: [0.7777777777777778, 0.7611111111111111, 0.7870370370370371, 0.7592592592592593]
val_acc: [0.75, 0.7833333333333333, 0.75, 0.7888888888888889]
Mean train_acc: 77.13%
Mean val_acc: 76.81%
```








```
Classification report:
              precision    recall  f1-score   support

         0.0       0.80      0.78      0.79        91
         1.0       0.78      0.80      0.79        89

    accuracy                           0.79       180
   macro avg       0.79      0.79      0.79       180
weighted avg       0.79      0.79      0.79       180
```

The above graph shows that training accuracy and validation accuracy are very close. The best accuracy for training and validation is about 77% after performing 5 fold cross validation. This tells us that the sigmoid kernel is not the best fit as compared to the other kernels.

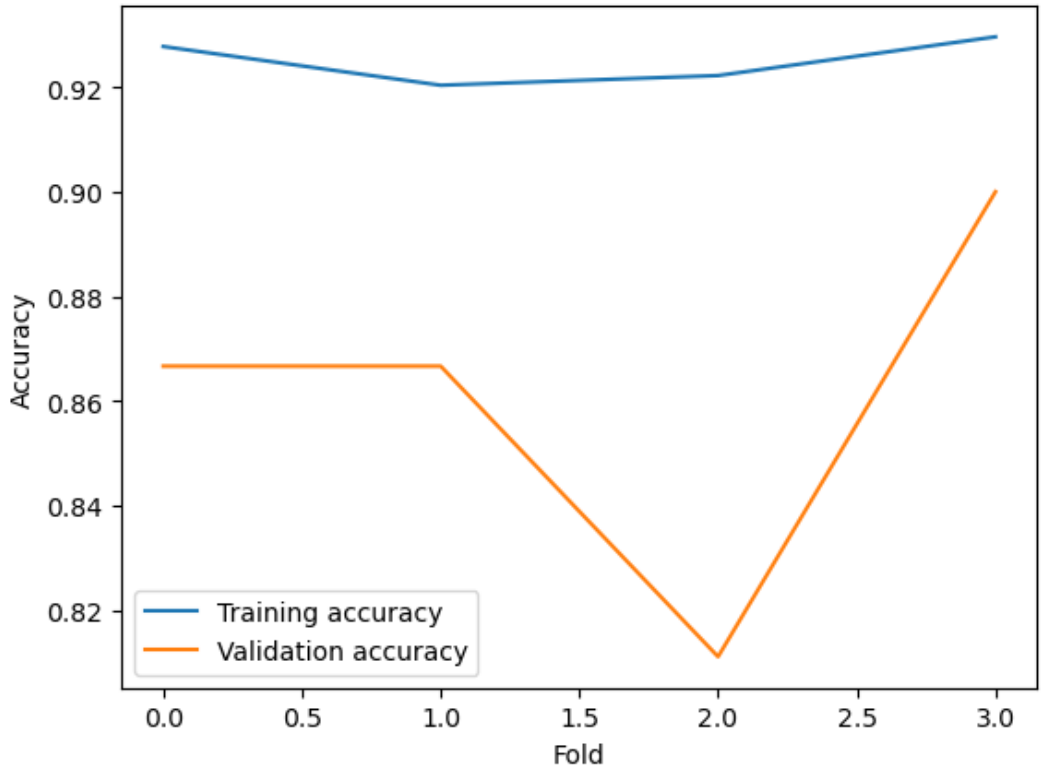
Random Forest Classifier

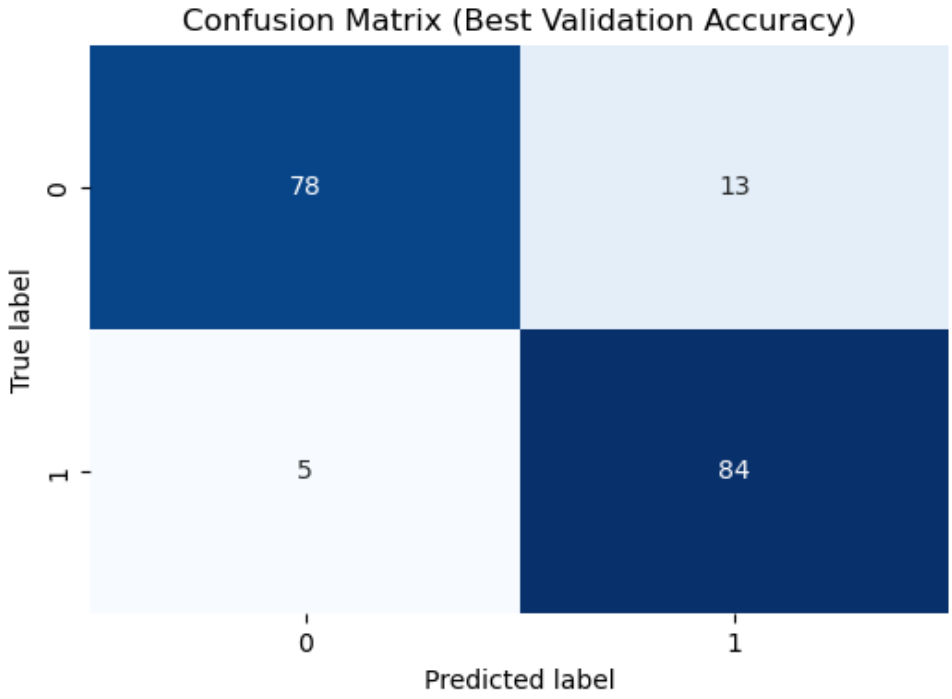
In [314]:

```
#random forest
evaluate_model(X_train_scaled, y_trainn, model = RandomForestClassifier(n_estimators=100,
max_depth=5, random_state=42))
```

```
Fold 1
Fold 2
Fold 3
Fold 4
train_acc: [0.9277777777777778, 0.9203703703703704, 0.9222222222222223, 0.929629629629629
6]
```

```
val_acc: [0.8666666666666667, 0.8666666666666667, 0.8111111111111111, 0.9]
Mean train_acc: 92.50%
Mean val_acc: 86.11%
```






```
Classification report:
              precision    recall  f1-score   support

         0.0       0.94      0.86      0.90        91
         1.0       0.87      0.94      0.90        89

    accuracy                           0.90       180
   macro avg       0.90      0.90      0.90       180
weighted avg       0.90      0.90      0.90       180
```

The above graph shows that training accuracy and validation accuracy is increasing at 92% and 86% respectively. This tells us that the random forest classifier model is well fit. It does not seem to be overfitting. The data is very small to be trained on and hence we see these graphs.

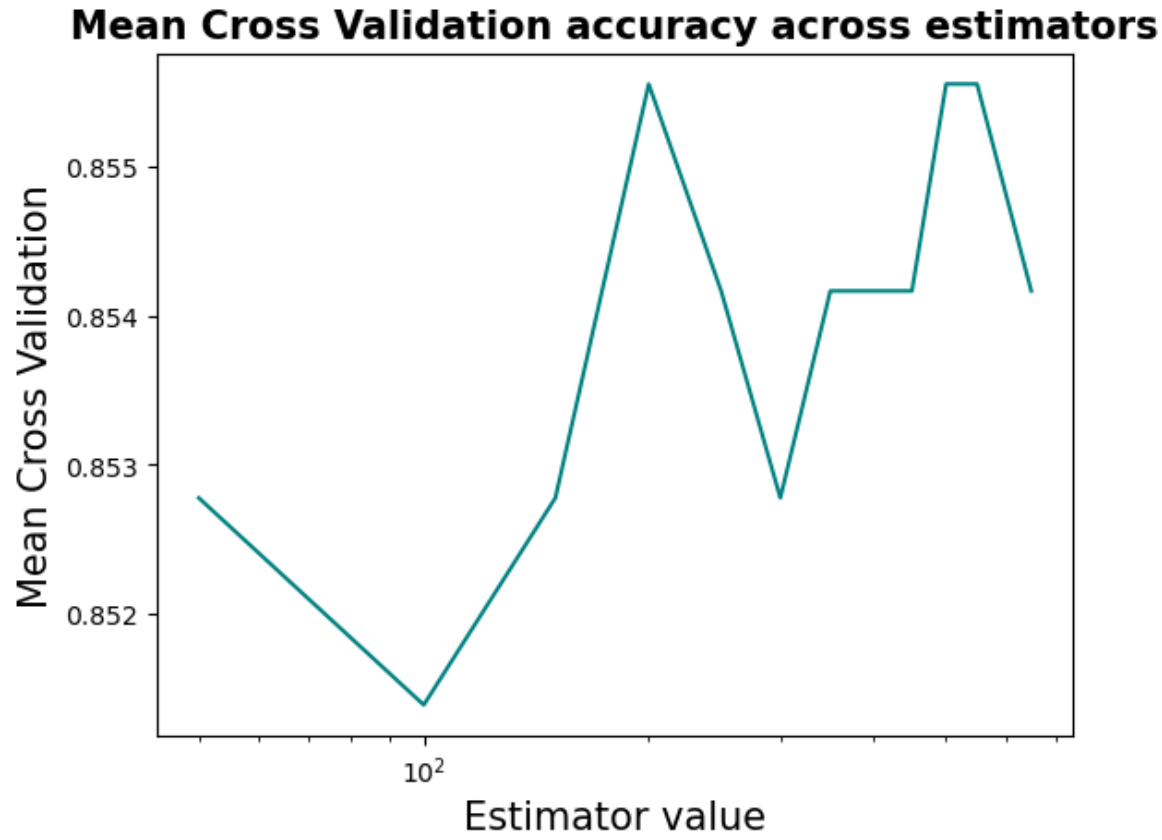
Hyperparameter tuning for Random Forest

In [315]:

```
def variation_wtih_esti(X_trainn, y_trainn, model):

    estimators = [50,100,150,200,250,300,350,400,450,500,550,650]
    MCV_list = []


    for e in estimators:
        # Initialize RBF Kernel SVM classifier
        current_rf =  RandomForestClassifier(n_estimators= e, max_depth=5, random_state=
42)
        #current_svm = model
        kf = KFold(n_splits=3, random_state=1, shuffle=True)
        # Cross validation 3-Fold scores
        mean_crossval = np.mean(cross_val_score(current_rf, X_trainn, y_trainn, cv=kf))
        MCV_list.append(mean_crossval)
        #print("On C=", C, "\tMCV=", mean_crossval)


    plt.plot(estimators, MCV_list, color= 'teal')
    plt.title("Mean Cross Validation accuracy across estimators" ,fontsize=15, fontweigh
t="bold")
    plt.xlabel('Estimator value', fontsize = 15)
    plt.xscale("log")
    plt.ylabel('Mean Cross Validation', fontsize = 15)
    plt.show()

    print("Highest val_accuracy : ", max(MCV_list))
    print("The optimum estimator_value being: ",estimators[MCV_list.index(max(MCV_list))]
)
```

In [316]:

```
variation_wtih_esti(X_train_scaled, y_trainn, model = "rf")
```




```
Highest val_accuracy :  0.8555555555555556
The optimum estimator_value being:  200
```

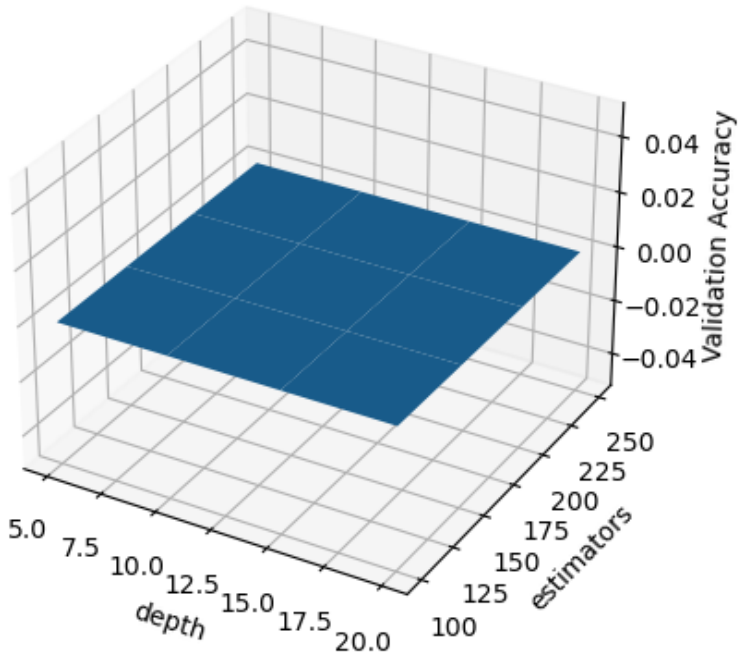
The validation accuracy has come out to be lower than before. Hence, let's try another approach to

hyperparameter tuning.

Trying to find the best values of gamma and and C below and creating a 3D visualization.

In [317]:

```
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D


X = X_train_scaled
y = y_trainn

# Define a range of gamma and C values
depth_range = [i for i in range(5, 21, 5)]
esti_range = [100,150,200,250]

# Create a grid of gamma and C values
depth_grid, esti_grid = np.meshgrid(depth_range, esti_range)

# Calculate the validation accuracy for each combination of gamma and C
scores = np.zeros_like(depth_grid)
for i in range(len(depth_range)):
    for j in range(len(esti_range)):
        clf = RandomForestClassifier(n_estimators= esti_range[j], max_depth=depth_range[
i], random_state=42)
        scores[j, i] = np.mean(cross_val_score(clf, X, y, cv=4))

# Create a 3D plot of the validation accuracy surface
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.plot_surface(depth_grid, esti_grid, scores)
ax.set_xlabel('depth')
ax.set_ylabel('estimators')
ax.set_zlabel('Validation Accuracy')
plt.show()

# Get the combination of gamma and C values for which the validation accuracy was the hig
hest
max_indices = np.unravel_index(np.argmax(scores), scores.shape)
best_depth = depth_range[max_indices[1]]
best_esti = esti_range[max_indices[0]]
print("Best combination of depth and esti:", (best_depth, best_esti))
```



```
Best combination of depth and esti: (5, 100)
```

Grid search for random forest to find best parameters

In [319]:

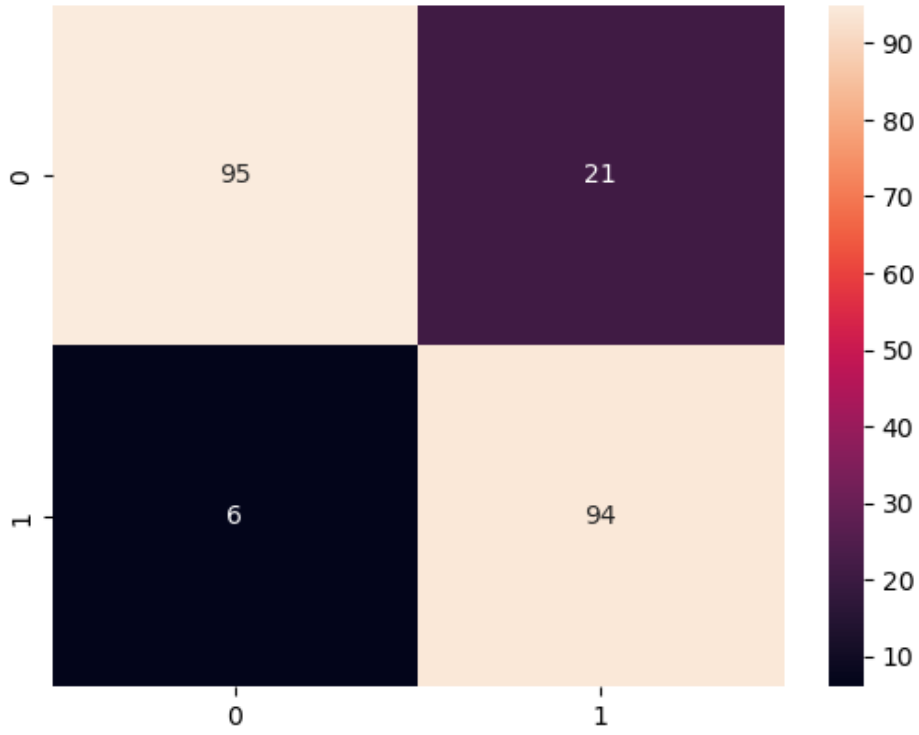
```
# Define the Random Forest model
rf_model = RandomForestClassifier()

# Define the hyperparameters to search
param_grid = {'n_estimators': [10, 50, 100,150,200,250,300],
              'max_depth': [None, 5, 10],
              'min_samples_split': [2, 5],
              'min_samples_leaf': [1, 2],
              'max_features': ['sqrt', 'log2']}

# Perform grid search with 4-fold cross-validation
grid_search = GridSearchCV(rf_model, param_grid, cv=4)

# Fit the grid search to the data
grid_search.fit(X_train_scaled, y_trainn)

# Print the best hyperparameters found
print("Best hyperparameters:", grid_search.best_params_)
print("Best validation accuracy:", grid_search.best_score_)
```

```
Best hyperparameters: {'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 2, 'm
in_samples_split': 5, 'n_estimators': 100}
Best validation accuracy: 0.8638888888888889
```

In [321]:

```
run_the_best_model(X_train_scaled, y_trainn, model=RandomForestClassifier(max_depth= 10,
max_features= 'sqrt', min_samples_leaf= 2, min_samples_split= 5, n_estimators= 100))
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.82      0.88       116
         1.0       0.82      0.94      0.87       100

    accuracy                           0.88       216
   macro avg       0.88      0.88      0.87       216
weighted avg       0.88      0.88      0.88       216

0.875
```



We can see the validation accuracy with the best parameters has come out to be 87.5% which was previously 86.38%. This model has overall performed better.

Testing for random forest

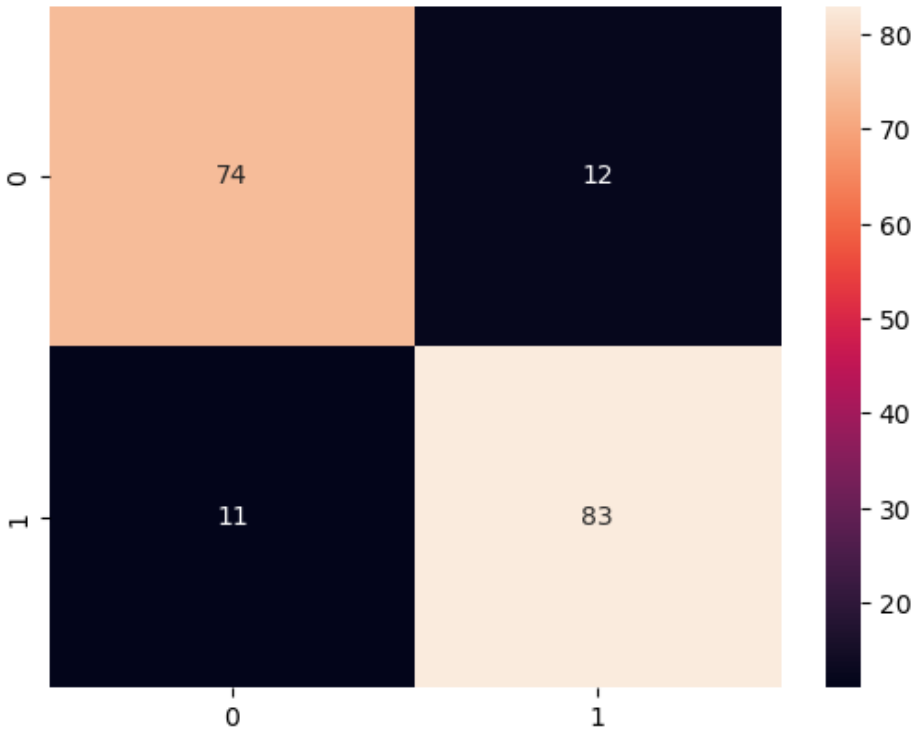
In [375]:

```
run_the_best_model(X_train_scaled, y_trainn, X_test_scaled, y_testt, model=RandomForestCl
assifier(max_depth= 10, max_features= 'sqrt', min_samples_leaf= 2, min_samples_split= 5,
n_estimators= 100))
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.86      0.87        86
         1.0       0.87      0.88      0.88        94

    accuracy                           0.87       180
   macro avg       0.87      0.87      0.87       180
weighted avg       0.87      0.87      0.87       180

0.8722222222222222
```

Out[375]:

```
0.8722222222222222
```



In [326]:

```
clf = clf1 = RandomForestClassifier(max_depth= 10, max_features= 'sqrt', min_samples_lea
f= 2, min_samples_split= 5, n_estimators= 100)
clf.fit(X_train_scaled, y_trainn)
importances = clf.feature_importances_
```

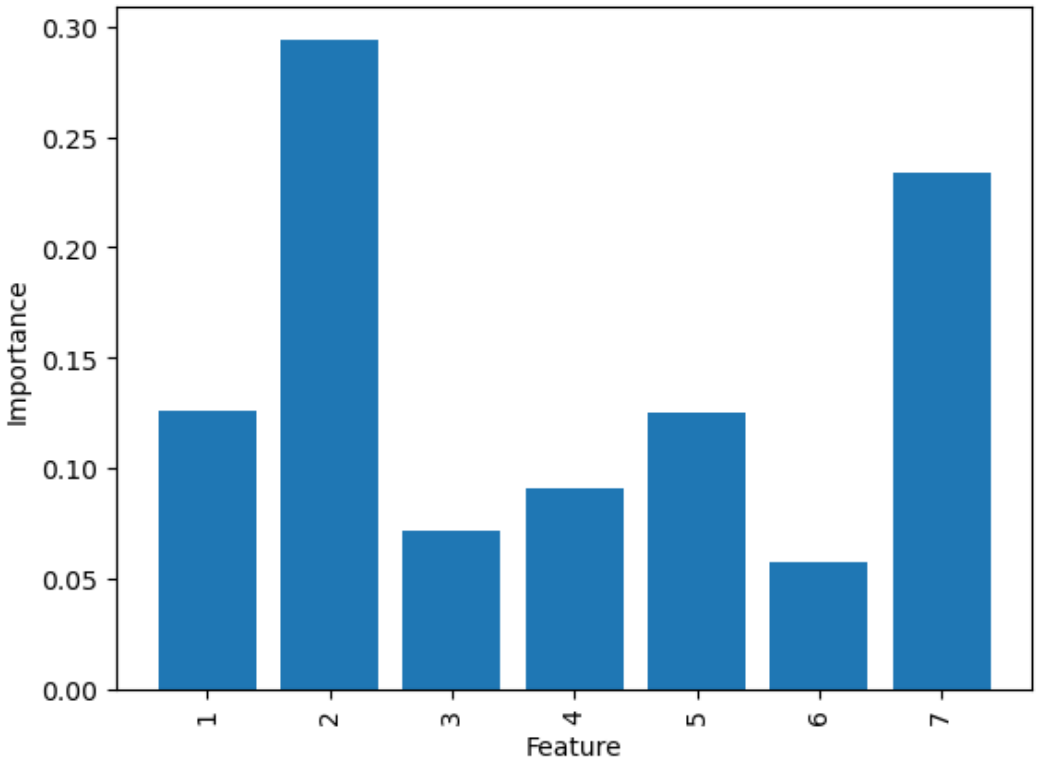
In [327]:

```
feature_names = df.columns.tolist()
```

In [328]:

```
plt.bar(range(X_train_scaled.shape[1]), importances)
plt.xticks(range(X_train_scaled.shape[1]), range(1, X_train_scaled.shape[1]+1), rotation
=90)
plt.xlabel('Feature')
```

```
plt.ylabel('Importance')
plt.show()
```



The feature number 2 and 7 are MajorAxisLength and Perimeter are the highest and have the most importance. This will be useful in the overall process of classifying raisins.

In [329]:

```
df.head()
```

Out[329]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class
0	**87524**	**442.246011**	**253.291155**	**0.819738**	**90546**	**0.758651**	**1184.040**	**1**
1	**75166**	**406.690687**	**243.032436**	**0.801805**	**78789**	**0.684130**	**1121.786**	**1**
2	**90856**	**442.267048**	**266.328318**	**0.798354**	**93717**	**0.637613**	**1208.575**	**1**
3	**45928**	**286.540559**	**208.760042**	**0.684989**	**47336**	**0.699599**	**844.162**	**1**
4	**79408**	**352.190770**	**290.827533**	**0.564011**	**81463**	**0.792772**	**1073.251**	**1**

Ensemble modeling with best parameters of all three models

In [334]:

```
def ensemble_accuracy(X_train_scaled, y_train):

    clf1 = RandomForestClassifier(max_depth= 10, max_features= 'sqrt', min_samples_leaf=
2, min_samples_split= 5, n_estimators= 100)
    clf2 = LogisticRegression(C =3.90, max_iter =500, penalty = 'l2', solver= 'lbfgs')
    clf3 = SVC(kernel='rbf', C=10, degree=2, gamma=1)

    # Create the voting classifier
    ensemble_clf = VotingClassifier( estimators=[('dt', clf1), ('lr', clf2), ('svm', clf
3)], voting='hard')

    # Load data and target variables
    X_new = X_train_scaled  # input features
    y_new = y_train  # target variable
```

```
    #aplitting the into training and validation set
    X_train, X_val, y_train, y_val = train_test_split(X_new, y_new, test_size=0.3, rando
m_state=42)
    ensemble_clf.fit(X_train, y_train)

     # Test the ensemble classifier
    acc = ensemble_clf.score(X_val, y_val)

    print(f"Best validation accuracy: {acc}")
```

In [335]:

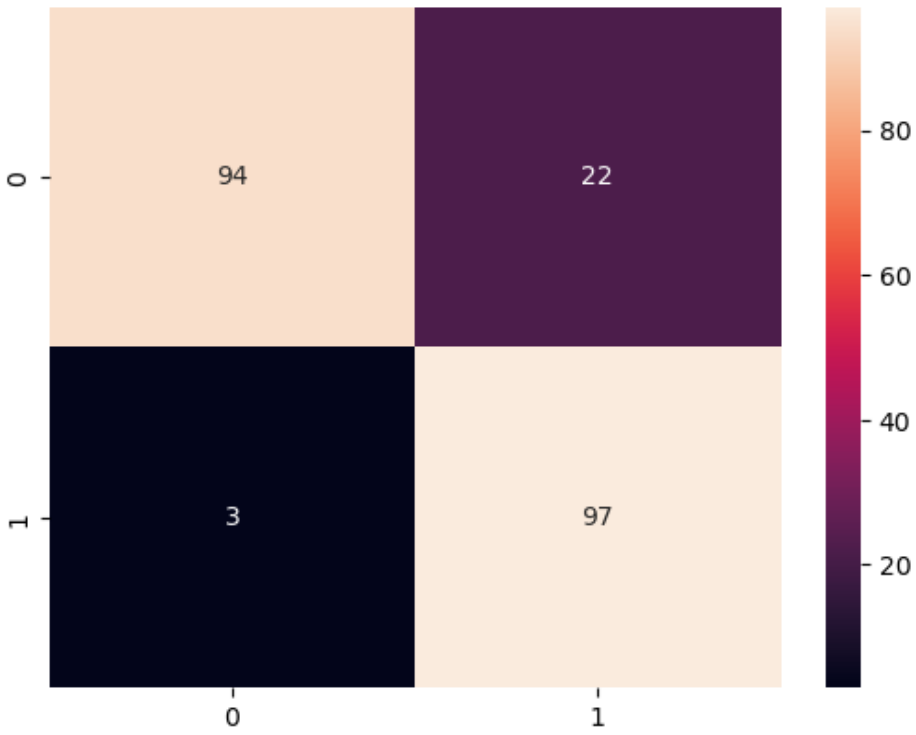
```
ensemble_accuracy(X_train_scaled, y_trainn)
```

```
Best validation accuracy: 0.8842592592592593
```

In [336]:

```
run_the_best_model(X_train_scaled, y_trainn, model=VotingClassifier(estimators=[('dt', cl
f1), ('lr', clf2), ('svm', clf3)], voting='hard'))
```

```
              precision    recall  f1-score   support

         0.0       0.97      0.81      0.88       116
         1.0       0.82      0.97      0.89       100

    accuracy                           0.88       216
   macro avg       0.89      0.89      0.88       216
weighted avg       0.90      0.88      0.88       216

0.8842592592592593
```

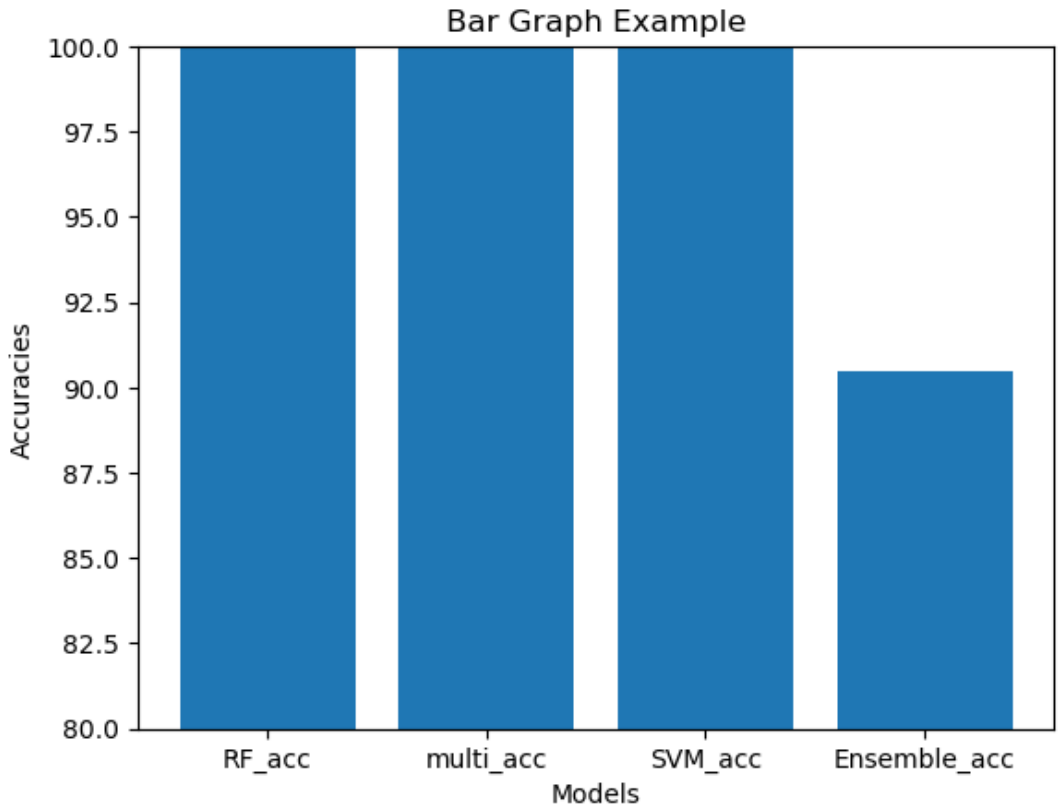


The Ensemble of all three models have given a best accuracy of 88.42% which is higher than the validation accuracies of all three models even with the best parameters.

In [376]:

```
values = [(87.5)*100, (88.8)*100, (88.42)*100, 90.47]

labels = ['RF_acc', 'multi_acc', 'SVM_acc', 'Ensemble_acc']

# Create a bar plot

plt.bar(labels, values)
```

```
# Set the title and axis labels

plt.title('Bar Graph Example')

plt.xlabel('Models')

plt.ylabel('Accuracies')

plt.ylim(80, 100)

# Show the plot

plt.show()

print("The accuracy of the ensemble data is the highest and outperforms the individual cl
assifiers")
```




```
The accuracy of the ensemble data is the highest and outperforms the individual classifie
rs
```

Testing on the test set

In [366]:

```
ensemble_accuracy(X_test_scaled, y_testt)
```

```
Best validation accuracy: 0.8703703703703703
```

The testing accuracy is 87.03% which is quiet close to the validation accuracy.

In [ ]:

In [ ]:

In [ ]:

References : Github : https://github.com/ageron/handson-ml2/blob/master/07_ensemble_learning_and_random_forests.ipynb Textbook : Hands on machine learning with scikit-learn and tensorflow