Type: Supervised Learning

SubType: Classification

Data Type: Structured

Analytics Type: Predictive

Predicting Car Acceptability Using Classification Algorithms

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter('ignore')
```

In [5]:
```
df = pd.read_csv('cars.csv')
```

In [6]:
```
df
```

Out[6]:

	buying	maint	doors	persons	lug_boot	safety	class
0	vhigh	vhigh	2	2	small	low	unacc
1	vhigh	vhigh	2	2	small	med	unacc
2	vhigh	vhigh	2	2	small	high	unacc
3	vhigh	vhigh	2	2	med	low	unacc
4	vhigh	vhigh	2	2	med	med	unacc
...	...	...	...	...	...	...	...
1723	low	low	5more	more	med	med	good
1724	low	low	5more	more	med	high	vgood
1725	low	low	5more	more	big	low	unacc
1726	low	low	5more	more	big	med	good
1727	low	low	5more	more	big	high	vgood

1728 rows × 7 columns

In [7]:
```
df.columns
```

Out[7]:
```
Index(['buying', 'maint', 'doors', 'persons', 'lug_boot', 'safety', 'class'], dtype='object')
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
buying      0
maint       0
doors       0
persons     0
lug_boot    0
safety      0
class       0
dtype: int64
```

In [9]:
```
df['buying'].unique()
```

Out[9]:
```
array(['vhigh', 'high', 'med', 'low'], dtype=object)
```

In [10]:
```
for col in df:
    print(f'Column - {col}')
    print(df[col].unique())
    print('---')
    print(df[col].value_counts())
    print('--'*10)
```

```
Column - buying
['vhigh' 'high' 'med' 'low']
---
buying
vhigh    432
high     432
med      432
low      432
Name: count, dtype: int64
--------------------
Column - maint
['vhigh' 'high' 'med' 'low']
---
maint
vhigh    432
high     432
med      432
low      432
Name: count, dtype: int64
--------------------
Column - doors
['2' '3' '4' '5more']
---
doors
2        432
3        432
4        432
5more    432
Name: count, dtype: int64
--------------------
Column - persons
['2' '4' 'more']
---
persons
2       576
4       576
more    576
Name: count, dtype: int64
--------------------
Column - lug_boot
['small' 'med' 'big']
---
lug_boot
small    576
med      576
big      576
Name: count, dtype: int64
--------------------
Column - safety
['low' 'med' 'high']
---
safety
low     576
med     576
high    576
Name: count, dtype: int64
--------------------
Column - class
['unacc' 'acc' 'vgood' 'good']
---
class
unacc    1210
acc       384
good       69
vgood      65
Name: count, dtype: int64
--------------------
```

Feature Explanations

Column Name	Type	Description
buying	Categorical (Ordinal)	**Buying price** of the car — indicates the initial cost of purchasing the car. Possible values: `vhigh` (very high), `high` , `med` (medium), `low` .
maint	Categorical (Ordinal)	**Maintenance cost** of the car — ongoing cost to maintain the car. Possible values: `vhigh` , `high` , `med` , `low` .
doors	Categorical	Number of **doors** in the car. Helps assess practicality and size. Possible values: `2` , `3` , `4` , `5more` .
persons	Categorical (Ordinal)	Number of **passengers** the car can carry — a key factor in utility. Possible values: `2` , `4` , `more` .
lug_boot	Categorical (Ordinal)	**Luggage boot size** — how much storage the car has.

lug_boot	Categorical (Ordinal)	Possible values: `small`, `med`, `big`.
safety	Categorical (Ordinal)	**Safety level** of the car — essential for decision-making. Possible values: `low`, `med`, `high`.
class	Categorical (Target Variable)	The **acceptability** of the car based on all the above features. This is the label you're predicting. Possible values: `unacc` (unacceptable), `acc` (acceptable), `good`, `vgood` (very good).

Ordinal Encoding

In [13]:
```
df['buying'] = df['buying'].map({'vhigh': 3,
                                 'high':2,
                                 'med':1,
                                 'low':0})
```

In [14]:
```
df['maint'] = df['maint'].map({'vhigh':3,
                               'high':2,
                               'med':1,
                               'low':0})
```

In [15]:
```
df['doors'] = df['doors'].map({'2': 0,
                               '3':1,
                               '4':2,
                               '5more':3})
```

In [16]:
```
df['persons'] = df['persons'].map({'2':0,
                                   '4':1,
                                   'more':2}).astype(int)
```

In [17]:
```
df['lug_boot'] = df['lug_boot'].map({'small':0,
                                     'med':1,
                                     'big':2}).astype(int)
```

In [18]:
```
df['safety'] = df['safety'].map({'low':0,
                                 'med':1,
                                 'high':2})
```

In [19]:
```
#Target Variable
df['class'] = df['class'].map({'unacc':0,
                               'acc':1,
                               'good':2,
                               'vgood':3})
```

In [20]:
```
df.head()
```

Out[20]:

	buying	maint	doors	persons	lug_boot	safety	class
0	3	3	0	0	0	0	0
1	3	3	0	0	0	1	0
2	3	3	0	0	0	2	0
3	3	3	0	0	1	0	0
4	3	3	0	0	1	1	0

In [21]:
```
df.isnull().sum()
```

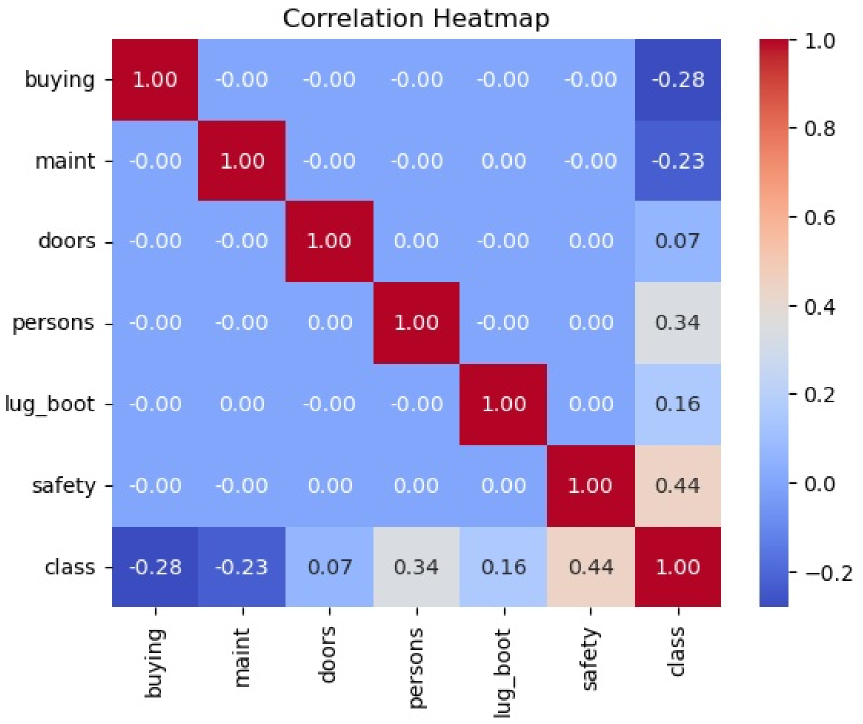
Out[21]:
```
buying      0
maint       0
doors       0
persons     0
lug_boot    0
safety      0
class       0
dtype: int64
```

Encoding Legend

Feature	Categories	Encoding
`buying`	low, med, high, vhigh	0, 1, 2, 3
`maint`	low, med, high, vhigh	0, 1, 2, 3
`doors`	2, 3, 4, 5more	0, 1, 2, 3
`persons`	2, 4, more	0, 1, 2
`lug_boot`	small, med, big	0, 1, 2

safety	low, med, high	0, 1, 2
class	unacc, acc, good, vgood	0, 1, 2, 3

In [23]:
```
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



Feature Selection

In [25]:
```
X = df[['buying', 'maint', 'doors', 'persons', 'lug_boot','safety']]
y = df['class']
```

Train Test Split

In [27]:
```
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 = 43)
```

Modeling

1. Logistic Regression

In [30]:
```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
```

Out[30]:
```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

In [31]:
```
ypred_train = model.predict(X_train)
ypred_test = model.predict(X_test)
```

In [32]:
```
from sklearn.metrics import accuracy_score

print('Train Accuracy:',accuracy_score(y_train, ypred_train))
print('Test Accuracy:',accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 0.829232995658466
Test Accuracy: 0.8323699421965318
```

In [33]:
```
from sklearn.model_selection import cross_val_score

print('CV Score:',cross_val_score(model, X_train, y_train, cv=5,
```

```
                                 scoring='accuracy').mean())
```

```
CV Score: 0.8263145503060745
```

In [34]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, ypred_test))
```

```
              precision    recall  f1-score   support

           0       0.89      0.92      0.90       231
           1       0.69      0.68      0.68        84
           2       0.50      0.36      0.42        14
           3       1.00      0.82      0.90        17

    accuracy                           0.83       346
   macro avg       0.77      0.69      0.73       346
weighted avg       0.83      0.83      0.83       346
```

Hyperparameter tuning using GridSearchCV

In [36]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000],
    'solver': ['liblinear', 'saga', 'lbfgs', 'newton-cg'],
    'max_iter': [100, 500, 1000, 2000],

}



grid = GridSearchCV(LogisticRegression(max_iter=1000), param_grid,
                    cv=5, scoring='accuracy')

grid.fit(X_train, y_train)


print("Best Parameters:", grid.best_params_)
print("Best Cross-Validated Accuracy:", grid.best_score_)

# Predict with best model
best_model = grid.best_estimator_
y_pred = best_model.predict(X_test)

# Evaluate
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

print("\nTest Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Best Parameters: {'C': 100, 'max_iter': 100, 'solver': 'lbfgs'}
Best Cross-Validated Accuracy: 0.8313896300947

Test Accuracy: 0.8410404624277457

Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.91      0.90       231
           1       0.72      0.68      0.70        84
           2       0.57      0.57      0.57        14
           3       0.94      0.88      0.91        17

    accuracy                           0.84       346
   macro avg       0.78      0.76      0.77       346
weighted avg       0.84      0.84      0.84       346
```

No improvement after applying Hypertuning

2. Ridge Classifier

In [39]:
```
X = df[['buying', 'maint', 'doors', 'persons', 'lug_boot','safety']]
y = df['class']
```

In [40]:
```
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 = 43)
```

Hyperparameter Tuning

In [42]:
```
from sklearn.linear_model import RidgeClassifier

ridge = RidgeClassifier()

param_grid = {'alpha': [0.01, 0.1, 1.0, 10.0, 100.0]}

grid = GridSearchCV(ridge, param_grid, cv=5)
grid.fit(X_train, y_train)
grid.best_estimator_
```

Out[42]:
```
RidgeClassifier
RidgeClassifier(alpha=10.0)
```

In [43]:
```
from sklearn.linear_model import RidgeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score

# Create the model
ridge = RidgeClassifier(alpha=10)
ridge.fit(X_train, y_train)
```

Out[43]:
```
RidgeClassifier
RidgeClassifier(alpha=10)
```

In [44]:
```
ypred_train = ridge.predict(X_train)
ypred_test = ridge.predict(X_test)
```

In [45]:
```
from sklearn.metrics import accuracy_score

print('Train Accuracy:',accuracy_score(y_train, ypred_train))
print('Test Accuracy:',accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 0.7771345875542692
Test Accuracy: 0.7398843930635838
```

In [46]:
```
from sklearn.model_selection import cross_val_score

print('CV Score:',cross_val_score(ridge, X_train, y_train, cv=5,scoring='accuracy').mean())
```

```
CV Score: 0.7771333647255795
```

In [47]:
```
from sklearn.metrics import classification_report, confusion_matrix

print("\nClassification Report:\n", classification_report(y_test, ypred_test))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_test))
```

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

           0       0.81      0.95      0.88       231
           1       0.48      0.43      0.45        84
           2       0.00      0.00      0.00        14
           3       0.00      0.00      0.00        17

    accuracy                           0.74       346
   macro avg       0.32      0.35      0.33       346
weighted avg       0.66      0.74      0.70       346


Confusion Matrix:
 [[231   0   0   0]
 [  0  84   0   0]
 [  0   0  14   0]
 [  0   0   0  17]]
```

3. K Nearest Neighbour

In [49]:
```
X = df[['buying', 'maint', 'doors', 'persons', 'lug_boot','safety']]
y = df['class']
```

In [50]:
```
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 = 43)
```

Scaling Data

In [52]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)
```

Hyperparameter tuning for KNN classifier

In [54]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier

param_grid = {
    'n_neighbors': list(range(1, 100)),
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean', 'manhattan']
}

grid_knn = GridSearchCV(KNeighborsClassifier(), param_grid, cv=5, scoring='accuracy')
grid_knn.fit(X_train, y_train)

print("Best Parameters:", grid_knn.best_params_)
print("Best Cross-Validation Score:", grid_knn.best_score_)
```

```
Best Parameters: {'metric': 'euclidean', 'n_neighbors': 6, 'weights': 'distance'}
Best Cross-Validation Score: 0.9573013132422957
```

KNN with Best HyperParameters

In [56]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors = 6,
                          metric = 'euclidean',
                          weights = 'distance')
knn.fit(X_train, y_train)
```

Out[56]:
```
KNeighborsClassifier

KNeighborsClassifier(metric='euclidean', n_neighbors=6, weights='distance')
```

In [57]:
```
ypred_test = knn.predict(X_test)
ypred_train = knn.predict(X_train)
```

In [58]:
```
from sklearn.metrics import accuracy_score
print('Train Accuracy:', accuracy_score(y_train, ypred_train))
print('Test Accuracy:', accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 1.0
Test Accuracy: 0.953757225433526
```

In [59]:
```
from sklearn.model_selection import cross_val_score

print('CV Score:', cross_val_score(knn, X_train,y_train, cv=5, scoring='accuracy').mean())
```

```
CV Score: 0.9573013132422957
```

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

print("\nClassification Report:\n", classification_report(y_test, ypred_test))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_test))
```

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

           0       0.97      1.00      0.98       231
           1       0.90      0.93      0.91        84
           2       1.00      0.64      0.78        14
           3       1.00      0.76      0.87        17

    accuracy                           0.95       346
   macro avg       0.97      0.83      0.89       346
weighted avg       0.96      0.95      0.95       346


Confusion Matrix:
 [[231   0   0   0]
 [  0  84   0   0]
 [  0   0  14   0]
 [  0   0   0  17]]
```

In [61]:
```
data = [[1,1,3,2,2,2]]

data_scaled = scaler.transform(data)
```

```python
pred = knn.predict(data_scaled)
print("Predicted Label:", pred[0])

if pred[0] == 0:
    print('unacceptable')
elif pred[0] == 1:
    print('accceptable')
elif pred[0] == 2:
    print('good')
else:
    print('vgood')
```

```
Predicted Label: 3
vgood
```

Tree Based Classifiers

4. Random Forest

In [64]:
```python
X = df[['buying', 'maint', 'doors', 'persons', 'lug_boot','safety']]
y = df['class']
```

In [65]:
```python
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 = 43)
```

In [66]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

rf = RandomForestClassifier(random_state=42)

param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'criterion': ['gini', 'entropy']
}


grid = GridSearchCV(rf, param_grid, cv=5)
grid.fit(X_train, y_train)

best_rf = grid.best_estimator_


print("Best Parameters:", grid.best_params_)
print("Best Cross-Validated Accuracy:", grid.best_score_)
```

```
Best Parameters: {'criterion': 'entropy', 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_e
stimators': 200}
Best Cross-Validated Accuracy: 0.976134044890912
```

In [67]:
```python
rf = RandomForestClassifier(random_state =42, criterion = 'entropy',
                            max_depth = None, min_samples_leaf = 1,
                            min_samples_split = 2, n_estimators=200)

rf.fit(X_train, y_train)
```

Out[67]:
```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=200, random_state=42)
```

In [68]:
```python
ypred_train = rf.predict(X_train)
ypred_test = rf.predict(X_test)
```

In [69]:
```python
from sklearn.metrics import accuracy_score

print('Train Accuracy:',accuracy_score(y_train, ypred_train))
print('Test Accuracy:',accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 1.0
Test Accuracy: 0.9855491329479769
```

In [70]:
```python
from sklearn.model_selection import cross_val_score

print('CV Score:',cross_val_score(rf, X_train, y_train, cv=5, scoring='accuracy').mean())
```

```
CV Score: 0.976134044890912
```

In [71]:
```
from sklearn.metrics import classification_report, confusion_matrix

print("\nClassification Report:\n", classification_report(y_test, ypred_test))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_test))
```

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

           0       1.00      1.00      1.00       231
           1       0.98      0.96      0.97        84
           2       1.00      0.93      0.96        14
           3       0.85      1.00      0.92        17

    accuracy                           0.99       346
   macro avg       0.96      0.97      0.96       346
weighted avg       0.99      0.99      0.99       346


Confusion Matrix:
 [[231   0   0   0]
 [  0  84   0   0]
 [  0   0  14   0]
 [  0   0   0  17]]
```

In [72]:
```
data = [[1,1,3,2,2,2]]


pred = rf.predict(data)
print("Predicted Label:", pred[0])

if pred[0] == 0:
    print('unacceptable')
elif pred[0] == 1:
    print('accceptable')
elif pred[0] == 2:
    print('good')
else:
    print('vgood')
```

```
Predicted Label: 3
vgood
```

5. Decision Tree Classifier

In [74]:
```
X = df[['buying', 'maint', 'doors', 'persons', 'lug_boot','safety']]
y = df['class']
```

In [75]:
```
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 = 43)
```

Hyperparameter Tuning using GridSearchCV

In [77]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV

tree = DecisionTreeClassifier(random_state=42)

param_grid = {
    'criterion': ['gini', 'entropy', 'log_loss'],
    'max_depth': [None,5,10,20],
    'min_samples_split':[2,5,10],
    'min_samples_leaf':[1,2,4]
}

grid = GridSearchCV(tree, param_grid, cv=5)
grid.fit(X_train, y_train)


print("Best Parameters:", grid.best_params_)
print("Best Cross-Validated Accuracy:", grid.best_score_)
```

```
Best Parameters: {'criterion': 'entropy', 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best Cross-Validated Accuracy: 0.9790221315335114
```

In [78]:
```
tree = DecisionTreeClassifier(random_state=42, criterion = 'entropy',
                              max_depth=None, min_samples_leaf=1,
                              min_samples_split = 2)

tree.fit(X_train, y_train)
```

Out[78]:

```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=42)
```

In [79]:

```
ypred_train = tree.predict(X_train)
ypred_test = tree.predict(X_test)
```

In [80]:

```
from sklearn.metrics import accuracy_score

print('Train Accuracy:',accuracy_score(y_train, ypred_train))
print('Test Accuracy:',accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 1.0
Test Accuracy: 0.976878612716763
```

In [81]:

```
from sklearn.model_selection import cross_val_score

print('CV Score:',cross_val_score(tree, X_train, y_train, cv=5, scoring='accuracy').mean())
```

```
CV Score: 0.9790221315335114
```

In [82]:

```
from sklearn.metrics import classification_report, confusion_matrix

print("\nClassification Report:\n", classification_report(y_test, ypred_test))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_test))
```

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

           0       1.00      0.99      1.00       231
           1       0.96      0.94      0.95        84
           2       0.87      0.93      0.90        14
           3       0.85      1.00      0.92        17

    accuracy                           0.98       346
   macro avg       0.92      0.97      0.94       346
weighted avg       0.98      0.98      0.98       346


Confusion Matrix:
 [[231   0   0   0]
 [  0  84   0   0]
 [  0   0  14   0]
 [  0   0   0  17]]
```

In [83]:

```
data = [[1,1,3,2,2,3]]


pred = tree.predict(data)
print("Predicted Label:", pred[0])

if pred[0] == 0:
    print('unacceptable')
elif pred[0] == 1:
    print('accceptable')
elif pred[0] == 2:
    print('good')
else:
    print('vgood')
```

```
Predicted Label: 3
vgood
```

6. Gradient Boosting

In [85]:

```
X = df[['buying', 'maint', 'doors', 'persons', 'lug_boot','safety']]
y = df['class']
```

In [86]:

```
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 = 43)
```

In [87]:

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV

gb = GradientBoostingClassifier(random_state=42)
gb.fit(X_train, y_train)
```

Out[87]:

```
GradientBoostingClassifier
GradientBoostingClassifier(random_state=42)
```

In [88]:

```
ypred_train = gb.predict(X_train)
ypred_test = gb.predict(X_test)
```

In [89]:

```
from sklearn.metrics import accuracy_score

print('Train Accuracy:',accuracy_score(y_train, ypred_train))
print('Test Accuracy:',accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 0.9971056439942113
Test Accuracy: 0.9826589595375722
```

In [90]:

```
from sklearn.model_selection import cross_val_score

print('CV Score:',cross_val_score(gb, X_train, y_train, cv=5, scoring='accuracy').mean())
```

```
CV Score: 0.9862606602835766
```

In [91]:

```
from sklearn.metrics import classification_report, confusion_matrix

print("\nClassification Report:\n", classification_report(y_test, ypred_test))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_test))
```

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

           0       1.00      0.99      1.00       231
           1       0.96      0.96      0.96        84
           2       0.93      0.93      0.93        14
           3       0.89      1.00      0.94        17

    accuracy                           0.98       346
   macro avg       0.95      0.97      0.96       346
weighted avg       0.98      0.98      0.98       346


Confusion Matrix:
 [[231   0   0   0]
 [  0  84   0   0]
 [  0   0  14   0]
 [  0   0   0  17]]
```

In [92]:

```
data = [[1,1,3,2,2,2]]


pred = gb.predict(data)
print("Predicted Label:", pred[0])

if pred[0] == 0:
    print('unacceptable')
elif pred[0] == 1:
    print('accceptable')
elif pred[0] == 2:
    print('good')
else:
    print('vgood')
```

```
Predicted Label: 3
vgood
```

7. XGBoost Classifier

In [94]:

```
X = df[['buying', 'maint', 'doors', 'persons', 'lug_boot','safety']]
y = df['class']
```

In [95]:

```
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 = 43)
```

In [96]:

```
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV

xgb = XGBClassifier(use_label_encoder=False, eval_metric='mlogloss', random_state=42)

param_grid = {
    'n_estimators': [100, 200],
    'learning_rate': [0.05, 0.1],
    'max_depth': [3, 5],
```

```
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

grid = GridSearchCV(xgb, param_grid, cv=5)
grid.fit(X_train, y_train)

# Results
print("Best Parameters:", grid.best_params_)
print("Best CV Accuracy:", grid.best_score_)
```

```
Best Parameters: {'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200, 'subsample
': 0.8}
Best CV Accuracy: 0.9905927902474755
```

In [97]:
```
xgb = XGBClassifier(colsample_bytree = 1.0, learning_rate = 0.1,
                    max_depth = 5, n_estimators = 200, subsample = 0.8)

xgb.fit(X_train, y_train)
```

Out[97]:

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=1.0, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              feature_weights=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.1, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=5,
              max_leaves=None, min_child_weight=None, missing=nan,
```

In [98]:
```
ypred_train = xgb.predict(X_train)
ypred_test = xgb.predict(X_test)
```

In [99]:
```
from sklearn.metrics import accuracy_score

print('Train Accuracy:',accuracy_score(y_train, ypred_train))
print('Test Accuracy:',accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 1.0
Test Accuracy: 0.9855491329479769
```

In [100…
```
from sklearn.model_selection import cross_val_score

print('CV Score:',cross_val_score(xgb, X_train, y_train, cv=5, scoring='accuracy').mean())
```

```
CV Score: 0.9920368335687751
```

In [101…
```
from sklearn.metrics import classification_report, confusion_matrix

print("\nClassification Report:\n", classification_report(y_test, ypred_test))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_test))
```

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

           0       1.00      1.00      1.00       231
           1       0.98      0.96      0.97        84
           2       0.93      0.93      0.93        14
           3       0.89      1.00      0.94        17

    accuracy                           0.99       346
   macro avg       0.95      0.97      0.96       346
weighted avg       0.99      0.99      0.99       346


Confusion Matrix:
 [[231   0   0   0]
 [  0  84   0   0]
 [  0   0  14   0]
 [  0   0   0  17]]
```

Summary

Algorithm	Train Accuracy	Test Accuracy	CV Score	Overfitting	Verdict / Notes
XGBoost	1.000	**0.9855**	**0.9920**	✖ No	Best Generalization & Top CV Score
Gradient Boosting	0.9971	0.9827	0.9863	✖ No	High performance, great balance
Random Forest	1.000	0.9855	0.9761	✖ No	Excellent performance

Decision Tree	1.000	0.9769	0.9805	⚠ Mild	Slightly overfits
KNN	1.000	0.9538	0.9573	✅ Yes	High variance, overfitting
Logistic Regression	0.8292	0.8324	0.8263	❌ No	Basic baseline, not suitable
Ridge Classifier	0.7771	0.7399	0.7771	❌ No	Underperformed

Encoding Legend

Feature	Categories	Encoding
`buying`	low, med, high, vhigh	0, 1, 2, 3
`maint`	low, med, high, vhigh	0, 1, 2, 3
`doors`	2, 3, 4, 5more	0, 1, 2, 3
`persons`	2, 4, more	0, 1, 2
`lug_boot`	small, med, big	0, 1, 2
`safety`	low, med, high	0, 1, 2
`class`	unacc, acc, good, vgood	0, 1, 2, 3

In [104…
```
data = [[1,1,3,2,2,2]]
# [buying=med, maint=med, doors=5more,
#  persons=more, lug_boot=big, safety=high]

pred = xgb.predict(data)
print("Predicted Label:", pred[0])

if pred[0] == 0:
    print('unacceptable')
elif pred[0] == 1:
    print('accceptable')
elif pred[0] == 2:
    print('good')
else:
    print('vgood')
```

```
Predicted Label: 3
vgood
```

In [105…
```
import pickle

# Assuming 'xgb_model' is your trained XGBoost model
with open('model.pkl', 'wb') as f:
    pickle.dump(xgb, f)

print("Model exported successfully!")
```

```
Model exported successfully!
```

In [106…
```
import pickle

# Load the model
with open('model.pkl', 'rb') as f:
    loaded_model = pickle.load(f)

# Now, you can use 'loaded_model' for predictions
```

In [107…
```
data = [[1,1,3,2,2,2]]
# [buying=med, maint=med, doors=5more,
#  persons=more, lug_boot=big, safety=high]

pred = loaded_model.predict(data)
print("Predicted Label:", pred[0])

if pred[0] == 0:
    print('unacceptable')
elif pred[0] == 1:
    print('accceptable')
elif pred[0] == 2:
    print('good')
else:
    print('vgood')
```

```
Predicted Label: 3
vgood
```