Predicting Insurance Claim

Using sample data set of historical insurance claims to develop a model for Insurance claim prediction.

In [1]:
```
import pandas as pd

#loading the data set

df = pd.read_csv('./insurance2.csv')
df.head()
```

Out[1]:

	age	sex	bmi	children	smoker	region	charges	insuranceclaim
0	19	0	27.900	0	1	3	16884.92400	1
1	18	1	33.770	1	0	2	1725.55230	1
2	28	1	33.000	3	0	2	4449.46200	0
3	33	1	22.705	0	0	1	21984.47061	0
4	32	1	28.880	0	0	1	3866.85520	1

Data Preprocessing

In [2]:
```
df.shape
```

Out[2]:
```
(1338, 8)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             1338 non-null   int64  
 1   sex             1338 non-null   int64  
 2   bmi             1338 non-null   float64
 3   children        1338 non-null   int64  
 4   smoker          1338 non-null   int64  
 5   region          1338 non-null   int64  
 6   charges         1338 non-null   float64
 7   insuranceclaim  1338 non-null   int64  
dtypes: float64(2), int64(6)
memory usage: 83.8 KB
```

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

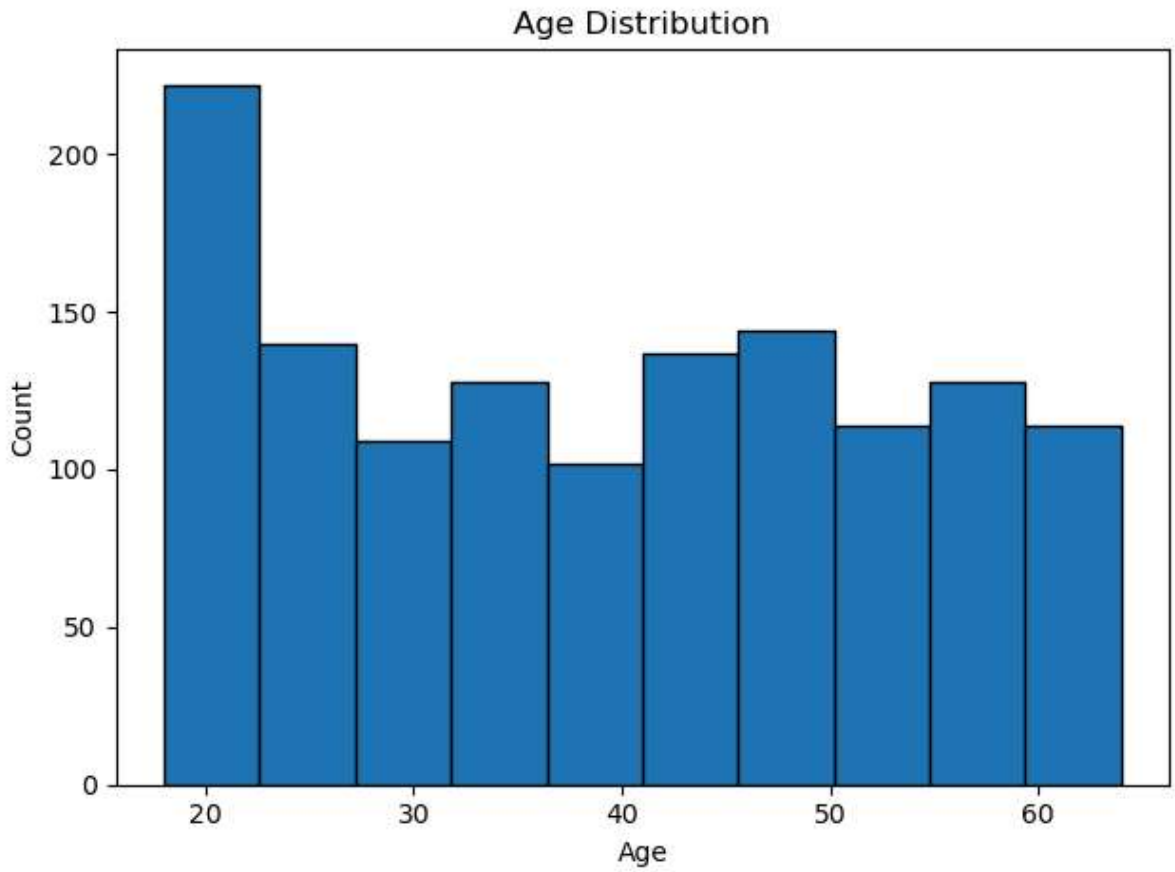
Out[4]:

	age	sex	bmi	children	smoker	region	charg
count	1338.000000	1338.000000	1338.000000	1338.000000	1338.000000	1338.000000	1338.000(
mean	39.207025	0.505232	30.663397	1.094918	0.204783	1.515695	13270.422
std	14.049960	0.500160	6.098187	1.205493	0.403694	1.104885	12110.011
min	18.000000	0.000000	15.960000	0.000000	0.000000	0.000000	1121.873
25%	27.000000	0.000000	26.296250	0.000000	0.000000	1.000000	4740.287
50%	39.000000	1.000000	30.400000	1.000000	0.000000	2.000000	9382.033(
75%	51.000000	1.000000	34.693750	2.000000	0.000000	2.000000	16639.912
max	64.000000	1.000000	53.130000	5.000000	1.000000	3.000000	63770.428(

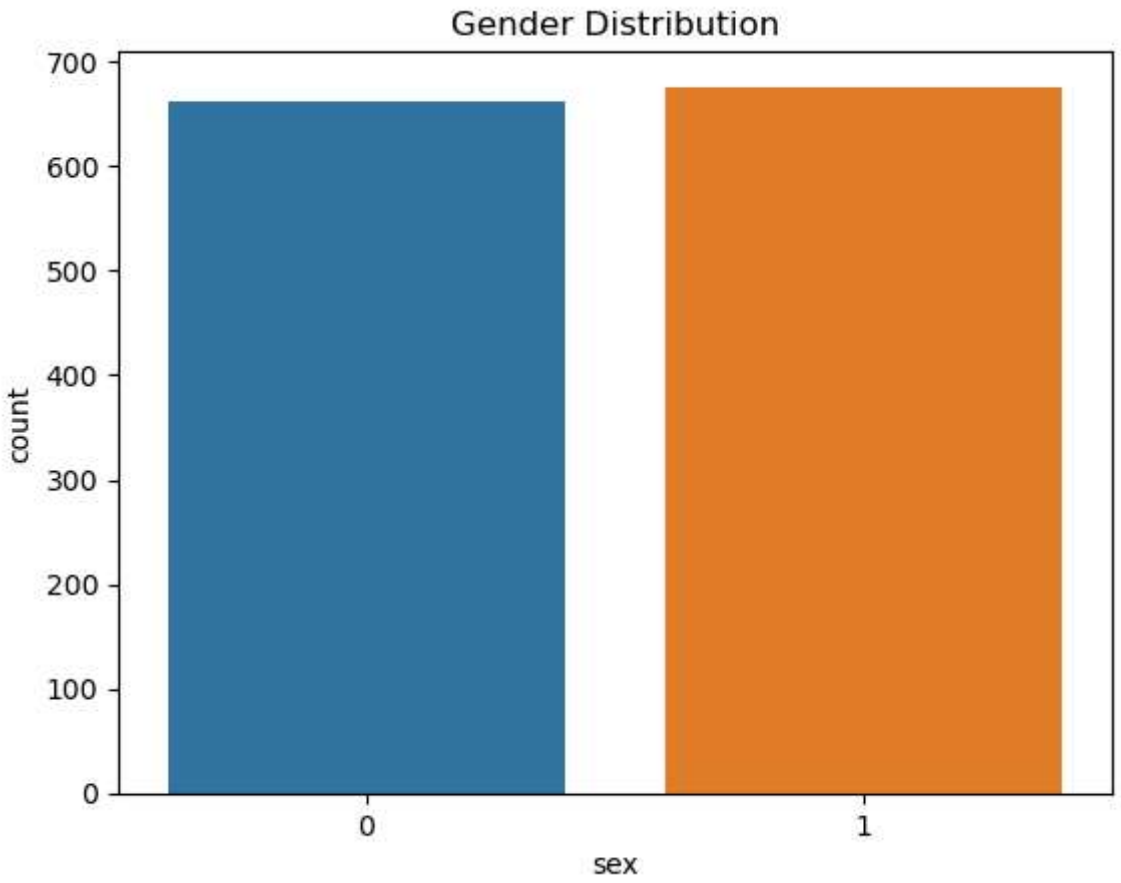
Exploratory Data Analysis(EDA)

In [5]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.hist(df['age'], edgecolor='black')
plt.tight_layout()
plt.show()
```

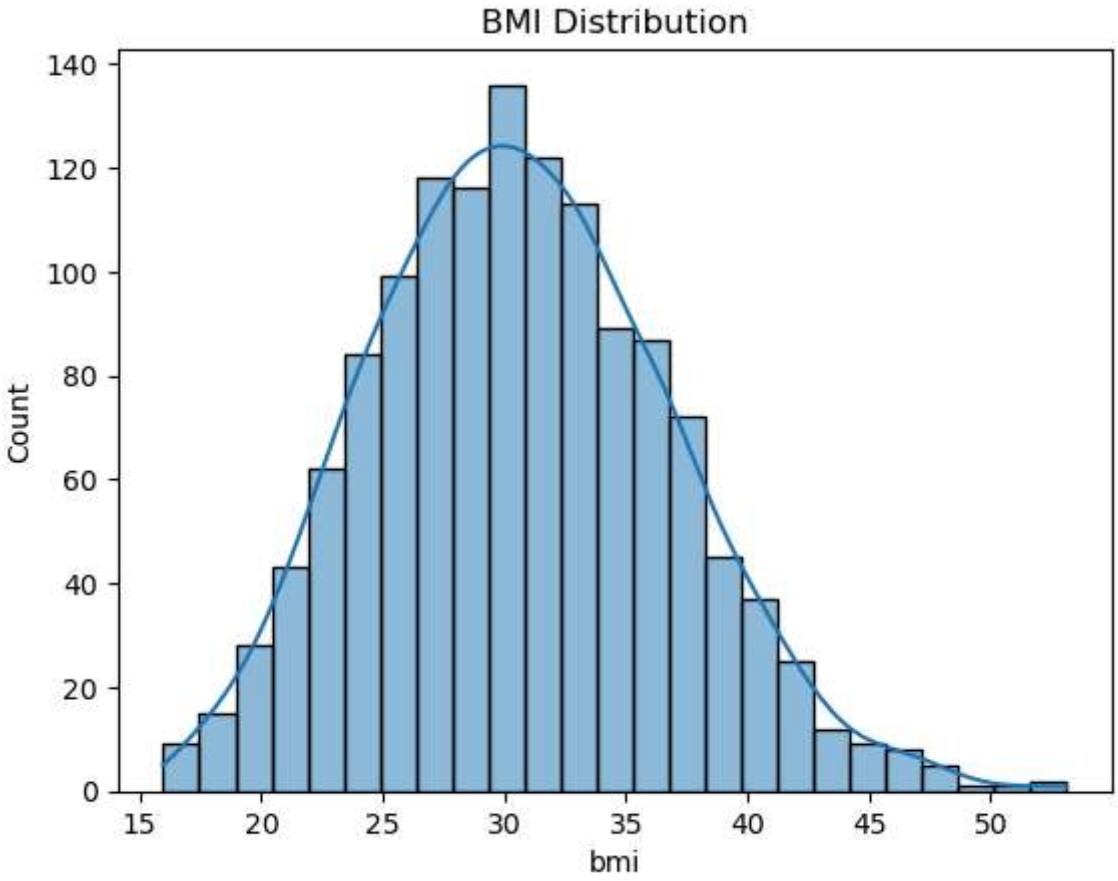
```
C:\Users\SatyendraSingh\anaconda3\lib\site-packages\scipy\__init__.py:155: Us
erWarning: A NumPy version >=1.18.5 and <1.25.0 is required for this version
of SciPy (detected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```



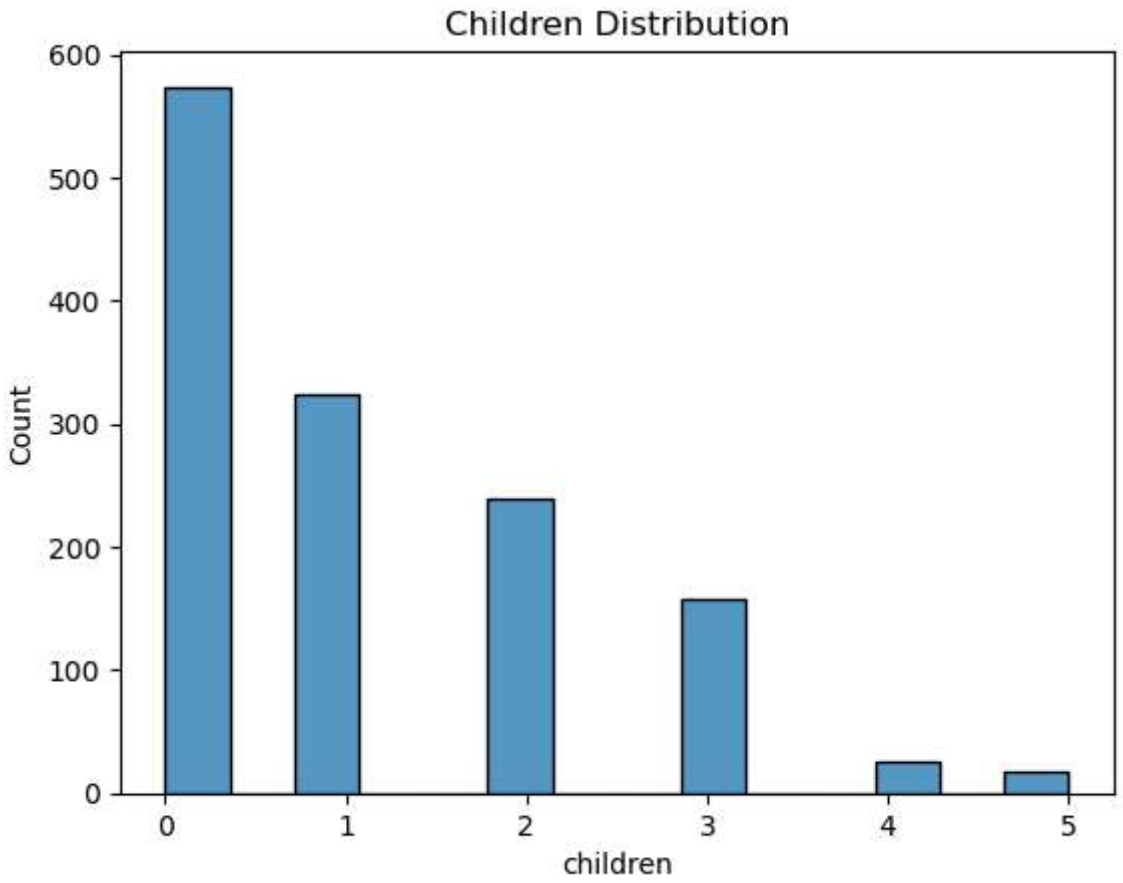
In [6]:
```
plt.title('Gender Distribution')
sns.countplot(x= 'sex', data= df)
plt.show()
```



In [7]:
```
plt.title ('BMI Distribution')
sns.histplot(df['bmi'],kde = True)
plt.show()
```

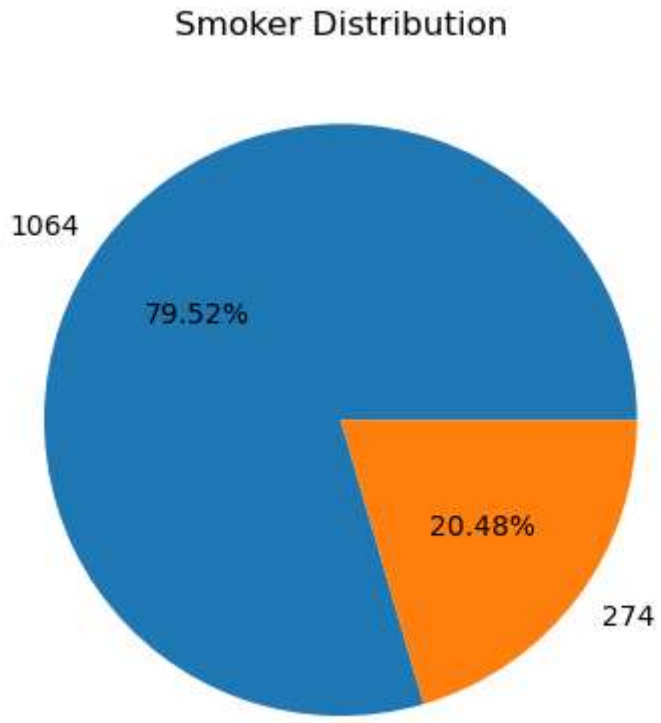


In [8]:
```
plt.title('Children Distribution')
sns.histplot(df.children)
plt.show()
```



In [9]:
```
plt.title('Smoker Distribution')
plt.pie(df.smoker.value_counts(),labels= df.smoker.value_counts(),autopct='%.2
plt.show
```

Out[9]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Correlation Matrix

In [10]:
```
df.corr()
```

Out[10]:

	age	sex	bmi	children	smoker	region	charges	insurar
age	1.000000	-0.020856	0.109272	0.042469	-0.025019	0.002127	0.299008	
sex	-0.020856	1.000000	0.046371	0.017163	0.076185	0.004588	0.057292	
bmi	0.109272	0.046371	1.000000	0.012759	0.003750	0.157566	0.198341	
children	0.042469	0.017163	0.012759	1.000000	0.007673	0.016569	0.067998	-(
smoker	-0.025019	0.076185	0.003750	0.007673	1.000000	-0.002181	0.787251	
region	0.002127	0.004588	0.157566	0.016569	-0.002181	1.000000	-0.006208	
charges	0.299008	0.057292	0.198341	0.067998	0.787251	-0.006208	1.000000	
insuranceclaim	0.113723	0.031565	0.384198	-0.409526	0.333261	0.020891	0.309418	

In [11]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score, accuracy_score, confusion_matrix, classi
```

Spliting the data into training and test data

In [12]:
```
#plotting the data in x and y
y = df['insuranceclaim']
X = df.drop( ['insuranceclaim'],axis=1)

#train test split()
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.30)
```

Baseline Model

In [13]:
```
dummy_clf = DummyClassifier(strategy="stratified")
dummy_clf.fit(X_train, y_train)
dummy_clf.predict(X_test)
dummy_clf.score(X_test, y_test)
```

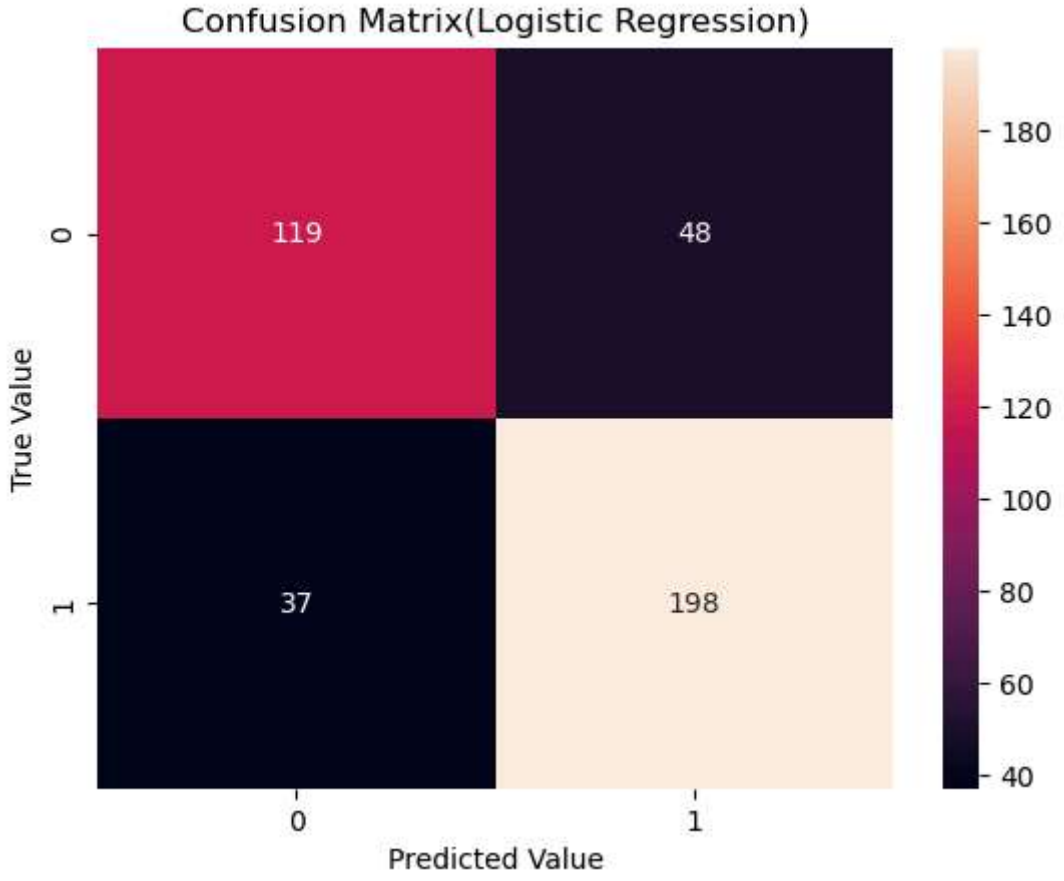
Out[13]:
```
0.5373134328358209
```

Logistic Regression

In [14]:
```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred_log = logreg.predict(X_test)
lr_acc_score = accuracy_score(y_test,y_pred_log)
lr_f1_score = f1_score(y_test,y_pred_log)
lr_conf_matrix = confusion_matrix(y_test,y_pred_log)

##Print
print(f"Test Accuracy score : {lr_acc_score}")
print(f"Test F1 : {lr_f1_score}")
print('\n')
print("Confusion matrix")
print(lr_conf_matrix)

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

```
Test Accuracy score : 0.7885572139303483
Test F1 : 0.8232848232848233


Confusion matrix
[[119  48]
 [ 37 198]]
              precision    recall  f1-score   support

           0       0.76      0.71      0.74       167
           1       0.80      0.84      0.82       235

    accuracy                           0.79       402
   macro avg       0.78      0.78      0.78       402
weighted avg       0.79      0.79      0.79       402
```

In [15]:
```
plt.title("Confusion Matrix(Logistic Regression)")
sns.heatmap(lr_conf_matrix,annot = True,fmt='d')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()
```

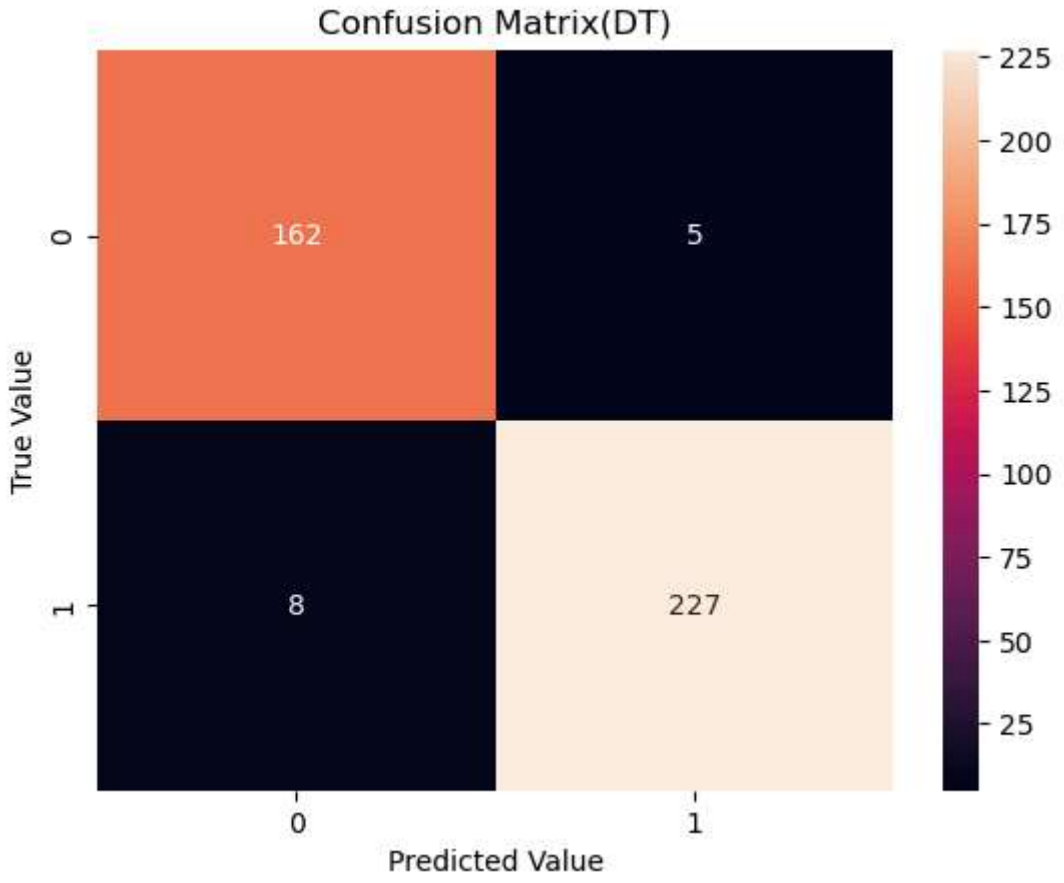


Decision Tree

In [16]:
```
from sklearn.tree import DecisionTreeClassifier
Tree = DecisionTreeClassifier()
Tree.fit(X_train,y_train)
y_pred_Tree = Tree.predict(X_test)

Tree_acc_score = accuracy_score(y_test,y_pred_Tree)
Tree_f1_score = f1_score(y_test,y_pred_Tree)
Tree_conf_matrix = confusion_matrix(y_test,y_pred_Tree)
print(f"Test acc Score : {Tree_acc_score}")
print(f"Test F1 Score : {Tree_f1_score}")
print(Tree_conf_matrix)

print(classification_report(y_test, y_pred_Tree))
```

```
Test acc Score : 0.9676616915422885
Test F1 Score : 0.9721627408993575
[[162   5]
 [  8 227]]
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       167
           1       0.98      0.97      0.97       235

    accuracy                           0.97       402
   macro avg       0.97      0.97      0.97       402
weighted avg       0.97      0.97      0.97       402
```

In [17]:
```
plt.title("Confusion Matrix(DT)")
sns.heatmap(Tree_conf_matrix,annot = True,fmt='d')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()
```

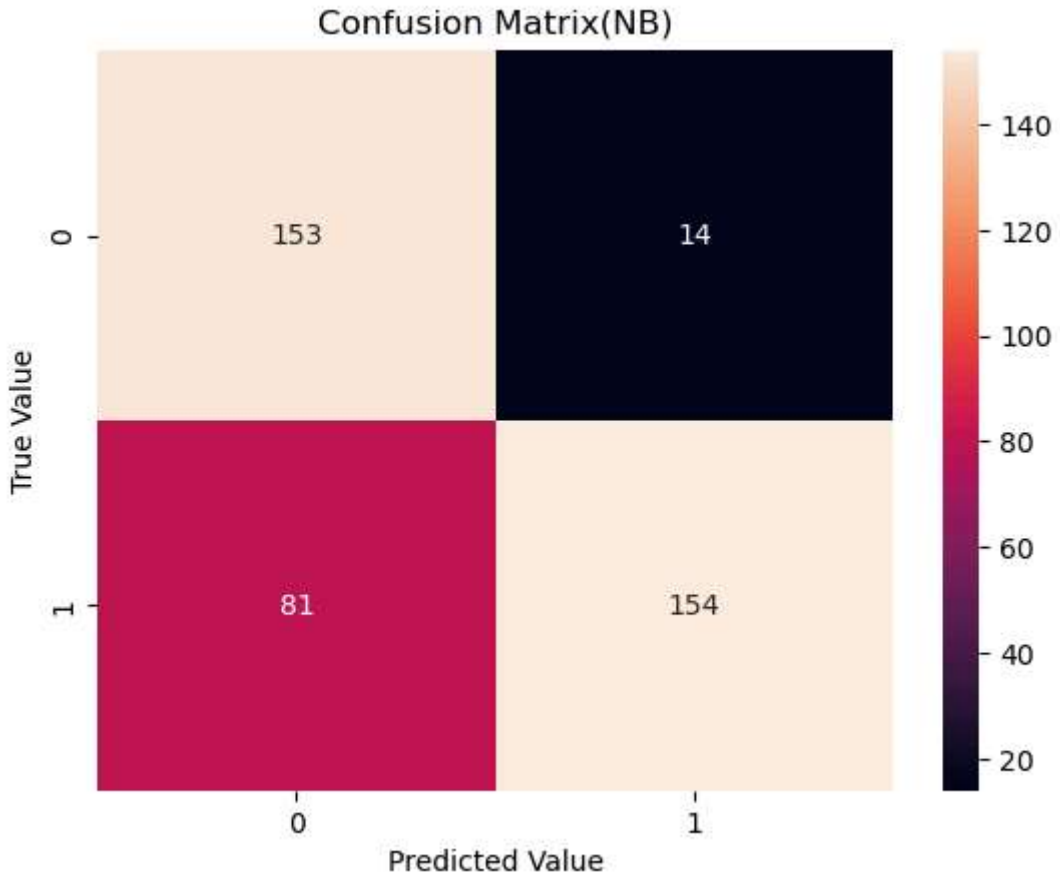


Naive Bayes

In [18]:
```
from sklearn.naive_bayes import GaussianNB

NB = GaussianNB()
NB.fit(X_train,y_train)
y_pred_NB = NB.predict(X_test)
NB_acc_score = accuracy_score(y_test,y_pred_NB)
NB_f1_score = f1_score(y_test,y_pred_NB)
NB_conf_matrix = confusion_matrix(y_test,y_pred_NB)
print(f"Test aCC score : {NB_acc_score}")
print(f"Test f1 SCORE : {NB_f1_score}")
print("Confusion matrix")
print(NB_conf_matrix)

print(classification_report(y_test, y_pred_NB))
```

```
Test aCC score : 0.763681592039801
Test f1 SCORE : 0.7642679900744417
Confusion matrix
[[153  14]
 [ 81 154]]
              precision    recall  f1-score   support

           0       0.65      0.92      0.76       167
           1       0.92      0.66      0.76       235

    accuracy                           0.76       402
   macro avg       0.79      0.79      0.76       402
weighted avg       0.81      0.76      0.76       402
```

In [19]:
```
plt.title("Confusion Matrix(NB)")
sns.heatmap(NB_conf_matrix,annot = True,fmt='d')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()
```

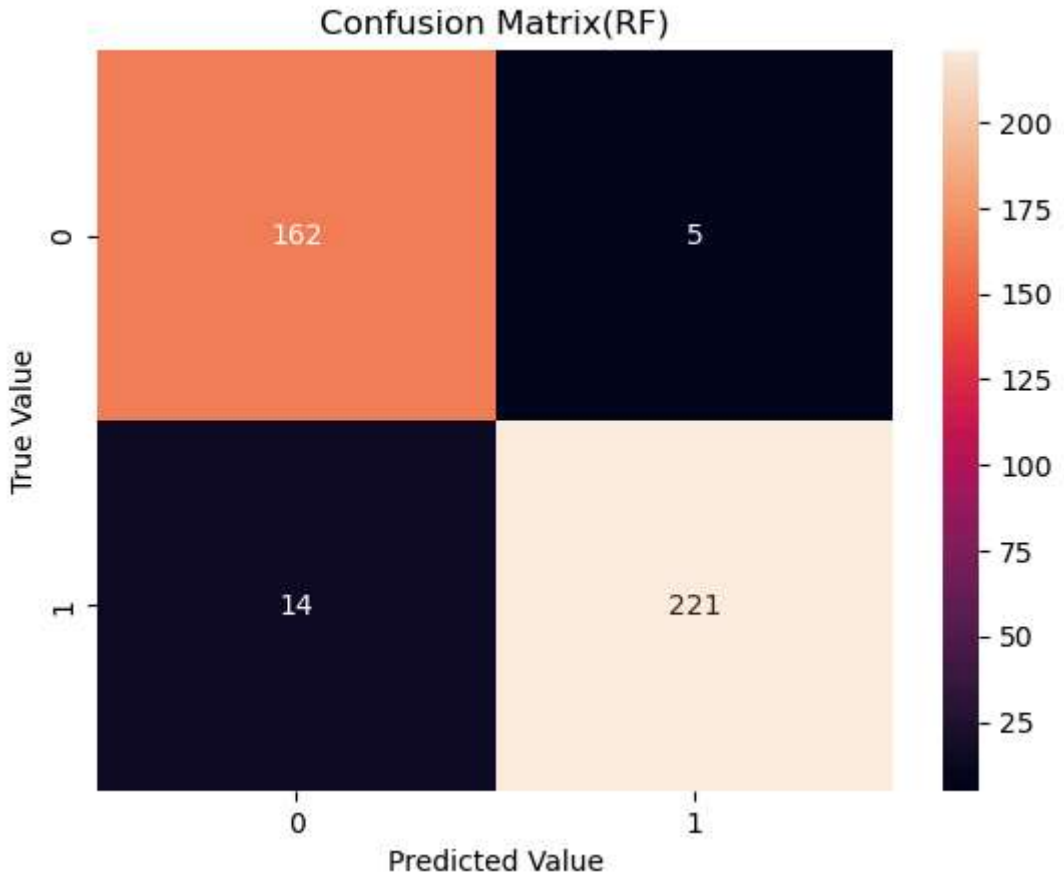


Random Forest

In [20]:
```
from sklearn.ensemble import RandomForestClassifier

RF = RandomForestClassifier()
RF.fit(X_train,y_train)
RF_y_pred = RF.predict(X_test)

RF_acc_score = accuracy_score(y_test,RF_y_pred)
RF_f1_score = f1_score(y_test,RF_y_pred)
RF_Conf_Matrix = confusion_matrix(y_test,RF_y_pred)

print(f"Test aCC score : {RF_acc_score}")
print(f"Test f1 SCORE : {RF_f1_score}")
print("Confusion matrix")
print(RF_Conf_Matrix)

print(classification_report(y_test, RF_y_pred))
```

```
Test aCC score : 0.9527363184079602
Test f1 SCORE : 0.9587852494577007
Confusion matrix
[[162   5]
 [ 14 221]]
              precision    recall  f1-score   support

           0       0.92      0.97      0.94       167
           1       0.98      0.94      0.96       235

    accuracy                           0.95       402
   macro avg       0.95      0.96      0.95       402
weighted avg       0.95      0.95      0.95       402
```

In [21]:
```
plt.title("Confusion Matrix(RF)")
sns.heatmap(RF_Conf_Matrix,annot = True,fmt='d')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()
```



In [22]:
```
model_perf = pd.DataFrame({'Model':['Dummy Classifer',"Logistic Regression","De
                                    "Acuuracy":[dummy_clf.score(X_test, y_test),lr_acc_s
model_perf
```

Out[22]:

	Model	Acuuracy
0	Dummy Classifer	0.475124
1	Logistic Regression	0.788557
2	Decision Tree	0.967662
3	Random Forest	0.952736
4	Naive Byes	0.763682

Conclusion: From all 5 classification model used for the input dataset, Decision Tree has the best Accuracy.

Prediciting sample values

In [23]:
```
## Predicting Couple of sample values a & b which are not part of Input Data Se

a = [28,1,44,2,0,2,1600]
b = [64,1,53,3,1,3,3600]
y_pred_log = Tree.predict([a,b])
y_pred_log
```

```
C:\Users\SatyendraSingh\anaconda3\lib\site-packages\sklearn\base.py:450: User
Warning: X does not have valid feature names, but DecisionTreeClassifier was
fitted with feature names
  warnings.warn(
```

Out[23]:
```
array([0, 1], dtype=int64)
```

Conclusion : Sample values 'a' has predicted claim values as 0 whereas 'b' has 1.