Social Network Ads - Decision Tree and Random Forest

1. Decision Tree

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

1. Data Pre-Processing :

In [2]:
```
df = pd.read_csv('Social_Network_Ads.csv')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   User ID          400 non-null    int64 
 1   Gender           400 non-null    object
 2   Age              400 non-null    int64 
 3   EstimatedSalary  400 non-null    int64 
 4   Purchased        400 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 15.8+ KB
```

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

Out[4]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

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

Out[5]:

	User ID	Gender	Age	EstimatedSalary	Purchased
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

In [6]:
```
df.describe()
```

Out[6]:

	User ID	Age	EstimatedSalary	Purchased
count	4.000000e+02	400.000000	400.000000	400.000000
mean	1.569154e+07	37.655000	69742.500000	0.357500
std	7.165832e+04	10.482877	34096.960282	0.479864
min	1.556669e+07	18.000000	15000.000000	0.000000
25%	1.562676e+07	29.750000	43000.000000	0.000000
50%	1.569434e+07	37.000000	70000.000000	0.000000
75%	1.575036e+07	46.000000	88000.000000	1.000000
max	1.581524e+07	60.000000	150000.000000	1.000000

2. Fitting Decision Tree Algorithm using Training Data :

In [7]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [8]:
```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
df['Gender'] = label_encoder.fit_transform(df['Gender'])
```

In [9]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

X = df.drop('Purchased', axis=1)
Y = df['Purchased']

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.20, random_state=42)

classifier = DecisionTreeClassifier(criterion='entropy')
model = classifier.fit(x_train, y_train)
```

3. Predicting the Test Set Results :

In [10]:
```python
y_pred = classifier.predict(x_test)
```

4. Evaluate Performance of the Model :

In [11]:
```python
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

In [12]:
```python
mat = confusion_matrix(y_test, y_pred)
mat
```

Out[12]:
```
array([[48,  4],
       [ 6, 22]], dtype=int64)
```

In [13]:
```python
report = classification_report(y_test, y_pred)
print(report)
```

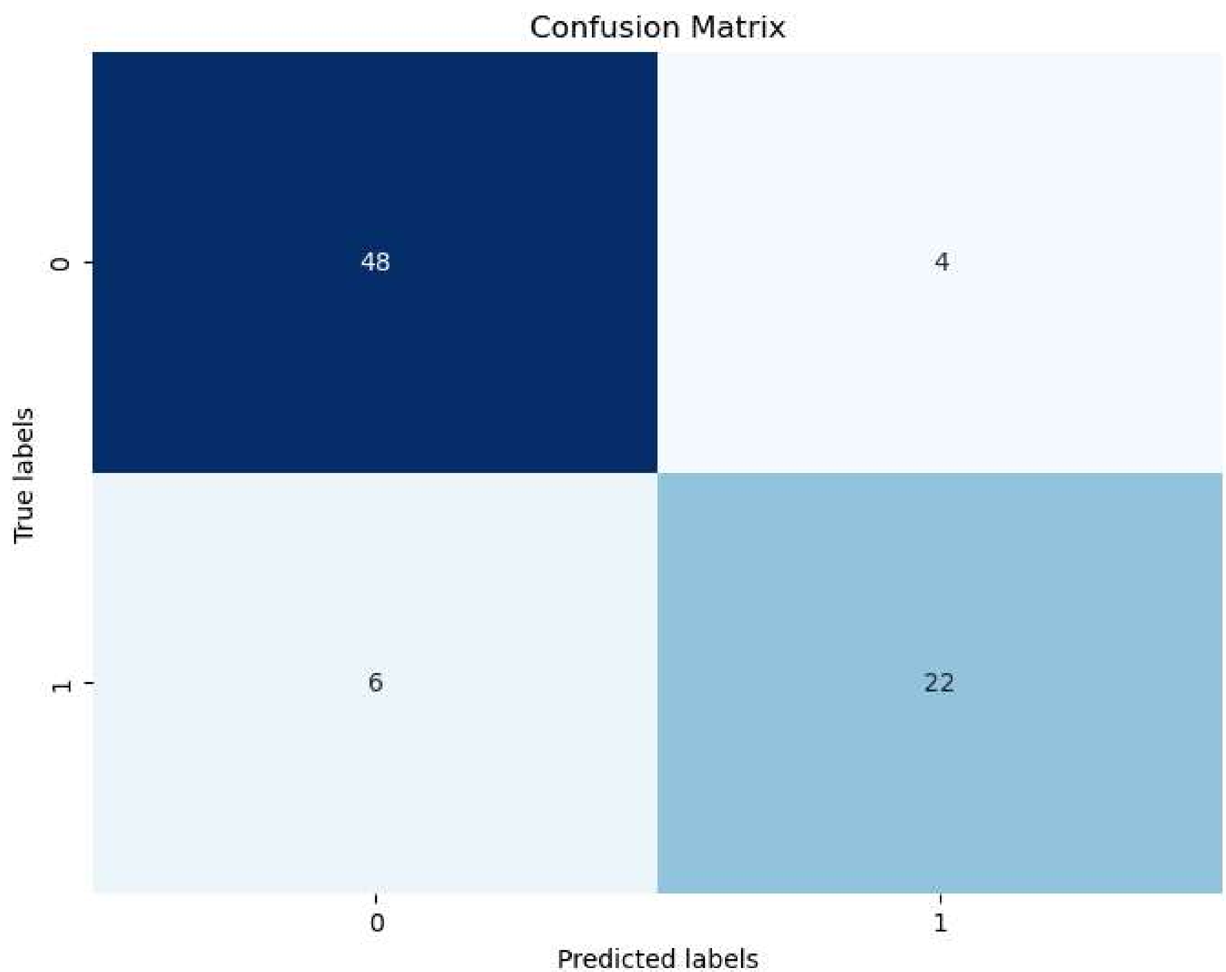
```
              precision    recall  f1-score   support

           0       0.89      0.92      0.91        52
           1       0.85      0.79      0.81        28

    accuracy                           0.88        80
   macro avg       0.87      0.85      0.86        80
weighted avg       0.87      0.88      0.87        80
```

In [14]:
```python
score = accuracy_score(y_test, y_pred)
print(score)
```

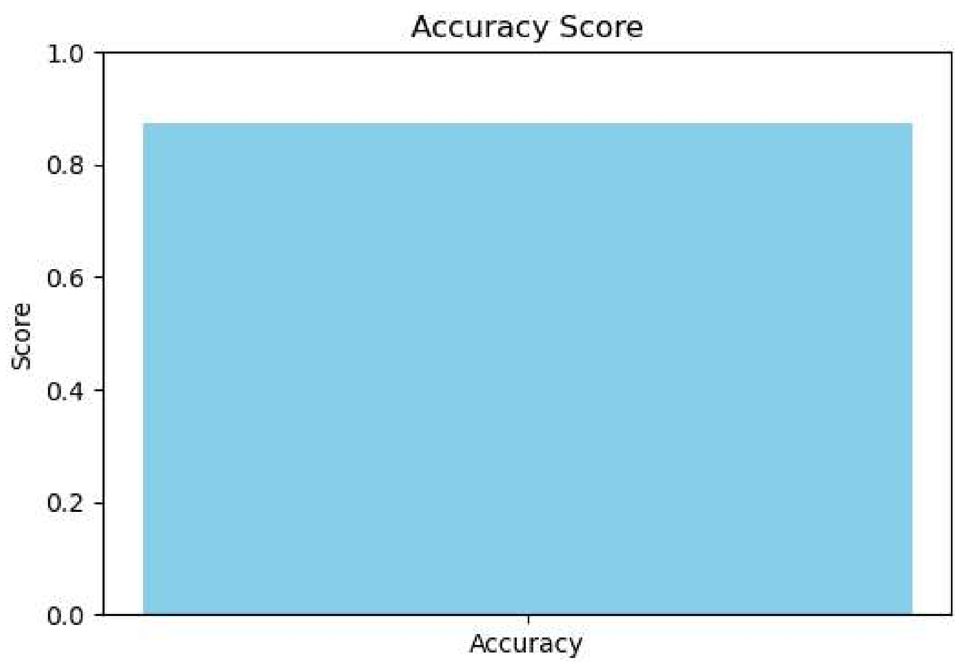
```
0.875
```

In [15]:

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

# Confusion Matrix Visualization
plt.figure(figsize=(8, 6))
sns.heatmap(mat, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

# Classification Report Visualization
print("Classification Report:")
print(report)

# Accuracy Score Visualization
plt.figure(figsize=(6, 4))
plt.bar(['Accuracy'], [score], color='skyblue')
plt.title('Accuracy Score')
plt.ylabel('Score')
plt.ylim(0, 1)
plt.show()
```



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

           0       0.89      0.92      0.91        52
           1       0.85      0.79      0.81        28

    accuracy                           0.88        80
   macro avg       0.87      0.85      0.86        80
weighted avg       0.87      0.88      0.87        80
```



5. Plot the Decision Tree :

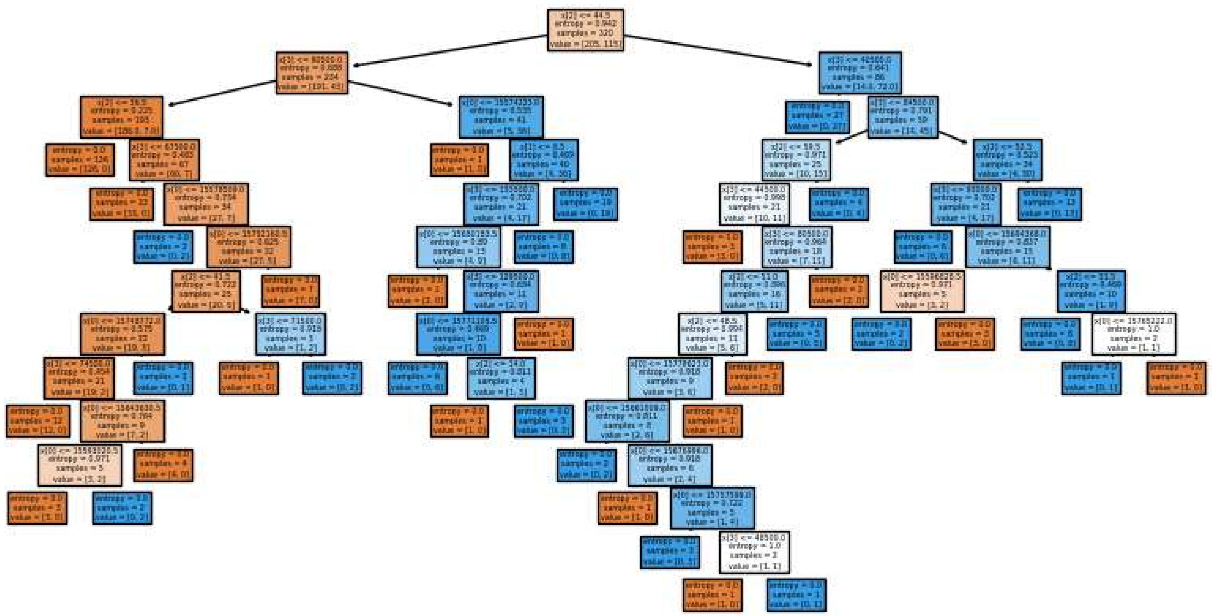
In [16]:
```python
from sklearn import tree
```

In [17]:
```
plt.figure(figsize = (10,5))
tree.plot_tree(model, filled=True)
```

Out[17]:
```
[Text(0.4827586206896552, 0.9642857142857143, 'x[2] <= 44.5\nentropy = 0.942\nsamples = 3
20\nvalue = [205, 115]'),
 Text(0.25862068965517243, 0.8928571428571429, 'x[3] <= 90500.0\nentropy = 0.688\nsamples
= 234\nvalue = [191, 43]'),
 Text(0.10344827586206896, 0.8214285714285714, 'x[2] <= 36.5\nentropy = 0.225\nsamples =
193\nvalue = [186.0, 7.0]'),
 Text(0.06896551724137931, 0.75, 'entropy = 0.0\nsamples = 126\nvalue = [126, 0]'),
 Text(0.13793103448275862, 0.75, 'x[3] <= 67500.0\nentropy = 0.483\nsamples = 67\nvalue =
[60, 7]'),
 Text(0.10344827586206896, 0.6785714285714286, 'entropy = 0.0\nsamples = 33\nvalue = [33,
0]'),
 Text(0.1724137931034483, 0.6785714285714286, 'x[0] <= 15578509.0\nentropy = 0.734\nsampl
es = 34\nvalue = [27, 7]'),
 Text(0.13793103448275862, 0.6071428571428571, 'entropy = 0.0\nsamples = 2\nvalue = [0,
2]'),
 Text(0.20689655172413793, 0.6071428571428571, 'x[0] <= 15752160.5\nentropy = 0.625\nsamp
les = 32\nvalue = [27, 5]'),
 Text(0.1724137931034483, 0.5357142857142857, 'x[2] <= 41.5\nentropy = 0.722\nsamples = 2
5\nvalue = [20, 5]'),
 Text(0.10344827586206896, 0.4642857142857143, 'x[0] <= 15748772.0\nentropy = 0.575\nsamp
les = 22\nvalue = [19, 3]'),
 Text(0.06896551724137931, 0.39285714285714285, 'x[3] <= 74500.0\nentropy = 0.454\nsample
s = 21\nvalue = [19, 2]'),
 Text(0.034482758620689655, 0.32142857142857145, 'entropy = 0.0\nsamples = 12\nvalue = [1
2, 0]'),
 Text(0.10344827586206896, 0.32142857142857145, 'x[0] <= 15643630.5\nentropy = 0.764\nsam
ples = 9\nvalue = [7, 2]'),
 Text(0.06896551724137931, 0.25, 'x[0] <= 15593020.5\nentropy = 0.971\nsamples = 5\nvalue
= [3, 2]'),
 Text(0.034482758620689655, 0.17857142857142858, 'entropy = 0.0\nsamples = 3\nvalue = [3,
0]'),
 Text(0.10344827586206896, 0.17857142857142858, 'entropy = 0.0\nsamples = 2\nvalue = [0,
2]'),
 Text(0.13793103448275862, 0.25, 'entropy = 0.0\nsamples = 4\nvalue = [4, 0]'),
 Text(0.13793103448275862, 0.39285714285714285, 'entropy = 0.0\nsamples = 1\nvalue = [0,
1]'),
 Text(0.2413793103448276, 0.4642857142857143, 'x[3] <= 71500.0\nentropy = 0.918\nsamples
= 3\nvalue = [1, 2]'),
 Text(0.20689655172413793, 0.39285714285714285, 'entropy = 0.0\nsamples = 1\nvalue = [1,
0]'),
 Text(0.27586206896551724, 0.39285714285714285, 'entropy = 0.0\nsamples = 2\nvalue = [0,
2]'),
 Text(0.2413793103448276, 0.5357142857142857, 'entropy = 0.0\nsamples = 7\nvalue = [7,
0]'),
 Text(0.41379310344827586, 0.8214285714285714, 'x[0] <= 15574223.0\nentropy = 0.535\nsamp
les = 41\nvalue = [5, 36]'),
 Text(0.3793103448275862, 0.75, 'entropy = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.4482758620689655, 0.75, 'x[1] <= 0.5\nentropy = 0.469\nsamples = 40\nvalue = [4,
36]'),
 Text(0.41379310344827586, 0.6785714285714286, 'x[3] <= 133500.0\nentropy = 0.702\nsample
s = 21\nvalue = [4, 17]'),
 Text(0.3793103448275862, 0.6071428571428571, 'x[0] <= 15650183.5\nentropy = 0.89\nsample
s = 13\nvalue = [4, 9]'),
 Text(0.3448275862068966, 0.5357142857142857, 'entropy = 0.0\nsamples = 2\nvalue = [2,
0]'),
 Text(0.41379310344827586, 0.5357142857142857, 'x[3] <= 129500.0\nentropy = 0.684\nsample
s = 11\nvalue = [2, 9]'),
 Text(0.3793103448275862, 0.4642857142857143, 'x[0] <= 15771105.5\nentropy = 0.469\nsampl
es = 10\nvalue = [1, 9]'),
 Text(0.3448275862068966, 0.39285714285714285, 'entropy = 0.0\nsamples = 6\nvalue = [0,
6]'),
 Text(0.41379310344827586, 0.39285714285714285, 'x[2] <= 34.0\nentropy = 0.811\nsamples =
4\nvalue = [1, 3]'),
```

```
 Text(0.3793103448275862, 0.32142857142857145, 'entropy = 0.0\nsamples = 1\nvalue = [1,
0]'),
 Text(0.4482758620689655, 0.32142857142857145, 'entropy = 0.0\nsamples = 3\nvalue = [0,
3]'),
 Text(0.4482758620689655, 0.4642857142857143, 'entropy = 0.0\nsamples = 1\nvalue = [1,
0]'),
 Text(0.4482758620689655, 0.6071428571428571, 'entropy = 0.0\nsamples = 8\nvalue = [0,
8]'),
 Text(0.4827586206896552, 0.6785714285714286, 'entropy = 0.0\nsamples = 19\nvalue = [0, 1
9]'),
 Text(0.7068965517241379, 0.8928571428571429, 'x[3] <= 40500.0\nentropy = 0.641\nsamples
= 86\nvalue = [14.0, 72.0]'),
 Text(0.6724137931034483, 0.8214285714285714, 'entropy = 0.0\nsamples = 27\nvalue = [0, 2
7]'),
 Text(0.7413793103448276, 0.8214285714285714, 'x[3] <= 84500.0\nentropy = 0.791\nsamples
= 59\nvalue = [14, 45]'),
 Text(0.6551724137931034, 0.75, 'x[2] <= 59.5\nentropy = 0.971\nsamples = 25\nvalue = [1
0, 15]'),
 Text(0.6206896551724138, 0.6785714285714286, 'x[3] <= 44500.0\nentropy = 0.998\nsamples
= 21\nvalue = [10, 11]'),
 Text(0.5862068965517241, 0.6071428571428571, 'entropy = 0.0\nsamples = 3\nvalue = [3,
0]'),
 Text(0.6551724137931034, 0.6071428571428571, 'x[3] <= 80500.0\nentropy = 0.964\nsamples
= 18\nvalue = [7, 11]'),
 Text(0.6206896551724138, 0.5357142857142857, 'x[2] <= 51.0\nentropy = 0.896\nsamples = 1
6\nvalue = [5, 11]'),
 Text(0.5862068965517241, 0.4642857142857143, 'x[2] <= 48.5\nentropy = 0.994\nsamples = 1
1\nvalue = [5, 6]'),
 Text(0.5517241379310345, 0.39285714285714285, 'x[0] <= 15779623.0\nentropy = 0.918\nsamp
les = 9\nvalue = [3, 6]'),
 Text(0.5172413793103449, 0.32142857142857145, 'x[0] <= 15661009.0\nentropy = 0.811\nsamp
les = 8\nvalue = [2, 6]'),
 Text(0.4827586206896552, 0.25, 'entropy = 0.0\nsamples = 2\nvalue = [0, 2]'),
 Text(0.5517241379310345, 0.25, 'x[0] <= 15676996.0\nentropy = 0.918\nsamples = 6\nvalue
= [2, 4]'),
 Text(0.5172413793103449, 0.17857142857142858, 'entropy = 0.0\nsamples = 1\nvalue = [1,
0]'),
 Text(0.5862068965517241, 0.17857142857142858, 'x[0] <= 15757599.0\nentropy = 0.722\nsamp
les = 5\nvalue = [1, 4]'),
 Text(0.5517241379310345, 0.10714285714285714, 'entropy = 0.0\nsamples = 3\nvalue = [0,
3]'),
 Text(0.6206896551724138, 0.10714285714285714, 'x[3] <= 48500.0\nentropy = 1.0\nsamples =
2\nvalue = [1, 1]'),
 Text(0.5862068965517241, 0.03571428571428571, 'entropy = 0.0\nsamples = 1\nvalue = [1,
0]'),
 Text(0.6551724137931034, 0.03571428571428571, 'entropy = 0.0\nsamples = 1\nvalue = [0,
1]'),
 Text(0.5862068965517241, 0.32142857142857145, 'entropy = 0.0\nsamples = 1\nvalue = [1,
0]'),
 Text(0.6206896551724138, 0.39285714285714285, 'entropy = 0.0\nsamples = 2\nvalue = [2,
0]'),
 Text(0.6551724137931034, 0.4642857142857143, 'entropy = 0.0\nsamples = 5\nvalue = [0,
5]'),
 Text(0.6896551724137931, 0.5357142857142857, 'entropy = 0.0\nsamples = 2\nvalue = [2,
0]'),
 Text(0.6896551724137931, 0.6785714285714286, 'entropy = 0.0\nsamples = 4\nvalue = [0,
4]'),
 Text(0.8275862068965517, 0.75, 'x[2] <= 52.5\nentropy = 0.523\nsamples = 34\nvalue = [4,
30]'),
 Text(0.7931034482758621, 0.6785714285714286, 'x[3] <= 93000.0\nentropy = 0.702\nsamples
= 21\nvalue = [4, 17]'),
 Text(0.7586206896551724, 0.6071428571428571, 'entropy = 0.0\nsamples = 6\nvalue = [0,
6]'),
```

```
 Text(0.8275862068965517, 0.6071428571428571, 'x[0] <= 15694368.0\nentropy = 0.837\nsampl
es = 15\nvalue = [4, 11]'),
 Text(0.7586206896551724, 0.5357142857142857, 'x[0] <= 15596828.5\nentropy = 0.971\nsampl
es = 5\nvalue = [3, 2]'),
 Text(0.7241379310344828, 0.4642857142857143, 'entropy = 0.0\nsamples = 2\nvalue = [0,
2]'),
 Text(0.7931034482758621, 0.4642857142857143, 'entropy = 0.0\nsamples = 3\nvalue = [3,
0]'),
 Text(0.896551724137931, 0.5357142857142857, 'x[2] <= 51.5\nentropy = 0.469\nsamples = 10
\nvalue = [1, 9]'),
 Text(0.8620689655172413, 0.4642857142857143, 'entropy = 0.0\nsamples = 8\nvalue = [0,
8]'),
 Text(0.9310344827586207, 0.4642857142857143, 'x[0] <= 15765222.0\nentropy = 1.0\nsamples
= 2\nvalue = [1, 1]'),
 Text(0.896551724137931, 0.39285714285714285, 'entropy = 0.0\nsamples = 1\nvalue = [0,
1]'),
 Text(0.9655172413793104, 0.39285714285714285, 'entropy = 0.0\nsamples = 1\nvalue = [1,
0]'),
 Text(0.8620689655172413, 0.6785714285714286, 'entropy = 0.0\nsamples = 13\nvalue = [0, 1
3]')]
```



2. Random Forest

1. Fitting Random Forest Classifier on Training Data :

In [18]:
```python
from sklearn.ensemble import RandomForestClassifier
```

In [19]:
```python
rfc = RandomForestClassifier(n_estimators = 600)
rfc.fit(x_train, y_train)
```

Out[19]:
```
▾ RandomForestClassifier
RandomForestClassifier(n_estimators=600)
```
(https://scikit-learn.org/1.4/modules/generated/sklearn.ensemble.RandomForestC

2. Predicting the Test Set Results :

In [20]:
```
y_pred = rfc.predict(x_test)
```

3. Model Evaluation :

In [21]:
```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

In [22]:
```
mat = confusion_matrix(y_test, y_pred)
mat
```

Out[22]:
```
array([[47,  5],
       [ 1, 27]], dtype=int64)
```

In [23]:
```
report = classification_report(y_test, y_pred)
print(report)
```

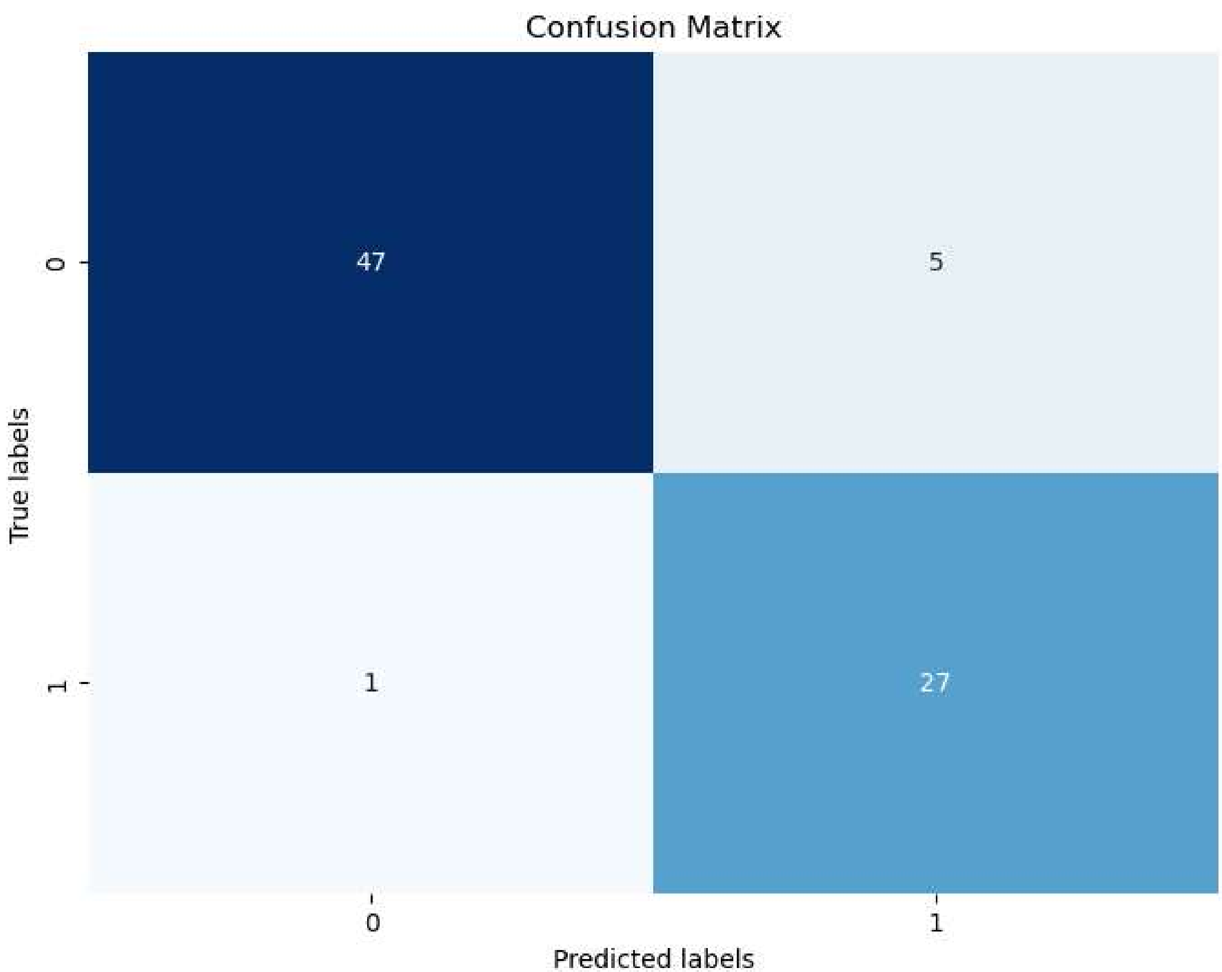
```
              precision    recall  f1-score   support

           0       0.98      0.90      0.94        52
           1       0.84      0.96      0.90        28

    accuracy                           0.93        80
   macro avg       0.91      0.93      0.92        80
weighted avg       0.93      0.93      0.93        80
```

In [24]:
```
score = accuracy_score(y_test, y_pred)
print(score)
```

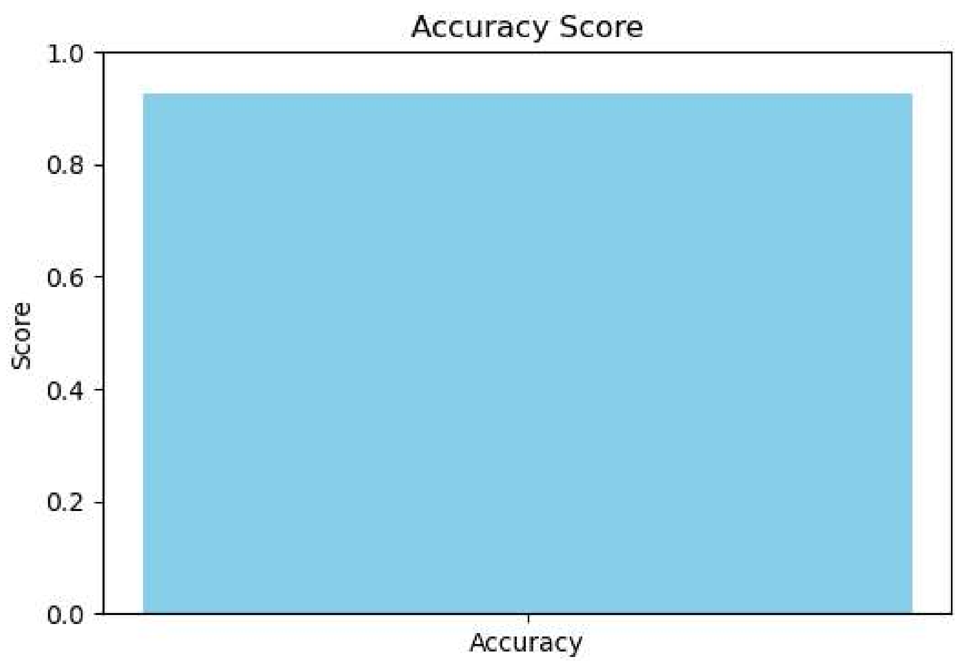
```
0.925
```

In [25]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

# Confusion Matrix Visualization
plt.figure(figsize=(8, 6))
sns.heatmap(mat, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

# Classification Report Visualization
print("Classification Report:")
print(report)

# Accuracy Score Visualization
plt.figure(figsize=(6, 4))
plt.bar(['Accuracy'], [score], color='skyblue')
plt.title('Accuracy Score')
plt.ylabel('Score')
plt.ylim(0, 1)
plt.show()
```



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

           0       0.98      0.90      0.94        52
           1       0.84      0.96      0.90        28

    accuracy                           0.93        80
   macro avg       0.91      0.93      0.92        80
weighted avg       0.93      0.93      0.93        80
```



Red Wine Quality Prediction using Random Forest

In [26]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

1. Data Pre-processing :

In [27]:
```python
df = pd.read_csv('winequality-red.csv')
```

In [28]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

In [29]:
```
df.head()
```

Out[29]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [30]:
```
df.tail()
```

Out[30]:

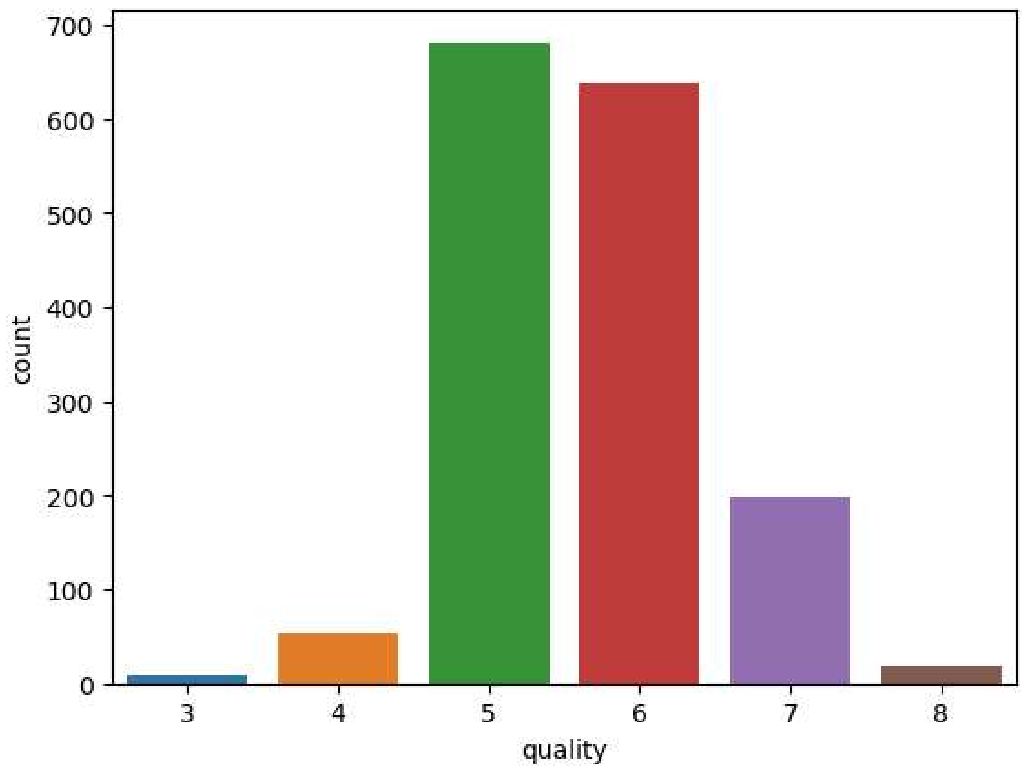
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6

In [31]:
```
df.describe().T
```

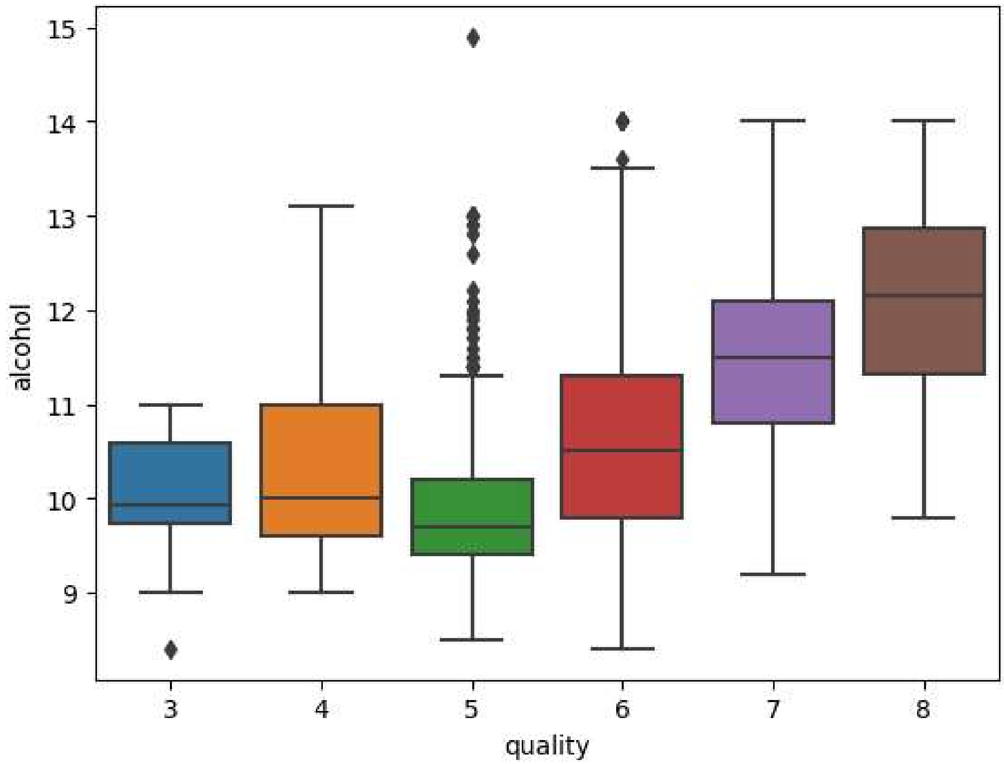
Out[31]:

	count	mean	std	min	25%	50%	75%	max
fixed acidity	1599.0	8.319637	1.741096	4.60000	7.1000	7.90000	9.200000	15.90000
volatile acidity	1599.0	0.527821	0.179060	0.12000	0.3900	0.52000	0.640000	1.58000
citric acid	1599.0	0.270976	0.194801	0.00000	0.0900	0.26000	0.420000	1.00000
residual sugar	1599.0	2.538806	1.409928	0.90000	1.9000	2.20000	2.600000	15.50000
chlorides	1599.0	0.087467	0.047065	0.01200	0.0700	0.07900	0.090000	0.61100
free sulfur dioxide	1599.0	15.874922	10.460157	1.00000	7.0000	14.00000	21.000000	72.00000
total sulfur dioxide	1599.0	46.467792	32.895324	6.00000	22.0000	38.00000	62.000000	289.00000
density	1599.0	0.996747	0.001887	0.99007	0.9956	0.99675	0.997835	1.00369
pH	1599.0	3.311113	0.154386	2.74000	3.2100	3.31000	3.400000	4.01000
sulphates	1599.0	0.658149	0.169507	0.33000	0.5500	0.62000	0.730000	2.00000
alcohol	1599.0	10.422983	1.065668	8.40000	9.5000	10.20000	11.100000	14.90000
quality	1599.0	5.636023	0.807569	3.00000	5.0000	6.00000	6.000000	8.00000

In [32]:
```
import seaborn as sns
sns.countplot(x='quality', data=df)
plt.show()
```



In [33]:
```
sns.boxplot(x='quality', y='alcohol', data=df)
plt.show()
```



In [34]:
```
X = df.drop('quality', axis=1)
Y = df['quality']
```

In [35]:
```
# Train-Test-Split

from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(X, Y, test_size=0.20, random_state=42)
```

2. Fitting Random Forest Algorithm to Training Data :

In [36]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [37]:
```
classifier = RandomForestClassifier(n_estimators=10, criterion='entropy')
classifier.fit(x_train, y_train)
```

Out[37]:
```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=10)
```
(https://scikit-learn.org/1.4/modules/generated/sklear

3. Predicting Test Set Results :

In [38]:
```
y_pred = classifier.predict(x_test)
```

4. Evaluate Performance of Model :

In [39]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
```

In [40]:
```
mat = confusion_matrix(y_test, y_pred)
mat
```

Out[40]:
```
array([[ 0,  0,  0,  1,  0,  0],
       [ 0,  0,  7,  3,  0,  0],
       [ 0,  2, 98, 30,  0,  0],
       [ 0,  0, 40, 81, 11,  0],
       [ 0,  0,  1, 19, 21,  1],
       [ 0,  0,  0,  2,  3,  0]], dtype=int64)
```

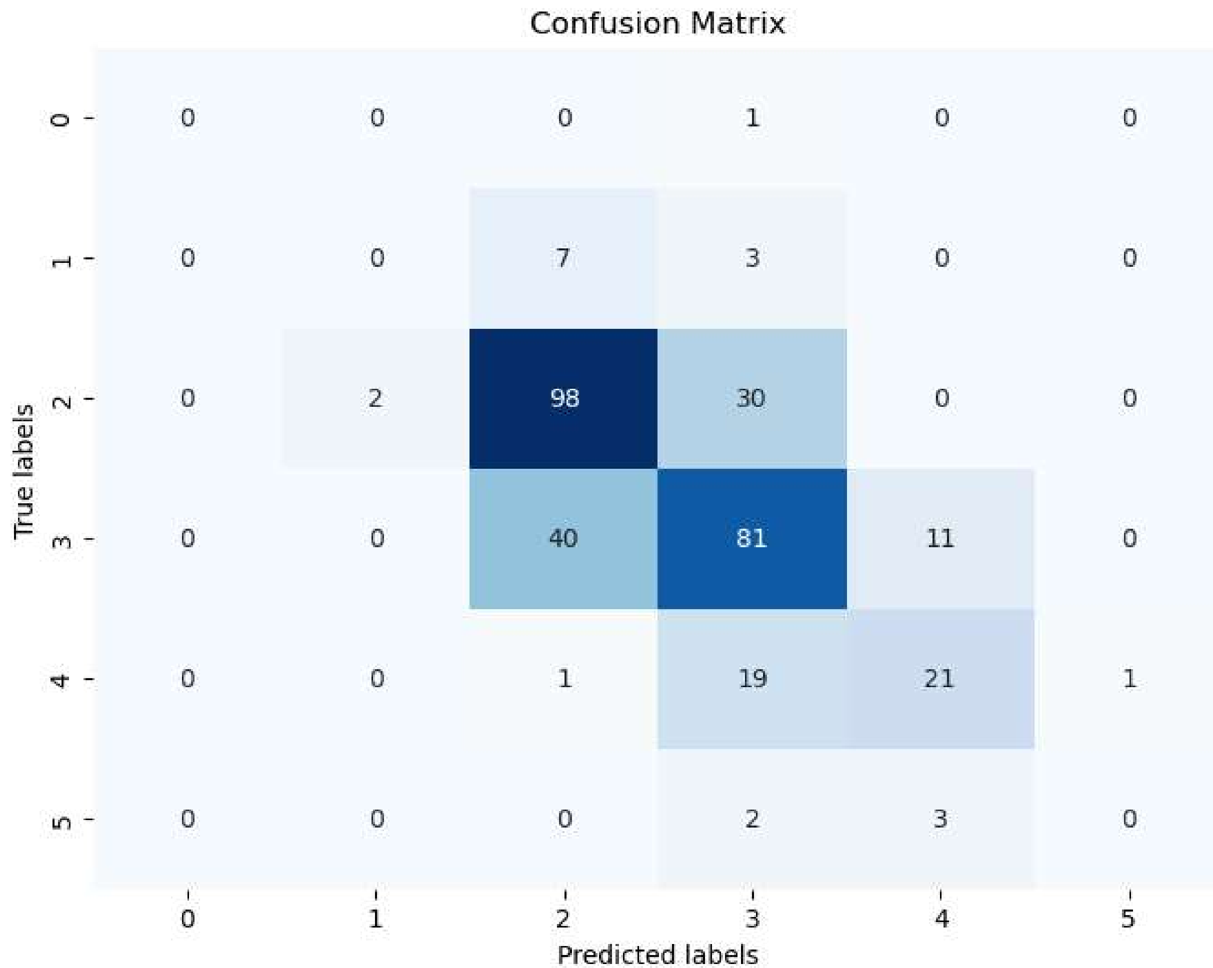
In [41]:
```
score = accuracy_score(y_test, y_pred)
score
```

Out[41]:
```
0.625
```

In [42]:
```
report = classification_report(y_test, y_pred,zero_division=1)
print(report)
```

```
              precision    recall  f1-score   support

           3       1.00      0.00      0.00         1
           4       0.00      0.00      0.00        10
           5       0.67      0.75      0.71       130
           6       0.60      0.61      0.60       132
           7       0.60      0.50      0.55        42
           8       0.00      0.00      0.00         5

    accuracy                           0.62       320
   macro avg       0.48      0.31      0.31       320
weighted avg       0.60      0.62      0.61       320
```

In [43]:
```
# Confusion Matrix Visualization
plt.figure(figsize=(8, 6))
sns.heatmap(mat, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()
```



Car Evaluation Using Random Forest

In [44]:
```
df = pd.read_csv("car_evaluation.csv")
```

In [45]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1727 entries, 0 to 1726
Data columns (total 7 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   vhigh    1727 non-null   object
 1   vhigh.1  1727 non-null   object
 2   2        1727 non-null   object
 3   2.1      1727 non-null   object
 4   small    1727 non-null   object
 5   low      1727 non-null   object
 6   unacc    1727 non-null   object
dtypes: object(7)
memory usage: 94.6+ KB
```

In [46]:
```
df.head()
```

Out[46]:

	vhigh	vhigh.1	2	2.1	small	low	unacc
0	vhigh	vhigh	2	2	small	med	unacc
1	vhigh	vhigh	2	2	small	high	unacc
2	vhigh	vhigh	2	2	med	low	unacc
3	vhigh	vhigh	2	2	med	med	unacc
4	vhigh	vhigh	2	2	med	high	unacc

In [47]:
```
df.shape
```

Out[47]: (1727, 7)

In [48]:
```
col_names = ['paint', 'break', 'alloy', 'wheel', 'headlight', 'gear', 'engine']
df.columns = col_names
col_names
```

Out[48]: ['paint', 'break', 'alloy', 'wheel', 'headlight', 'gear', 'engine']

In [49]:
```
df.head()
```

Out[49]:

	paint	break	alloy	wheel	headlight	gear	engine
0	vhigh	vhigh	2	2	small	med	unacc
1	vhigh	vhigh	2	2	small	high	unacc
2	vhigh	vhigh	2	2	med	low	unacc
3	vhigh	vhigh	2	2	med	med	unacc
4	vhigh	vhigh	2	2	med	high	unacc

In [50]:
```
col_names = ['paint', 'break', 'alloy', 'wheel', 'headlight', 'gear', 'engine']

for col in col_names:
  print(df[col].value_counts())
```

```
high     432
med      432
low      432
vhigh    431
Name: paint, dtype: int64
high     432
med      432
low      432
vhigh    431
Name: break, dtype: int64
3        432
4        432
5more    432
2        431
Name: alloy, dtype: int64
4       576
more    576
2       575
Name: wheel, dtype: int64
med      576
big      576
small    575
Name: headlight, dtype: int64
med     576
high    576
low     575
Name: gear, dtype: int64
unacc    1209
acc       384
good       69
vgood      65
Name: engine, dtype: int64
```

In [51]:
```
df['engine'].value_counts()
```

Out[51]:
```
unacc    1209
acc       384
good       69
vgood      65
Name: engine, dtype: int64
```

In [52]:
```
df.isnull().sum()
```

Out[52]:
```
paint        0
break        0
alloy        0
wheel        0
headlight    0
gear         0
engine       0
dtype: int64
```

In [53]:
```
X = df.drop(['engine'],axis=1)
y = df['engine']
```

In [54]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state=42
```

In [55]:
```
X_train.shape, X_test.shape
```

Out[55]: ((1381, 6), (346, 6))

In [56]:
```
# Perform one-hot encoding using pd.get_dummies() on the original DataFrame
X_train_encoded = pd.get_dummies(X_train, columns=['paint', 'break', 'alloy', 'wheel', 'he
X_test_encoded = pd.get_dummies(X_test, columns=['paint', 'break', 'alloy', 'wheel', 'head
```

In [57]:
```
X_train.head()
```

Out[57]:

	paint	break	alloy	wheel	headlight	gear
107	vhigh	high	2	2	small	low
900	med	vhigh	3	4	small	med
1708	low	low	5more	2	big	high
705	high	med	4	2	med	med
678	high	med	3	2	med	med

In [58]:
```
from sklearn.preprocessing import LabelEncoder

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Iterate over categorical columns and apply label encoding
for col in X_train.select_dtypes(include=['object']).columns:
    X_train[col] = label_encoder.fit_transform(X_train[col])
    X_test[col] = label_encoder.transform(X_test[col])

# Now, you can fit the Random Forest model
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

In [59]:
```
from sklearn.ensemble import RandomForestClassifier

# instantiate the classifier

model = RandomForestClassifier(random_state=0)

# fit the model

model.fit(X_train, y_train)

# Predict the Test set results

y_pred = model.predict(X_test)
```

In [60]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
```

```
0.9595375722543352
```

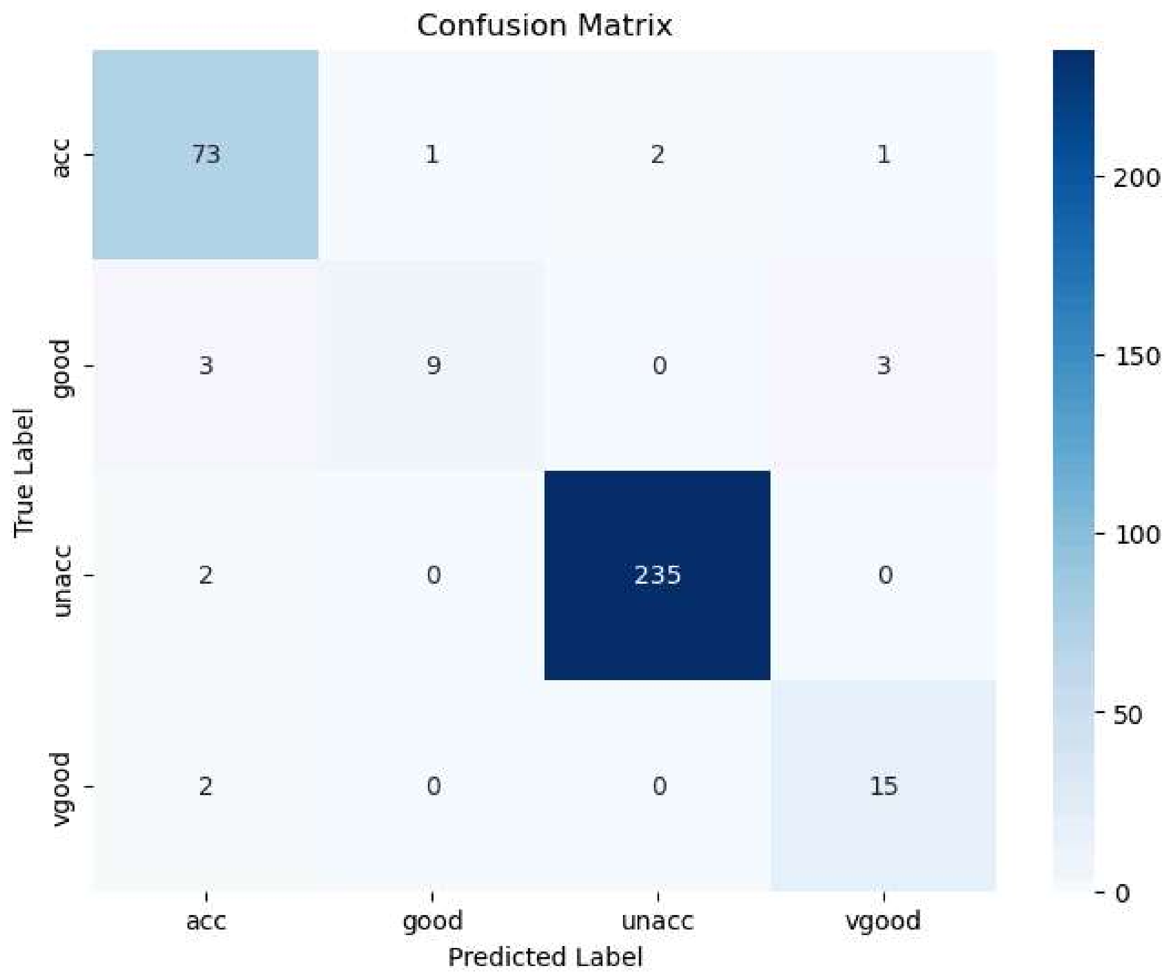
In [61]:
```
matrix = confusion_matrix(y_test, y_pred)
print(matrix)
```

```
[[ 73   1   2   1]
 [  3   9   0   3]
 [  2   0 235   0]
 [  2   0   0  15]]
```

In [62]:
```
report = classification_report(y_test, y_pred)
print(report)
```

```
              precision    recall  f1-score   support

         acc       0.91      0.95      0.93        77
        good       0.90      0.60      0.72        15
       unacc       0.99      0.99      0.99       237
       vgood       0.79      0.88      0.83        17

    accuracy                           0.96       346
   macro avg       0.90      0.86      0.87       346
weighted avg       0.96      0.96      0.96       346
```

In [63]:
```
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.heatmap(matrix, annot=True, fmt="d", cmap="Blues", xticklabels=model.classes_, ytickla
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```



Iris Data using Random Forest

In [64]:
```
df = pd.read_csv('IRIS.csv')
```

In [65]:
```
df.head()
```

Out[65]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [66]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [67]:
```
df['species'].unique()
```

Out[67]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [68]:
```
df['species'] = df['species'].replace({'Iris-setosa':1, 'Iris-versicolor':2, 'Iris-virgini
```

In [69]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    int64  
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
```

In [70]:
```
df.head()
```

Out[70]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	1
1	4.9	3.0	1.4	0.2	1
2	4.7	3.2	1.3	0.2	1
3	4.6	3.1	1.5	0.2	1
4	5.0	3.6	1.4	0.2	1

In [71]:
```
X = df.drop('species', axis=1)
Y = df['species']
```

In [72]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.20, random_state=42)
```

In [73]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[73]:
```
((120, 4), (30, 4), (120,), (30,))
```

In [74]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [75]:
```
classifier = RandomForestClassifier(n_estimators=10, criterion='entropy')
classifier.fit(x_train, y_train)
```

Out[75]:
```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=10)
```
(https://scikit-learn.org/1.4/modules/generated/sklear

In [76]:
```
y_pred = classifier.predict(x_test)
```

In [77]:
```
pd.DataFrame({'Actual':y_test, 'Predicted':y_pred})
```

Out[77]:

	Actual	Predicted
73	2	2
18	1	1
118	3	3
78	2	2
76	2	2
31	1	1
64	2	2
141	3	3
68	2	2
82	2	2
110	3	3
12	1	1
36	1	1
9	1	1
19	1	1
56	2	2
104	3	3
69	2	2
55	2	2
132	3	3
29	1	1
127	3	3
26	1	1
128	3	3
131	3	3
145	3	3
108	3	3
143	3	3
45	1	1
30	1	1

In [78]:
```
from sklearn.metrics import confusion_matrix
mat = confusion_matrix(y_test, y_pred)
mat
```

Out[78]:
```
array([[10,  0,  0],
       [ 0,  9,  0],
       [ 0,  0, 11]], dtype=int64)
```

In [79]:
```python
from sklearn.metrics import accuracy_score, classification_report

accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
```

```
1.0
```

In [80]:
```python
report = classification_report(y_test, y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        10
           2       1.00      1.00      1.00         9
           3       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

In [ ]: