Vietnam National University,
Ho Chi Minh City

University of Science

Faculty of Information Technology

Project 03: Decision Tree

CS14003 – Introduction to Artificial Intelligence

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April 22, 2025

Contents

1 Group Information

- **Subject:** Introduction to Artificial Intelligence.
- **Class:** 23CLC09.
- **Lecturer:** Bui Duy Dang, Le Nhut Nam.
- **Team members:**

No.	Fullname	Student ID	Email
1	Ngo Nguyen The Khoa	23127065	nntkhoa23@clc.fitus.edu.vn
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2 Project Information

- **Name:** Decision Tree Classifier.
- **Developing Environment:** Visual Studio Code (Windows).
- **Programming Language:** Python.
- **Libraries and Tools:**
  - **Libraries:**
    - **scikit-learn:** Machine learning library for training and evaluating decision tree models.
    - **pandas:** Data manipulation and analysis.
    - **numpy:** Numerical operations.
    - **matplotlib**, **seaborn:** Data visualization libraries.
    - **graphviz:** Visualization of decision trees.
  - **Tools:**
    - **Git**, **GitHub**: Source code version control.
    - **Visual Studio Code**: Code editor for Python, LaTeX.
- **Datasets:**
  - **Breast Cancer Wisconsin (Diagnostic)**
  - **Wine Quality**
  - **Car Evaluation**

3 Work Assignment Table

No.	Task Description	Assigned to	Rate
1	Prepare all three datasets with proper preprocessing and stratified splits.	T.Khoa, M.Duy	100%
2	Implement and train decision tree models for each dataset with different train/test splits.	T.Khoa, A.Khoa	100%
3	Visualize decision trees using Graphviz.	Anh Khoa	100%
4	Evaluate classifiers with classification reports and confusion matrices.	A.Khoa, T.Khoa	100%
5	Analyze impact of tree depth on accuracy (80/20 split, varying max_depth values).	Minh Duy	100%
6	Research and integrate additional dataset.	Anh Khoa	100%
7	Conduct comparative analysis across the 3 datasets.	The Khoa	100%
8	Visualize and format results (accuracy tables, charts, dataset distributions, etc.).	Minh Duy	100%
9	Write and format final report with all results, insights, and figures.	Minh Duy	100%
10	Ensure overall cohesion, proofreading, and prepare final PDF submission.	All	100%

4 Self-evaluation

No.	Task Description	Rate
1	Prepare datasets with stratified splits and visualize class distributions.	100%
2	Train and visualize decision tree models on all datasets using multiple train/test splits.	100%
3	Evaluate decision trees using classification reports and confusion matrices.	100%
4	Analyze the impact of decision tree depth on model accuracy.	100%
5	Research and integrate an additional dataset for training and evaluation.	100%
6	Conduct comparative analysis across all datasets.	100%
7	Create charts, tables, and visualizations to support findings.	100%
8	Write and format the final report with insights and well-organized results.	100%
9	Team collaboration and adherence to project schedule.	100%

5 Dataset Analysis and Experiments

5.1 Dataset Preparation and Preprocessing

```python
def split_and_visualize(X, y, dataset_name: str):
    splits = {}

    for ratio in [0.4, 0.6, 0.8, 0.9]:
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, train_size=ratio, stratify=y, shuffle=True, random_state=42
        )

        splits[ratio] = (X_train, X_test, y_train, y_test)

    return splits
```

To shuffle the dataset and ensure it is split in a stratified fashion, we use the `train_test_split` function from `sklearn.model_selection`. The function takes the dataset and the target variable as inputs, along with the desired train-test split ratio.

- The `shuffle` parameter randomizes the order of the samples before splitting.
- The `stratify` parameter ensures the dataset is split in a stratified fashion.

5.2 Interpreting Classification Report and Confusion Matrix

```python
def train_evaluate_decision_tree(
    X_train,
    y_train,
    X_test,
    y_test,
    dataset_name: str,
    split_ratio,
):
    # Dynamically set feature and class names
    feature_names = X_train.columns.tolist()
    class_names = [str(cls) for cls in np.unique(y_train)]

    # Train model
    clf = DecisionTreeClassifier(criterion="entropy", random_state=42)
    clf.fit(X_train, y_train)

    # Predictions
    y_pred = clf.predict(X_test)

    # Classification Report (with validation)
    print(f"\nClassification Report ({dataset_name}, {display_ratio(split_ratio)}):")
```

```
    print(
        classification_report(
            y_test,
            y_pred,
            target_names=class_names,
            labels=np.unique(y_test),  # Ensure alignment with actual classes
        )
    )

    # Confusion Matrix
    sns.heatmap(
        confusion_matrix(y_test, y_pred),
        annot=True,
        fmt="d",
        xticklabels=class_names,
        yticklabels=class_names,
    )
```

To generate the classification report and confusion matrix:

- The `classification_report` function provides a detailed report of the model's performance, including precision, recall, and F1-score for each class.
- The `confusion_matrix` function generates a matrix that shows the number of correct and incorrect predictions for each class.

5.3 Classification Report and Confusion Matrix Interpretion

- The classification report summarizes, for each class c:
  - **Precision** (Prec_c): measures the fraction of samples predicted as c that truly belong to c.
  - **Recall** (Rec_c): measures the fraction of true-c samples correctly identified.
  - **F1-score** (F1_c): the harmonic mean of precision and recall
  - **Support**: the number of true samples of class c.
- For example, with a binary problem (classes "positive"/"negative"), the confusion matrix is:

$$\mathbf{CM} = \begin{pmatrix} \text{TN} & \text{FP} \\ \text{FN} & \text{TP} \end{pmatrix},$$

where

TN **(True Negative):** correctly predicted negatives.

FP **(False Positive, Type I error):** negatives incorrectly predicted as positives.

FN **(False Negative, Type II error):** positives incorrectly predicted as negatives.

TP **(True Positive):** correctly predicted positives.

From these entries we derive:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}},$$
$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{FP} + \text{TN}},$$
$$\text{False Negative Rate (FNR)} = \frac{\text{FN}}{\text{FN} + \text{TP}}$$

$$\text{Specificity (True Negative Rate)} = \frac{\text{TN}}{\text{TN} + \text{FP}},$$
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}},$$
$$\text{Recall (Sensitivity)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

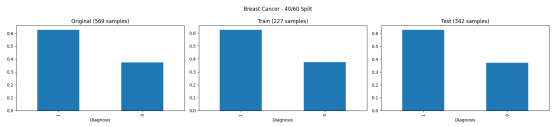
A well-performing classifier exhibits high TP and TN, and low FP and FN.

- *High FP* indicates many false alarms.
- *High FN* indicates many misses—critical in domains such as medical diagnosis.

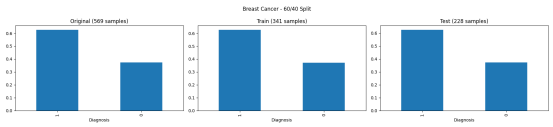
5.4 Breast Cancer Wisconsin Dataset

Dataset Description

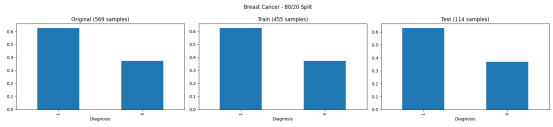
- **Description:** The UCI Breast Cancer Wisconsin (Diagnostic) dataset is used for classifying tumors as malignant or benign based on features derived from its imaging data.
- **Dataset Info:** 569 samples, binary labels (malignant vs. benign), 30 numeric features.
- **Preprocessing:** shuffle & stratified split at 40/60, 60/40, 80/20, 90/10.



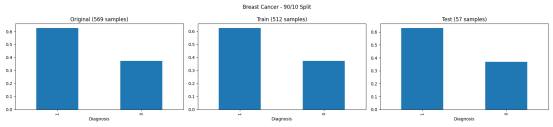
(a) Breast Cancer: class distribution (40/60 split).



(b) Breast Cancer: class distribution (60/40 split).



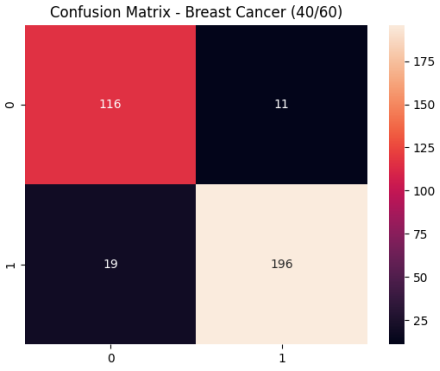
(c) Breast Cancer: class distribution (80/20 split).



(d) Breast Cancer: class distribution (90/10 split).

Figure 1: Class distributions

Evaluating the decision tree classifiers



(a) Breast Cancer: confusion matrix (40/60 split).

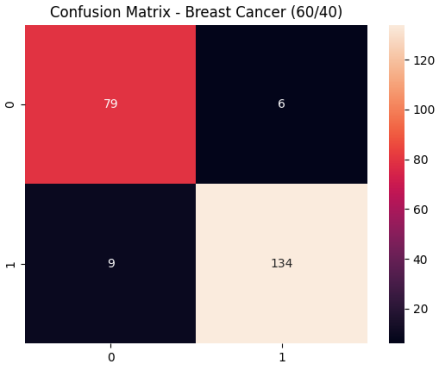
```
Classification Report (Breast Cancer, 40/60):
              precision    recall  f1-score   support

           0       0.86      0.91      0.89       127
           1       0.95      0.91      0.93       215

    accuracy                           0.91       342
   macro avg       0.90      0.91      0.91       342
weighted avg       0.91      0.91      0.91       342
```

(b) Breast Cancer: Classification Report (40/60 split).

Figure 2: Classification Report and Confusion Matrix (40/60 split)



(a) Breast Cancer: confusion matrix (60/40 split).

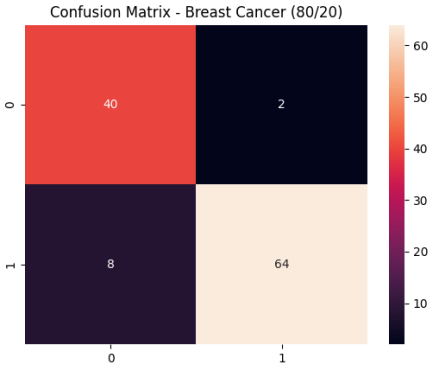
```
Classification Report (Breast Cancer, 60/40):
              precision    recall  f1-score   support

           0       0.90      0.93      0.91        85
           1       0.96      0.94      0.95       143

    accuracy                           0.93       228
   macro avg       0.93      0.93      0.93       228
weighted avg       0.93      0.93      0.93       228
```

(b) Breast Cancer: Classification Report (60/40 split).

Figure 3: Classification Report and Confusion Matrix (60/40 split)



(a) Breast Cancer: confusion matrix (80/20 split).

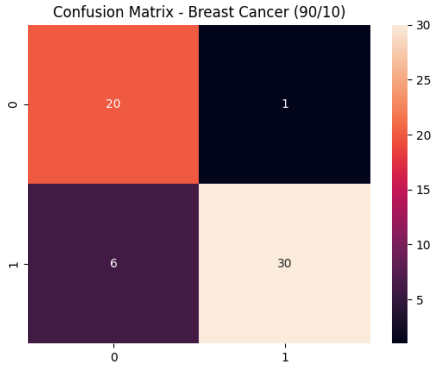
```
Classification Report (Breast Cancer, 80/20):
              precision    recall  f1-score   support

           0       0.83      0.95      0.89        42
           1       0.97      0.89      0.93        72

    accuracy                           0.91       114
   macro avg       0.90      0.92      0.91       114
weighted avg       0.92      0.91      0.91       114
```

(b) Breast Cancer: Classification Report (80/20 split).

Figure 4: Classification Report and Confusion Matrix (80/20 split)



(a) Breast Cancer: confusion matrix (90/10 split).

Classification Report (Breast Cancer, 90/10):

	precision	recall	f1-score	support
0	0.77	0.95	0.85	21
1	0.97	0.83	0.90	36
accuracy			0.88	57
macro avg	0.87	0.89	0.87	57
weighted avg	0.89	0.88	0.88	57

(b) Breast Cancer: Classification Report (90/10 split).

Figure 5: Classification Report and Confusion Matrix (90/10 split)

Insights into performance of these decision tree classifiers:

- sth
  - sth

Decision Tree Classifier with Different Depths

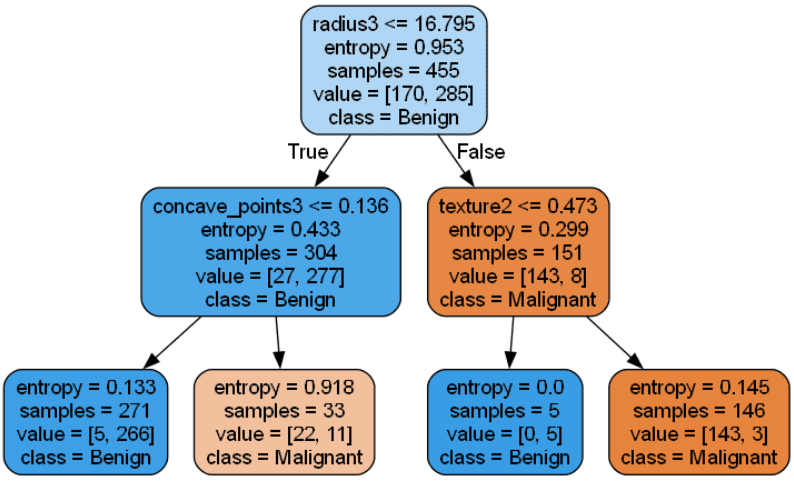


Figure 6: Breast Cancer: decision tree with `max_depth`=2 (80/20 split).

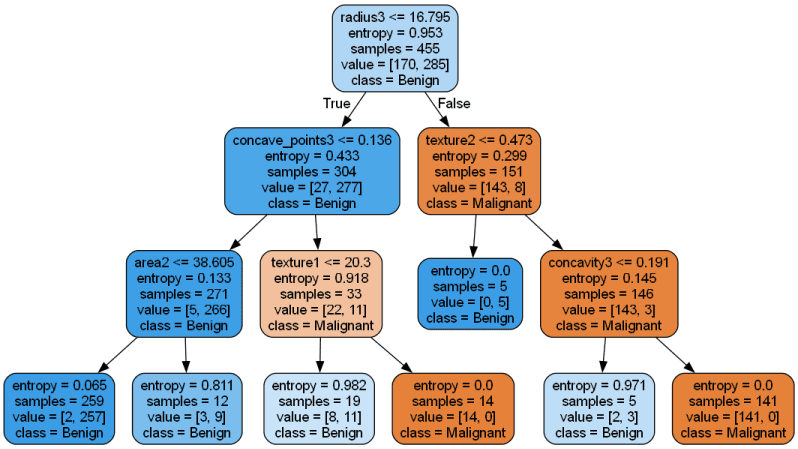


Figure 7: Breast Cancer: decision tree with `max_depth`=3 (80/20 split).

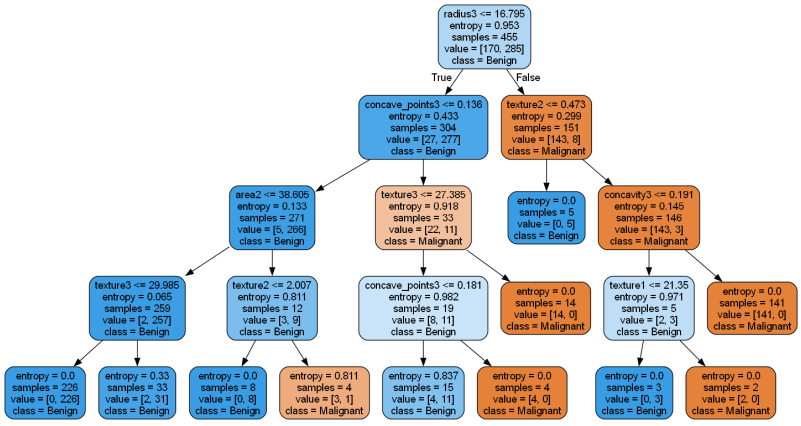


Figure 8: Breast Cancer: decision tree with `max_depth`=4 (80/20 split).

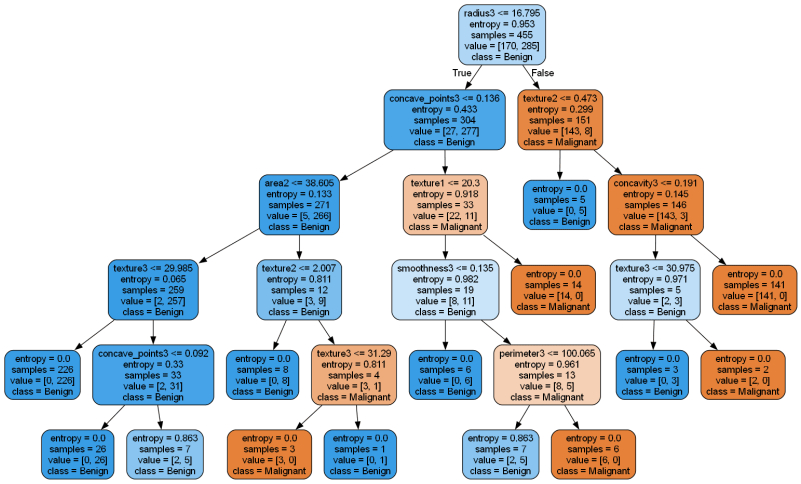


Figure 9: Breast Cancer: decision tree with `max_depth`=5 (80/20 split).

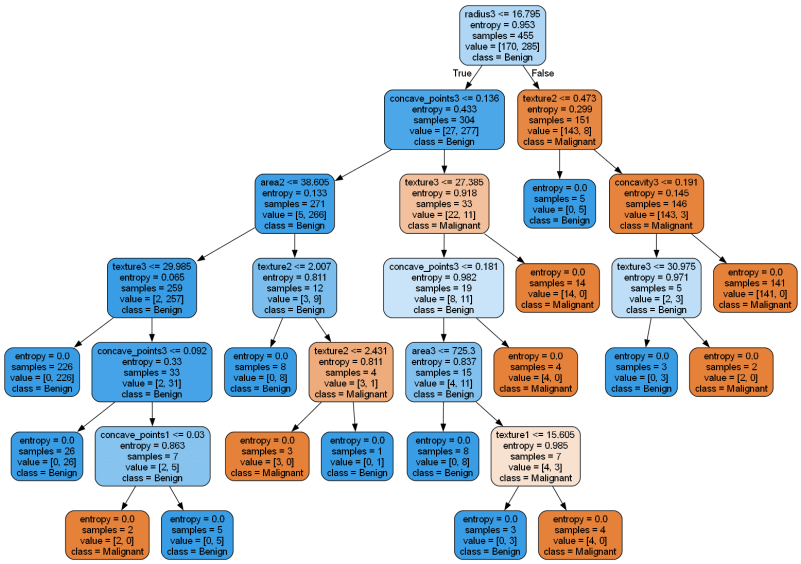


Figure 10: Breast Cancer: decision tree with `max_depth`=6 (80/20 split).

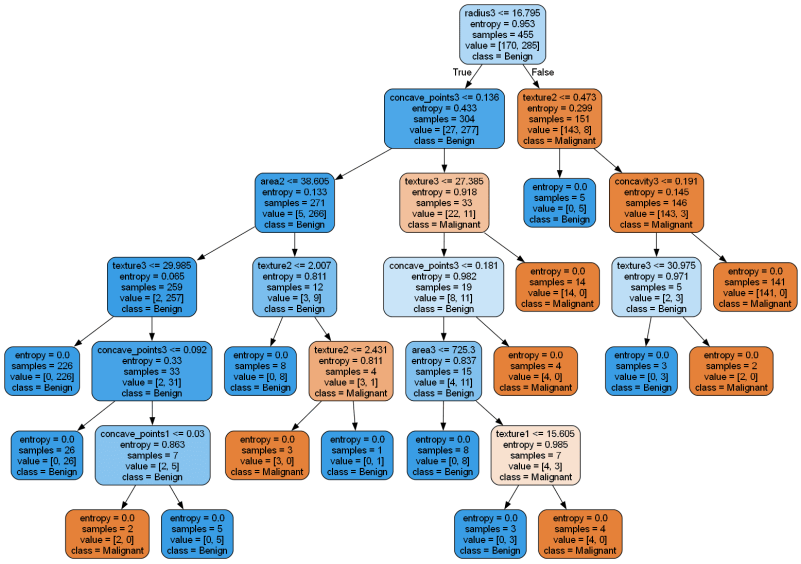


Figure 11: Breast Cancer: decision tree with `max_depth`=7 (80/20 split).

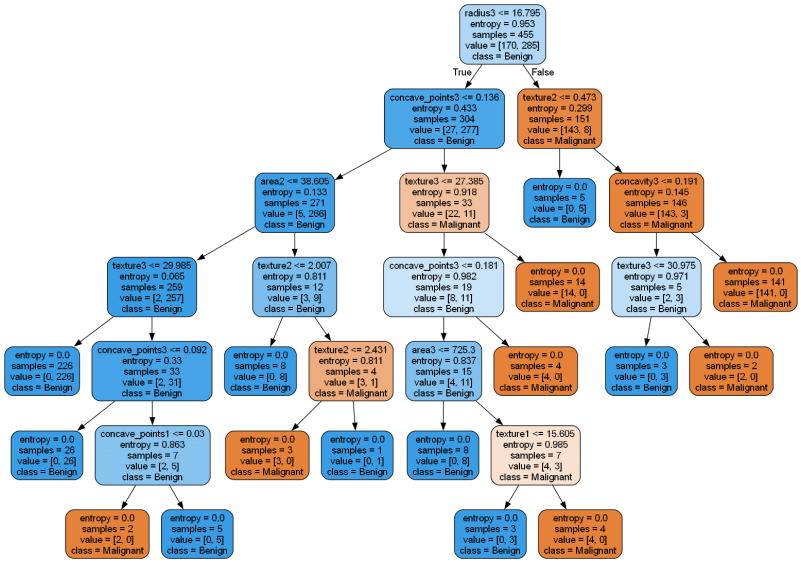
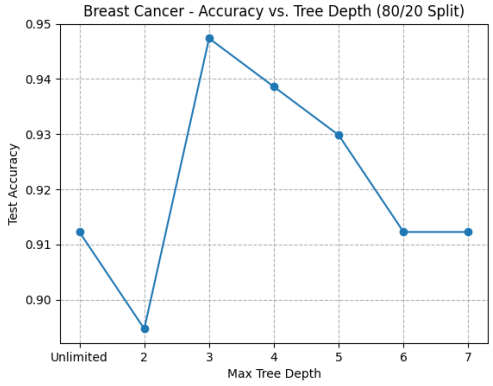


Figure 12: Breast Cancer: decision tree with `max_depth`=None (80/20 split).



Depth Analysis Results for Breast Cancer:

	Max Depth	Accuracy
0	None	0.912281
1	2	0.894737
2	3	0.947368
3	4	0.938596
4	5	0.929825
5	6	0.912281
6	7	0.912281

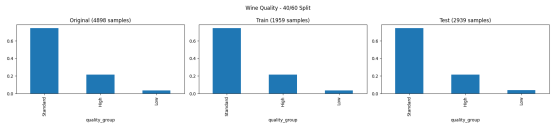
Insights

- sth
  - sth

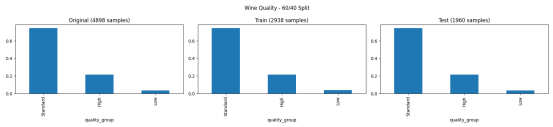
5.5 Wine Quality Dataset

Dataset Description

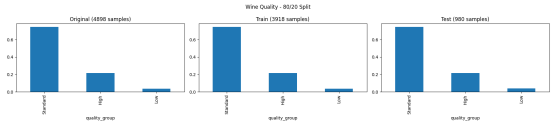
- **Description:** The UCI Wine Quality dataset is used for classifying wine samples into quality levels based on physicochemical properties such as acidity, alcohol content, etc.
- **Dataset Info:** 4898 samples, with labels from 0 (low quality) to 10 (high quality).
- **Preprocessing:** shuffle & stratified split at 40/60, 60/40, 80/20, 90/10.



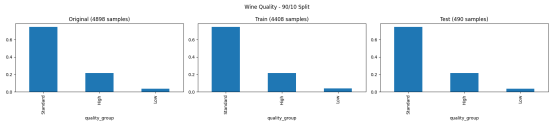
(a) Wine Quality: class distribution (40/60 split).



(b) Wine Quality: class distribution (60/40 split).



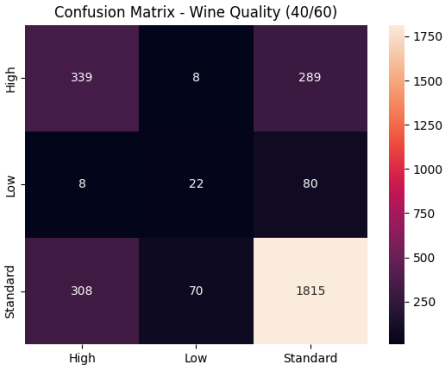
(c) Wine Quality: class distribution (80/20 split).



(d) Wine Quality: class distribution (90/10 split).

Figure 14: Class distributions

Evaluating the decision tree classifiers



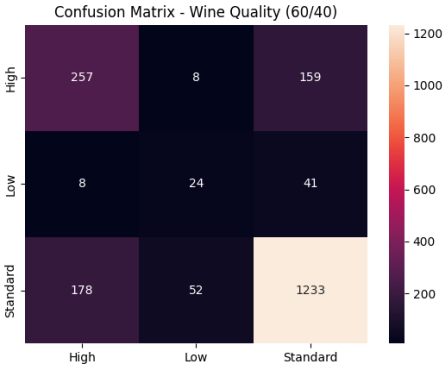
(a) Wine Quality: confusion matrix (40/60 split).

Classification Report (Wine Quality, 40/60):

	precision	recall	f1-score	support
High	0.52	0.53	0.53	636
Low	0.22	0.20	0.21	110
Standard	0.83	0.83	0.83	2193
accuracy			0.74	2939
macro avg	0.52	0.52	0.52	2939
weighted avg	0.74	0.74	0.74	2939

(b) Wine Quality: Classification Report (40/60 split).

Figure 15: Classification Report and Confusion Matrix (40/60 split)



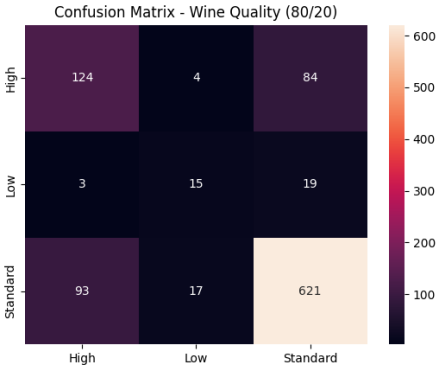
(a) Wine Quality: confusion matrix (60/40 split).

Classification Report (Wine Quality, 60/40):

	precision	recall	f1-score	support
High	0.58	0.61	0.59	424
Low	0.29	0.33	0.31	73
Standard	0.86	0.84	0.85	1463
accuracy			0.77	1960
macro avg	0.58	0.59	0.58	1960
weighted avg	0.78	0.77	0.78	1960

(b) Wine Quality: Classification Report (60/40 split).

Figure 16: Classification Report and Confusion Matrix (60/40 split)



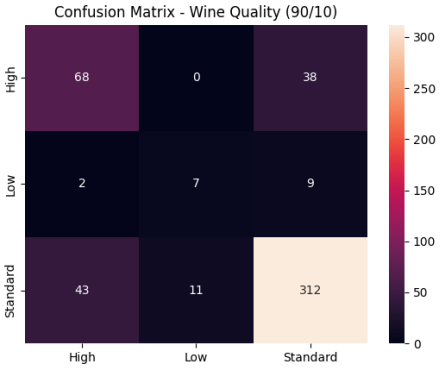
(a) Wine Quality: confusion matrix (80/20 split).

Classification Report (Wine Quality, 80/20):

	precision	recall	f1-score	support
High	0.56	0.58	0.57	212
Low	0.42	0.41	0.41	37
Standard	0.86	0.85	0.85	731
accuracy			0.78	980
macro avg	0.61	0.61	0.61	980
weighted avg	0.78	0.78	0.78	980

(b) Wine Quality: Classification Report (80/20 split).

Figure 17: Classification Report and Confusion Matrix (80/20 split)



(a) Wine Quality: confusion matrix (90/10 split).

Classification Report (Wine Quality, 90/10):

	precision	recall	f1-score	support
High	0.60	0.64	0.62	106
Low	0.39	0.39	0.39	18
Standard	0.87	0.85	0.86	366
accuracy			0.79	490
macro avg	0.62	0.63	0.62	490
weighted avg	0.79	0.79	0.79	490

(b) Wine Quality: Classification Report (90/10 split).

Figure 18: Classification Report and Confusion Matrix (90/10 split)

Insights into performance of these decision tree classifiers:

- sth
  - sth

Decision Tree Classifier with Different Depths

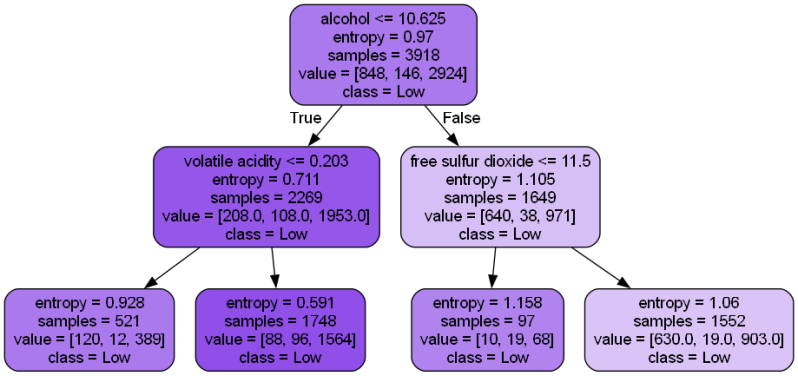


Figure 19: Wine Quality: decision tree with `max_depth`=2 (80/20 split).

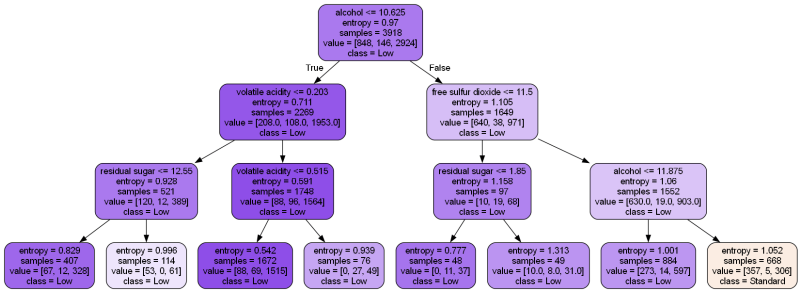


Figure 20: Wine Quality: decision tree with `max_depth`=3 (80/20 split).

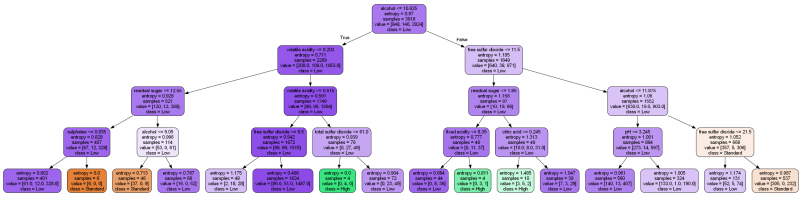
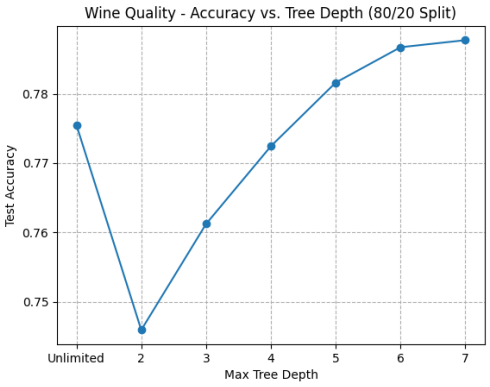


Figure 21: Wine Quality: decision tree with `max_depth`=4 (80/20 split).

Figure 22: Wine Quality: decision tree with `max_depth`=5 (80/20 split).

Figure 23: Wine Quality: decision tree with `max_depth`=6 (80/20 split).

Figure 24: Wine Quality: decision tree with `max_depth`=7 (80/20 split).




```
Depth Analysis Results for Wine Quality:
   Max Depth  Accuracy
0       None  0.775510
1          2  0.745918
2          3  0.761224
3          4  0.772449
4          5  0.781633
5          6  0.786735
6          7  0.787755
```

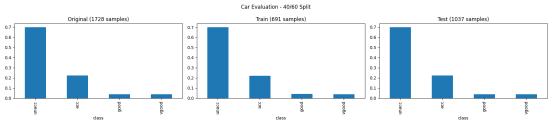
Insights

- sth
  - sth

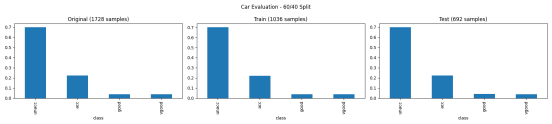
5.6 Car Evaluation Dataset

Dataset Description

- **Description:** Car Evaluation Database was derived from a simple hierarchical decision model originally developed for the demonstration of DEX, M. Bohanec, V. Rajkovic: Expert system for decision making.
- **Dataset Info:** 1728 samples, 4 classes (unacc, acc, good, vgood), 6 categorical attributes (buying price, maintenance cost, doors, etc.).
- **Preprocessing:** shuffle & stratified split at 40/60, 60/40, 80/20, 90/10.

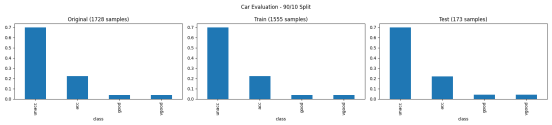


(a) Car Evaluation: class distribution (40/60 split).



(b) Car Evaluation: class distribution (60/40 split).

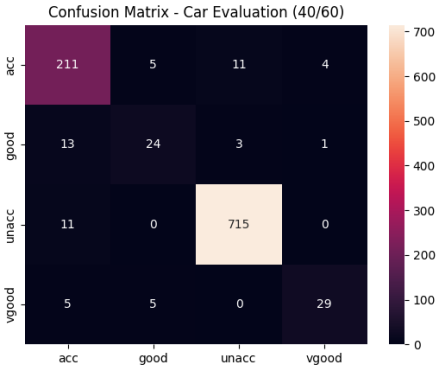
(c) Car Evaluation: class distribution (80/20 split).



(d) Car Evaluation: class distribution (90/10 split).

Figure 26: Class distributions

Evaluating the decision tree classifiers



(a) Car Evaluation: confusion matrix (40/60 split).

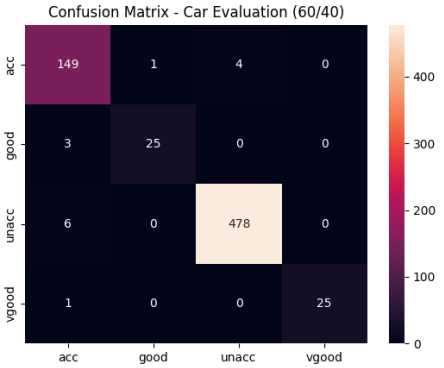
```
Classification Report (Car Evaluation, 40/60):
              precision    recall  f1-score   support

         acc       0.88      0.91      0.90       231
        good       0.71      0.59      0.64        41
       unacc       0.98      0.98      0.98       726
       vgood       0.85      0.74      0.79        39

    accuracy                           0.94      1037
   macro avg       0.85      0.81      0.83      1037
weighted avg       0.94      0.94      0.94      1037
```

(b) Car Evaluation: Classification Report (40/60 split).

Figure 27: Classification Report and Confusion Matrix (40/60 split)



(a) Car Evaluation: confusion matrix (60/40 split).

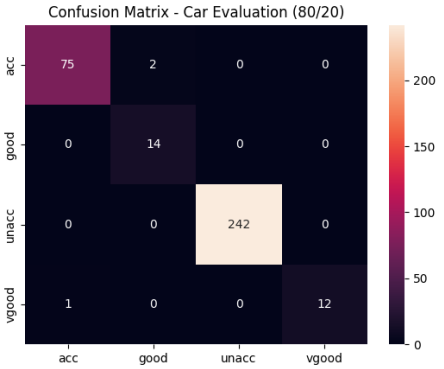
```
Classification Report (Car Evaluation, 60/40):
              precision    recall  f1-score   support

         acc       0.94      0.97      0.95       154
        good       0.96      0.89      0.93        28
       unacc       0.99      0.99      0.99       484
       vgood       1.00      0.96      0.98        26

    accuracy                           0.98       692
   macro avg       0.97      0.95      0.96       692
weighted avg       0.98      0.98      0.98       692
```

(b) Car Evaluation: Classification Report (60/40 split).

Figure 28: Classification Report and Confusion Matrix (60/40 split)



(a) Car Evaluation: confusion matrix (80/20 split).

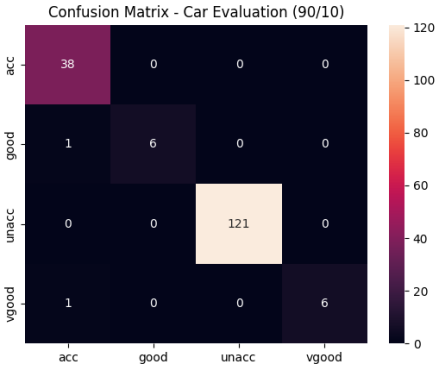
```
Classification Report (Car Evaluation, 80/20):
              precision    recall  f1-score   support

         acc       0.99      0.97      0.98        77
        good       0.88      1.00      0.93        14
       unacc       1.00      1.00      1.00       242
       vgood       1.00      0.92      0.96        13

    accuracy                           0.99       346
   macro avg       0.97      0.97      0.97       346
weighted avg       0.99      0.99      0.99       346
```

(b) Car Evaluation: Classification Report (80/20 split).

Figure 29: Classification Report and Confusion Matrix (80/20 split)



(a) Car Evaluation: confusion matrix (90/10 split).

Classification Report (Car Evaluation, 90/10):

	precision	recall	f1-score	support
acc	0.95	1.00	0.97	38
good	1.00	0.86	0.92	7
unacc	1.00	1.00	1.00	121
vgood	1.00	0.86	0.92	7
accuracy			0.99	173
macro avg	0.99	0.93	0.96	173
weighted avg	0.99	0.99	0.99	173

(b) Car Evaluation: Classification Report (90/10 split).

Figure 30: Classification Report and Confusion Matrix (90/10 split)

Insights into performance of these decision tree classifiers:

- sth
  - sth

Decision Tree Classifier with Different Depths

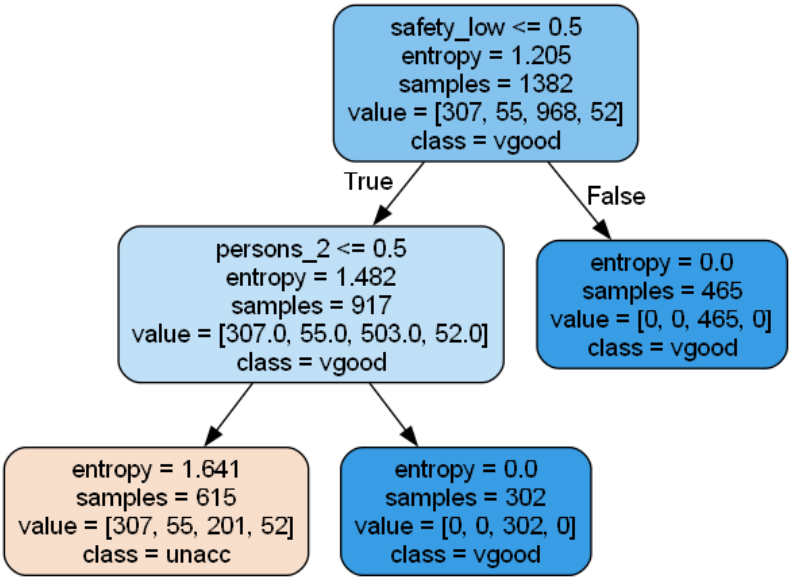


Figure 31: Car Evaluation: decision tree with `max_depth`=2 (80/20 split).

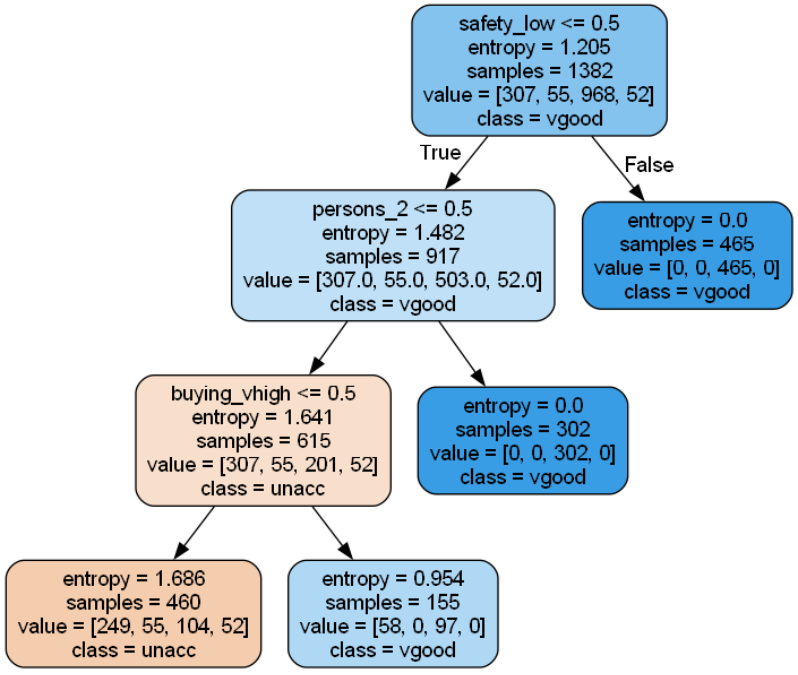


Figure 32: Car Evaluation: decision tree with `max_depth`=3 (80/20 split).

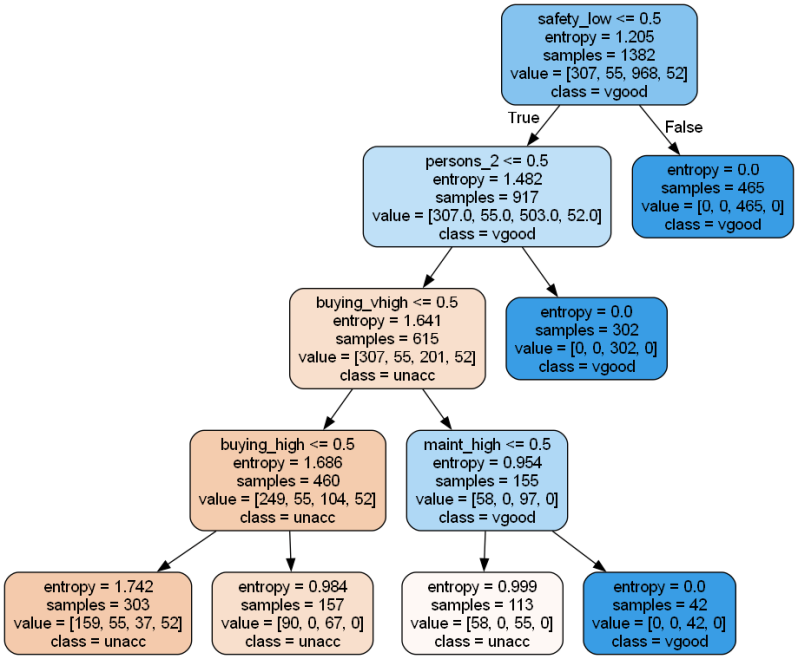


Figure 33: Car Evaluation: decision tree with `max_depth`=4 (80/20 split).

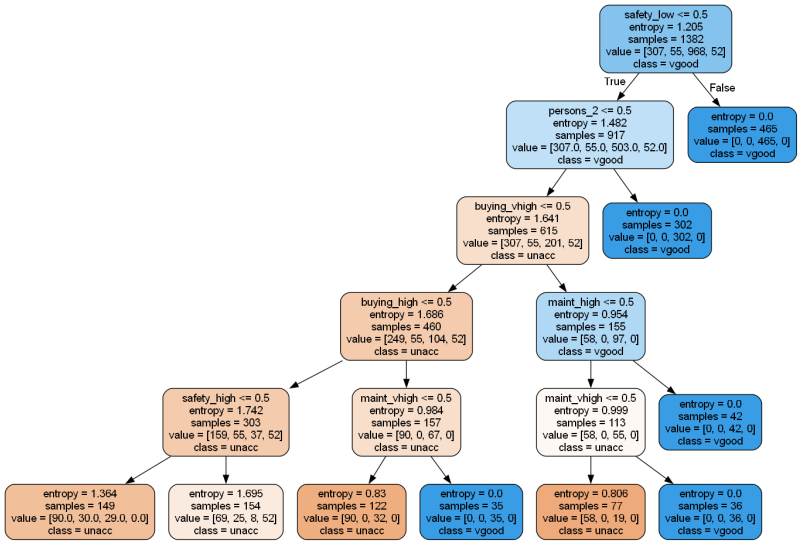


Figure 34: Car Evaluation: decision tree with `max_depth`=5 (80/20 split).

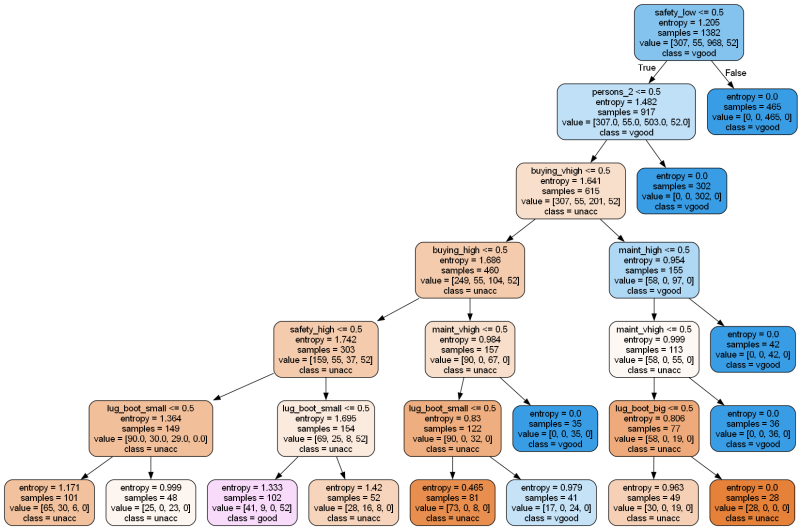


Figure 35: Car Evaluation: decision tree with `max_depth`=6 (80/20 split).

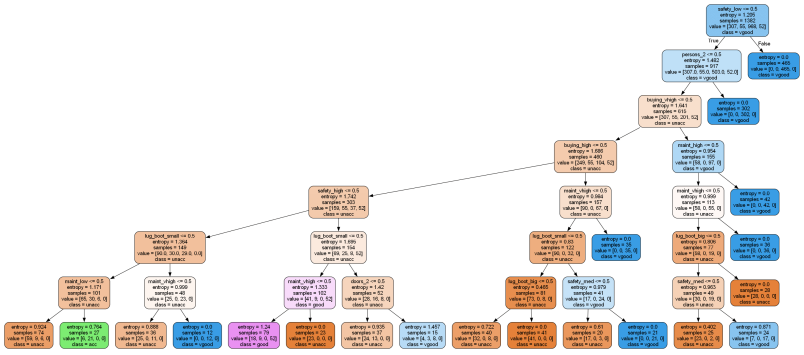


Figure 36: Car Evaluation: decision tree with `max_depth`=7 (80/20 split).

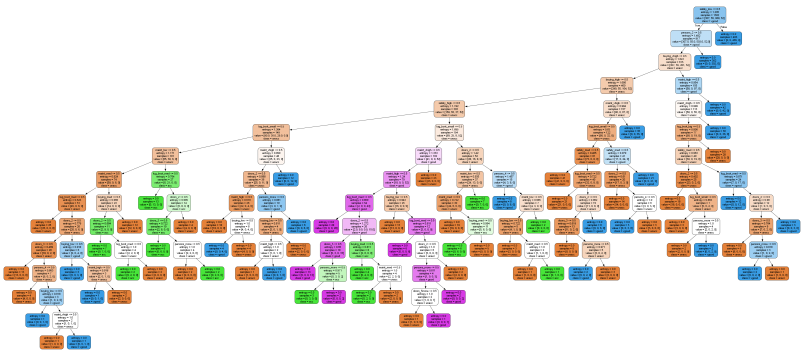
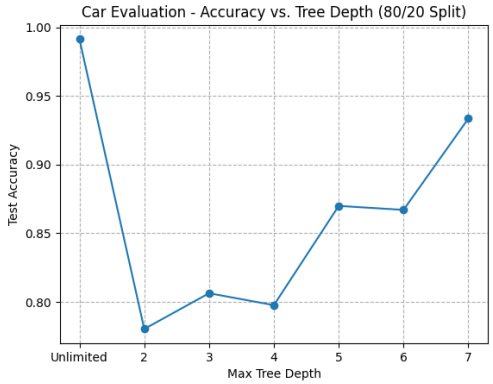


Figure 37: Car Evaluation: decision tree with `max_depth`=None (80/20 split).




```
Depth Analysis Results for Car Evaluation:
   Max Depth  Accuracy
0       None  0.991329
1          2  0.780347
2          3  0.806358
3          4  0.797688
4          5  0.869942
5          6  0.867052
6          7  0.933526
```

Insights

- sth
  - sth

6 Comparative Analysis

- **Objective:** Compare Decision Tree performance across:
  1. Breast Cancer (binary classification, continuous features)
  2. Wine Quality (multi-class, numerical features)
  3. Car Evaluation (multi-class, categorical features)
- **Comparison Criteria:**
  - Accuracy, Precision, Recall, F1-Score
  - Effect of feature type and count
  - Class distribution and balance
  - Impact of `max_depth` on overfitting
- **Observations:**
  - **Breast Cancer:** Highest accuracy; binary labels and well-separated numeric features helped model performance.
  - **Wine Quality:** Lower precision for middle-quality wines; overlapping features across quality groups reduced clarity.
  - **Car Evaluation:** Performed well despite 4 classes; decision tree easily handled categorical data. Slight overfitting observed at deep trees.
- **Conclusion:**
  - Decision Trees adapt well to both categorical and numerical data, but class imbalance and feature overlap affect performance.
  - Simpler datasets with clear boundaries (like Breast Cancer or Car Evaluation) yield higher accuracy.
  - Proper depth tuning is essential to maintain generalization.

7 References

1. DecisionTreeClassifier Documentation