In [1]:
```python
#Load required libraries

import pandas as pd
import numpy as np
import plotly.express as px
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.ticker import NullFormatter
import opendatasets as od

from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.feature_selection  import chi2, SelectKBest
from sklearn.metrics import accuracy_score, roc_curve, roc_auc_score,confusion_matrix, c
from imblearn.over_sampling import SMOTE

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
```

In [2]:
```python
#Download the creditcard fraud dataset from Kaggle
#od.download("https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction/data?
#od.download("https://www.kaggle.com/code/fahadmehfoooz/heartattack-prediction-with-91-8
```

In [3]:
```python
## Load the dataset
```

In [4]:
```python
heart_df = pd.read_csv("heart-2.csv")
heart_df.head(5)
```

Out[4]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	S
0	40	M	ATA	140	289	0	Normal	172	N	0.0	
1	49	F	NAP	160	180	0	Normal	156	N	1.0	
2	37	M	ATA	130	283	0	ST	98	N	0.0	
3	48	F	ASY	138	214	0	Normal	108	Y	1.5	
4	54	M	NAP	150	195	0	Normal	122	N	0.0	

Data Processing

Check for null columns

In [5]:
```python
heart_df.isna().sum()
```

Out[5]:
```
Age               0
Sex               0
ChestPainType     0
RestingBP         0
Cholesterol       0
FastingBS         0
RestingECG        0
MaxHR             0
```

```
ExerciseAngina     0
Oldpeak            0
ST_Slope           0
HeartDisease       0
dtype: int64
```

Chest Pain types Value 1: typical angina Value 2: atypical angina Value 3: non-anginal pain Value 4: asymptomatic

Check for duplicates

In [6]:
```
heart_df[heart_df.duplicated()==True]
```

Out[6]:

Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST

In [7]:
```
print('Dataframe before dropping duplicates :', heart_df.shape)
heart_df = heart_df.drop_duplicates()
print('Dataframe before dropping duplicates :', heart_df.shape)
```

```
Dataframe before dropping duplicates : (918, 12)
Dataframe before dropping duplicates : (918, 12)
```

There are no duplicates to drop.

Renaming columns

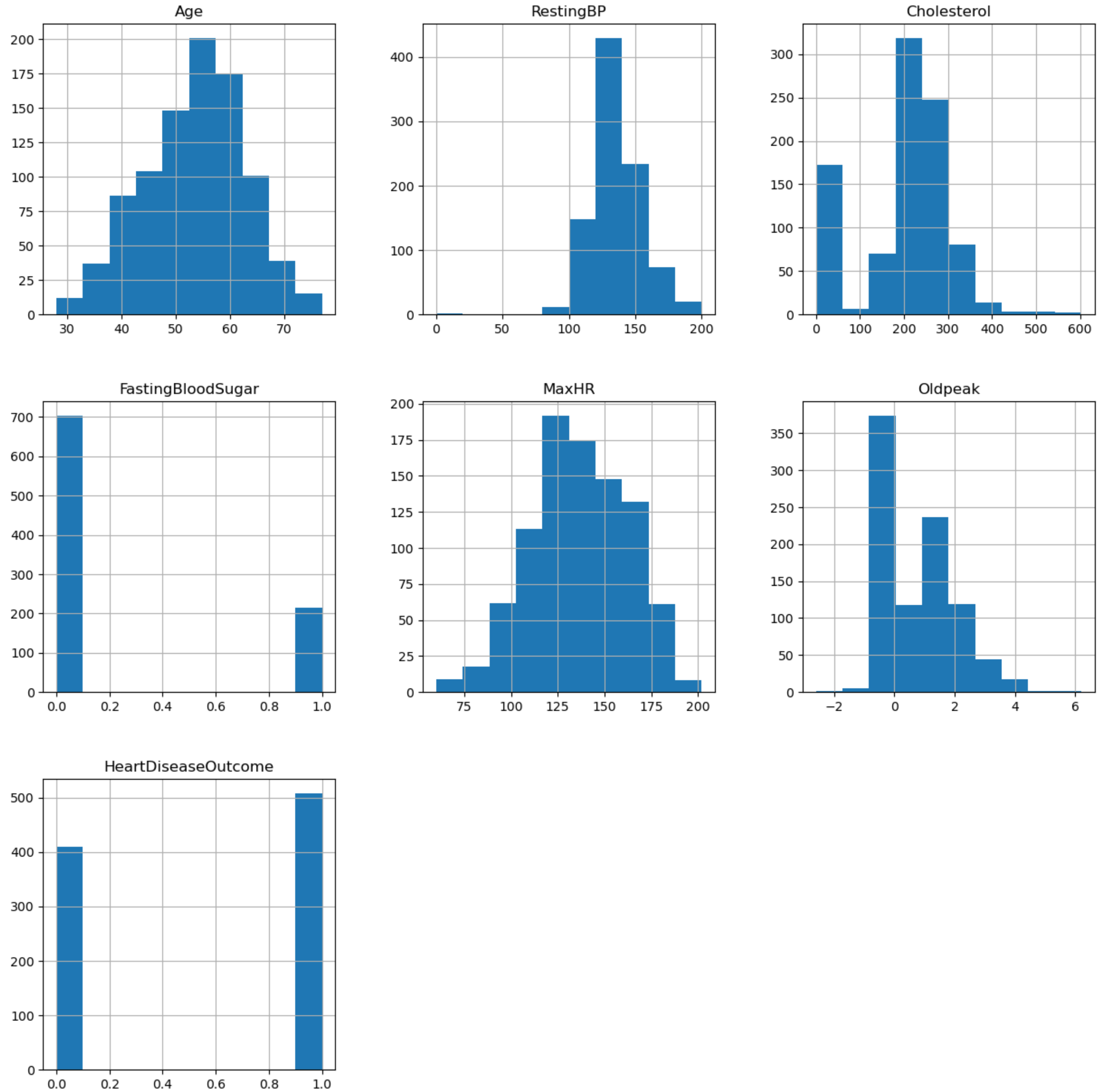
In [8]:
```
heart_df.columns = ['Age','Sex','ChestPainType','RestingBP','Cholesterol','FastingBloodS
'ST_Slope','HeartDiseaseOutcome']
heart_df.head(5)
```

Out[8]:

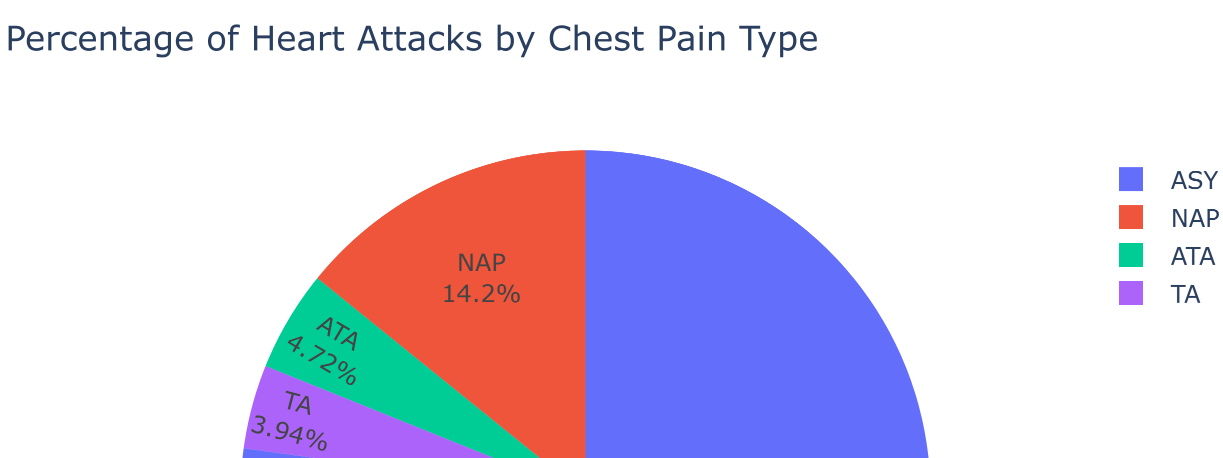
	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBloodSugar	RestingECG	MaxHR	ExerciseAngina	Ol
0	40	M	ATA	140	289	0	Normal	172	N	
1	49	F	NAP	160	180	0	Normal	156	N	
2	37	M	ATA	130	283	0	ST	98	N	
3	48	F	ASY	138	214	0	Normal	108	Y	
4	54	M	NAP	150	195	0	Normal	122	N	

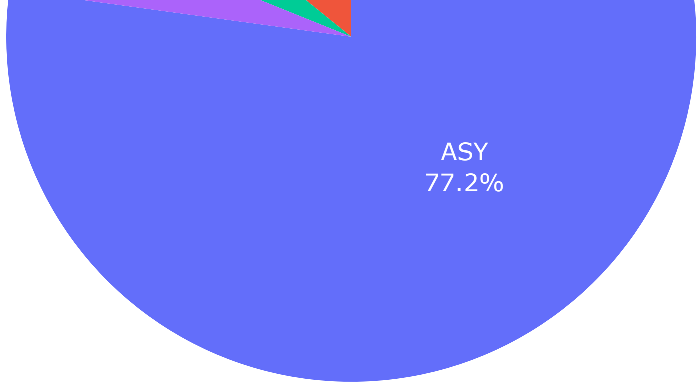
Data Visualizations

In [9]:
```
heart_df.hist(figsize = (15,15))
plt.show()
```



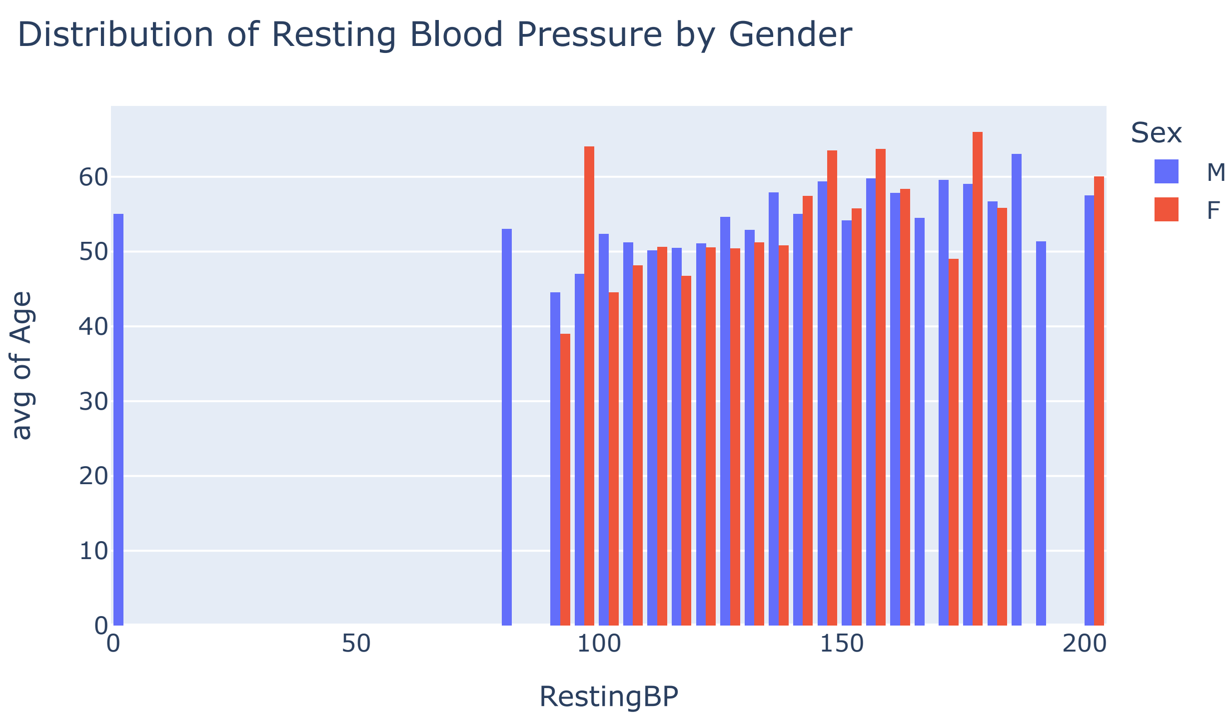

```
In [10]: fig = px.pie(heart_df[heart_df.HeartDiseaseOutcome==1],  names='ChestPainType', title='<
         fig.update_traces(textposition='inside', textinfo='percent+label')
         fig.update_layout(title = "Percentage of Heart Attacks by Chest Pain Type")
         fig.show("notebook")
```





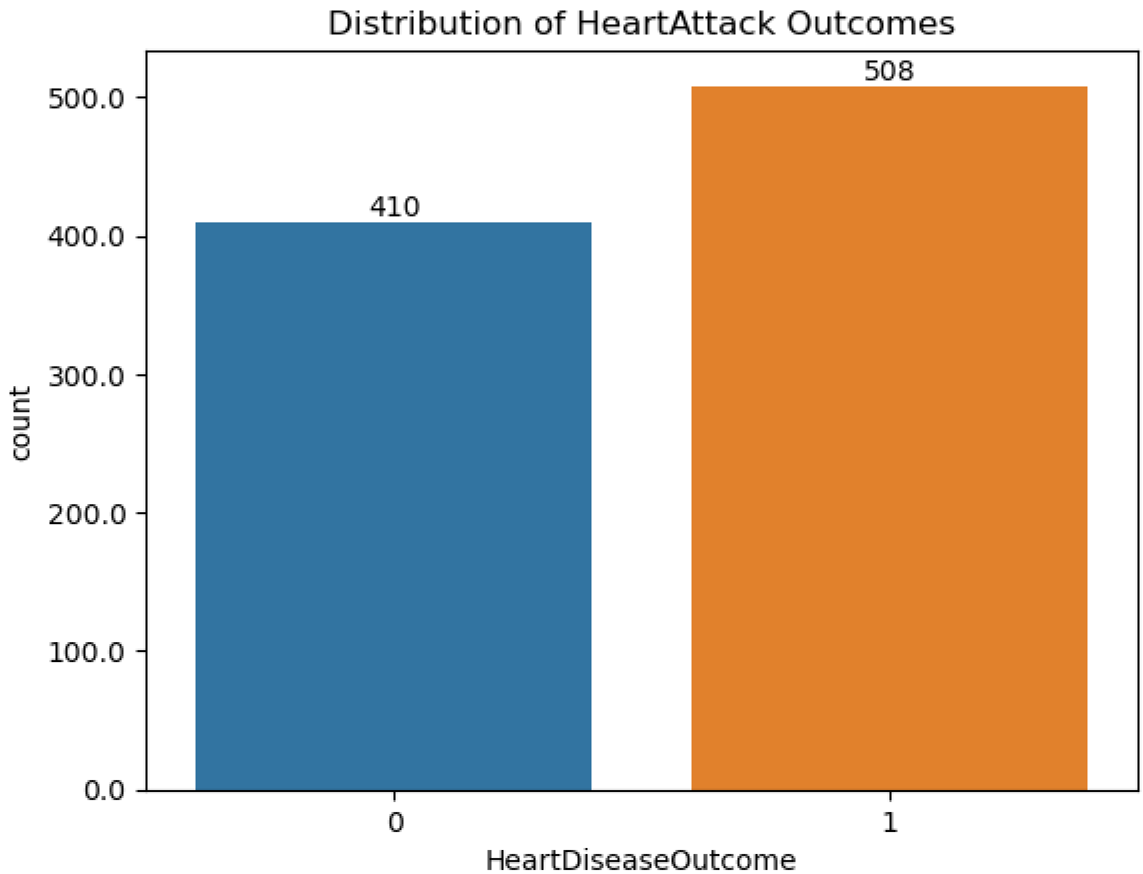
Sex: displays the gender of the individual using the following format : 1 = male 0 = female

In [45]:
```
fig = px.histogram(heart_df, y="Age", x="RestingBP",color='Sex', barmode='group',histfun
fig.update_layout(title = "Distribution of Resting Blood Pressure by Gender")
fig.show("notebook")
```



In [12]:
```
xx = heart_df['HeartDiseaseOutcome'].value_counts().reset_index()
def formatter(x, pos):
    return str(x)

ax = sns.barplot(x="HeartDiseaseOutcome",y="count",data=xx)
ax.set_title('Distribution of HeartAttack Outcomes')
ax.yaxis.set_major_formatter(formatter)
ax.yaxis.set_minor_formatter(NullFormatter())
for i in ax.containers:
    ax.bar_label(i,)
```



Model Building

In [13]:
```
X = heart_df.drop(['HeartDiseaseOutcome'],axis=1)
Y = heart_df['HeartDiseaseOutcome']
X.shape, Y.shape
```

Out[13]:
```
((918, 11), (918,))
```

In [14]:
```
X.dtypes
```

Out[14]:
```
Age                    int64
Sex                   object
ChestPainType         object
RestingBP              int64
Cholesterol            int64
FastingBloodSugar      int64
RestingECG            object
MaxHR                  int64
ExerciseAngina        object
Oldpeak              float64
ST_Slope              object
dtype: object
```

In [15]:
```
# Encode categorical variables (e.g., 'gender', 'category', 'state', etc.)
categorical_columns = ['Sex', 'ChestPainType','RestingECG', 'ExerciseAngina','ST_Slope']
for col in categorical_columns:
    le = LabelEncoder()
    X[col] = le.fit_transform(X[col])
```

Split dataset into Train and Test Sets

In [16]:
```
scaler = StandardScaler()
x = scaler.fit_transform(X)
```

```
X.shape, x.shape
```

Out[16]:
```
((918, 11), (918, 11))
```

In [17]:
```
# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(x,Y, test_size=0.2, random_state=42)
```

In [18]:
```
X_train.shape, X_test.shape, Y_train.shape, Y_test.shape
```

Out[18]:
```
((734, 11), (184, 11), (734,), (184,))
```

Models

Random Forest

In [19]:
```
# Use the RandomForestClassifier to fit balanced data
rfc = RandomForestClassifier()
rfc_model = rfc.fit(X_train,Y_train)

#Predict y data with classifier:
y_pred_rfc = rfc_model.predict(X_test)

# Evaluate the model
print(classification_report(Y_test, y_pred_rfc))
print(confusion_matrix(Y_test, y_pred_rfc))
print(f'ROC-AUC score : {roc_auc_score(Y_test, y_pred_rfc)}')
print(f'Accuracy score : {accuracy_score(Y_test, y_pred_rfc)}')
```

```
              precision    recall  f1-score   support

           0       0.84      0.90      0.87        77
           1       0.92      0.88      0.90       107

    accuracy                           0.89       184
   macro avg       0.88      0.89      0.88       184
weighted avg       0.89      0.89      0.89       184

[[69  8]
 [13 94]]
ROC-AUC score : 0.8873042845005461
Accuracy score : 0.8858695652173914
```

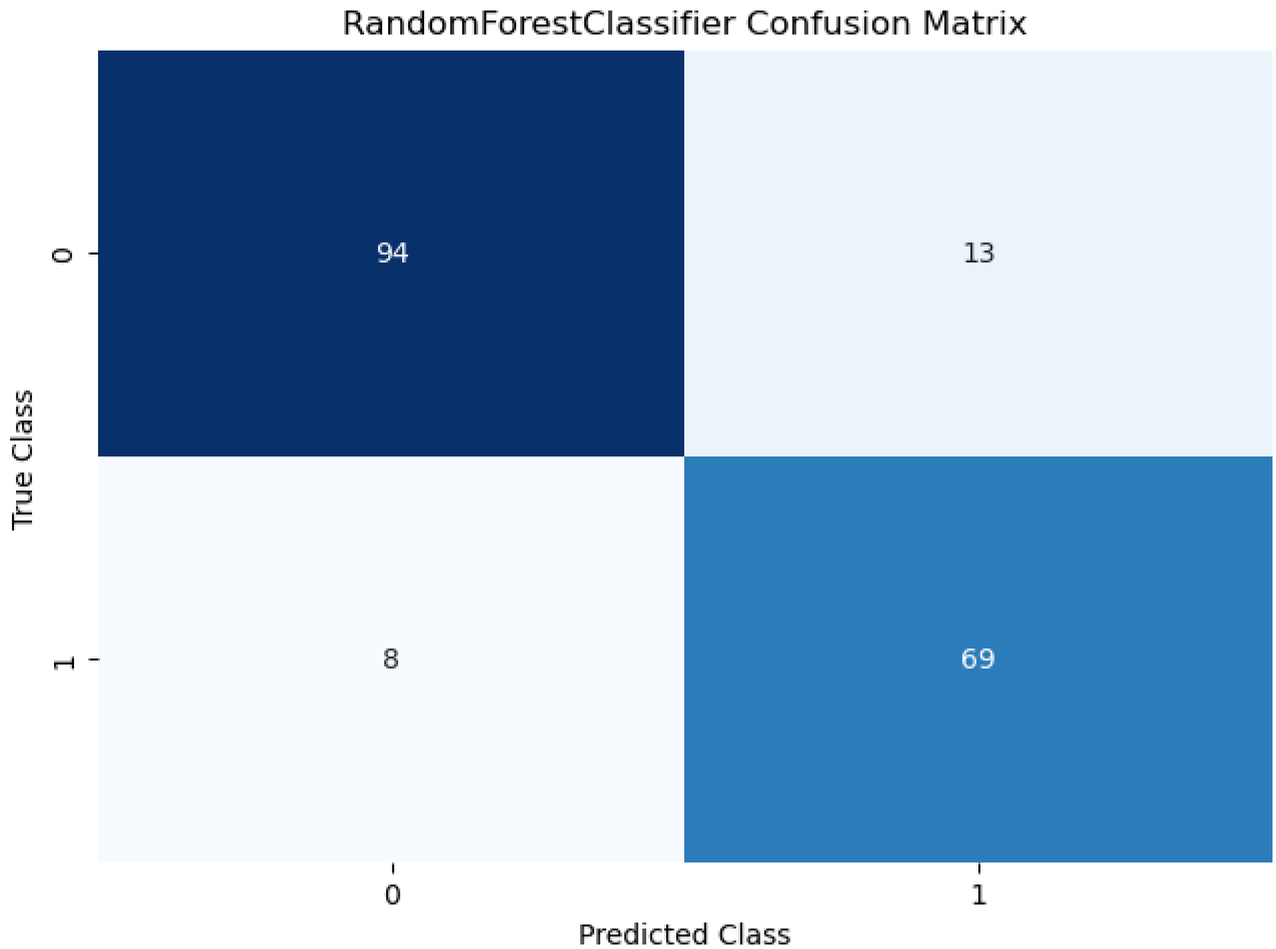
In [20]:
```
#Build the confusion matrix
matrix = confusion_matrix(Y_test, y_pred_rfc, labels=[1,0])

print(matrix)

# Create pandas dataframe
df = pd.DataFrame(matrix)

# Create a heatmap
sns.heatmap(df, annot=True, cbar=None, cmap="Blues",fmt='.0f')
plt.title("RandomForestClassifier Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```

```
[[94 13]
 [ 8 69]]
```



Logistic Regression

In [21]:
```
# Train a logistic regression model
logistic_model = LogisticRegression(solver='liblinear', random_state=42)
logistic_model.fit(X_train,Y_train)

# Make predictions on the test set
y_pred_lr = logistic_model.predict(X_test)

# Evaluate the model
print(classification_report(Y_test, y_pred_lr))
print(confusion_matrix(Y_test, y_pred_lr))
print(f'ROC-AUC score : {roc_auc_score(Y_test, y_pred_lr)}')
print(f'Accuracy score : {accuracy_score(Y_test, y_pred_lr)}')
```

```
              precision    recall  f1-score   support

           0       0.77      0.88      0.82        77
           1       0.91      0.81      0.86       107

    accuracy                           0.84       184
   macro avg       0.84      0.85      0.84       184
weighted avg       0.85      0.84      0.84       184

[[68  9]
 [20 87]]
ROC-AUC score : 0.8481004976332078
Accuracy score : 0.842391304347826
```

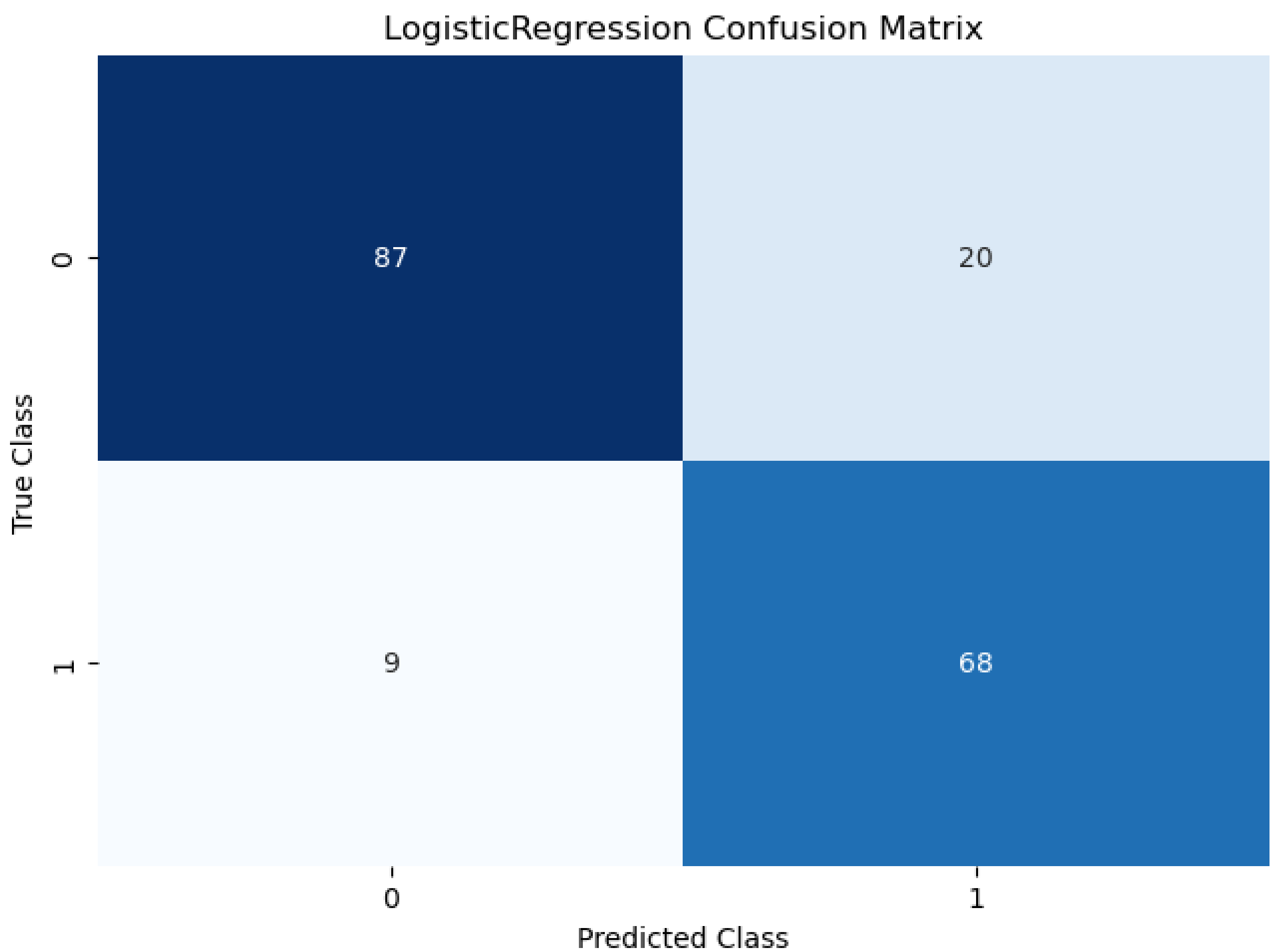
In [22]:
```
#Build the confusion matrix
matrix = confusion_matrix(Y_test, y_pred_lr, labels=[1,0])

print(matrix)
```

```
# Create pandas dataframe
df = pd.DataFrame(matrix)

# Create a heatmap
sns.heatmap(df, annot=True, cbar=None, cmap="Blues",fmt='.0f')
plt.title("LogisticRegression Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```

```
[[87 20]
 [ 9 68]]
```



Support Vector Machine (SVM)

In [23]:

```
svc_model = SVC()
svc_model.fit(X_train, Y_train)

y_pred_svc = svc_model.predict(X_test)

# Evaluate the model
print(classification_report(Y_test, y_pred_svc))
print(confusion_matrix(Y_test, y_pred_svc))
print(f'ROC-AUC score : {roc_auc_score(Y_test, y_pred_svc)}')
print(f'Accuracy score : {accuracy_score(Y_test, y_pred_svc)}')
```

```
              precision    recall  f1-score   support

           0       0.82      0.86      0.84        77
           1       0.89      0.87      0.88       107

    accuracy                           0.86       184
   macro avg       0.86      0.86      0.86       184
weighted avg       0.87      0.86      0.86       184
```

```
[[66 11]
 [14 93]]
ROC-AUC score : 0.863150867823765
Accuracy score : 0.8641304347826086
```

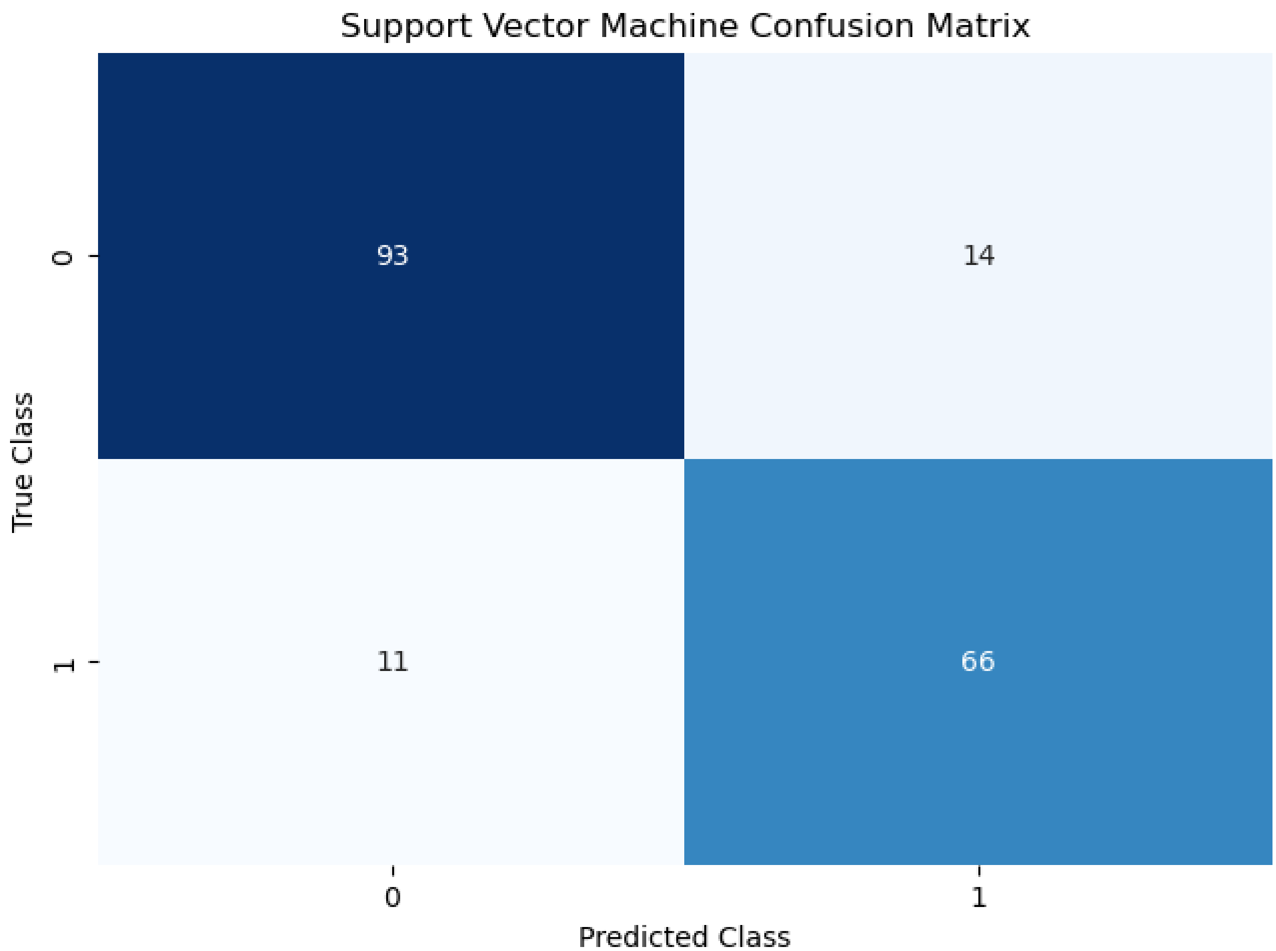
In [24]:
```
#Build the confusion matrix
matrix = confusion_matrix(Y_test, y_pred_svc, labels=[1,0])

print(matrix)

# Create pandas dataframe
df = pd.DataFrame(matrix)

# Create a heatmap
sns.heatmap(df, annot=True, cbar=None, cmap="Blues",fmt='.0f')
plt.title("Support Vector Machine Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```

```
[[93 14]
 [11 66]]
```



Naive Bayes

In [25]:
```
# Initialize and train the Multinomial Naive Bayes classifier

# Ensure non-negative values in the feature vectors
x_train = np.maximum(0, X_train)
x_test = np.maximum(0, X_test)


nb_model = MultinomialNB()
nb_model.fit(x_train, Y_train)
```

```python
# Make predictions on the test data
y_pred_nb = nb_model.predict(x_test)

# Evaluate the model
print(classification_report(Y_test, y_pred_nb))
print(confusion_matrix(Y_test, y_pred_nb))
print(f'ROC-AUC score : {roc_auc_score(Y_test, y_pred_nb)}')
print(f'Accuracy score : {accuracy_score(Y_test, y_pred_nb)}')
```

```
              precision    recall  f1-score   support

           0       0.73      0.87      0.79        77
           1       0.89      0.77      0.82       107

    accuracy                           0.81       184
   macro avg       0.81      0.82      0.81       184
weighted avg       0.82      0.81      0.81       184

[[67 10]
 [25 82]]
ROC-AUC score : 0.8182425051583929
Accuracy score : 0.8097826086956522
```

In [26]:

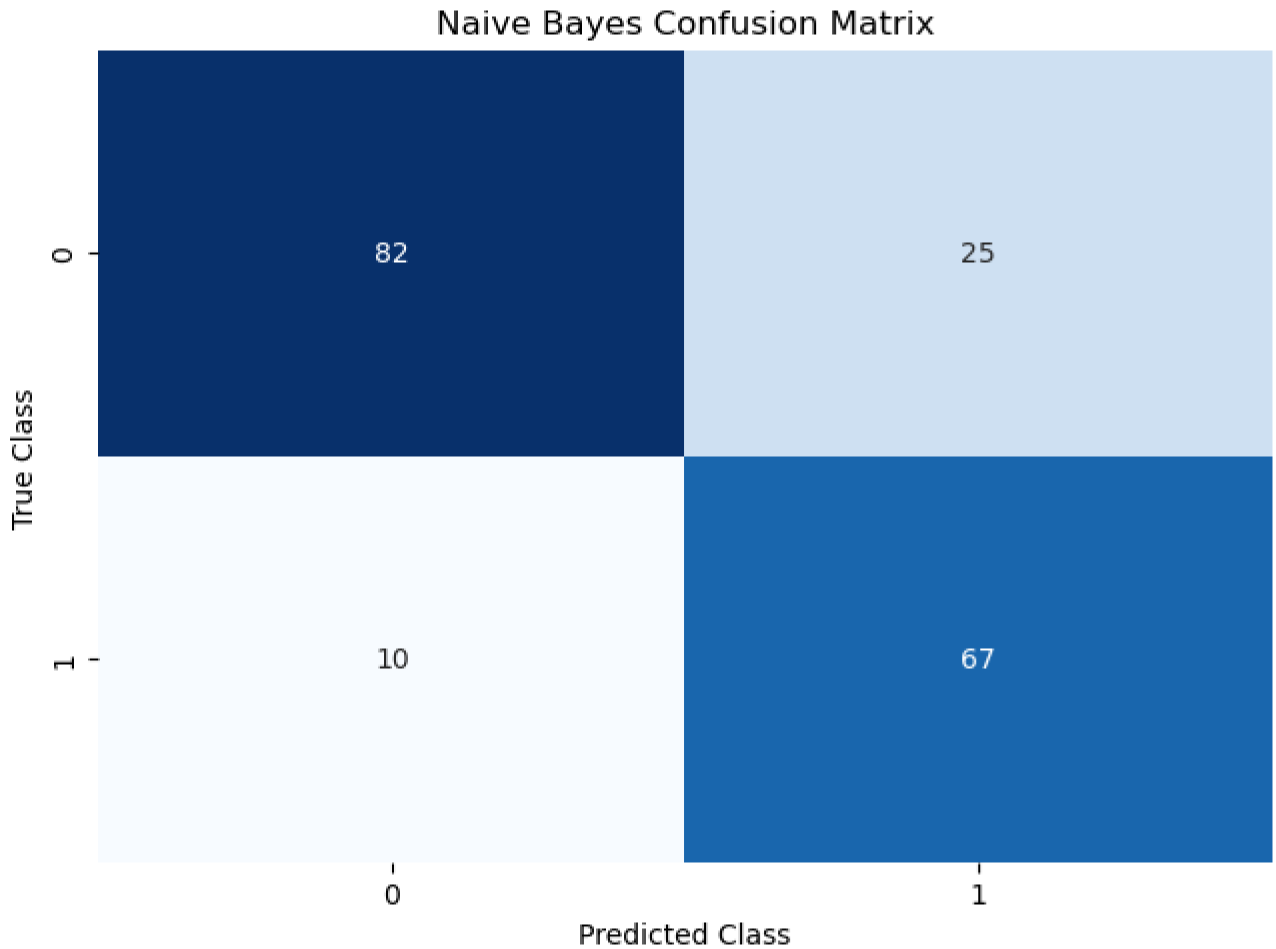
```python
#Build the confusion matrix
matrix = confusion_matrix(Y_test, y_pred_nb, labels=[1,0])

print(matrix)

# Create pandas dataframe
df = pd.DataFrame(matrix)

# Create a heatmap
sns.heatmap(df, annot=True, cbar=None, cmap="Blues",fmt='.0f')
plt.title("Naive Bayes Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```

```
[[82 25]
 [10 67]]
```


Naive Bayes Confusion Matrix
82
25
10
67
0
1
True Class
0
1
Predicted Class