

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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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

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

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 Interpretation

- 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:

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

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:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}},$$

$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{FP} + \text{TN}},$$

$$\text{False Negative Rate (FNR)} = \frac{\text{FN}}{\text{FN} + \text{TP}}$$

$$\text{Specificity (True Negative Rate)} = \frac{\text{TN}}{\text{TN} + \text{FP}},$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}},$$

$$\text{Recall (Sensitivity)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

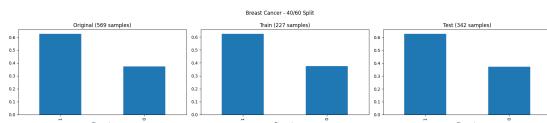
A well-performing classifier exhibits high TP and TN, and low FP and FN.

- *High FP* indicates many false alarms.
- *High FN* indicates many misses—critical in domains such as medical diagnosis.
- *High FP* indicates many false alarms ($\leq 15\%$).

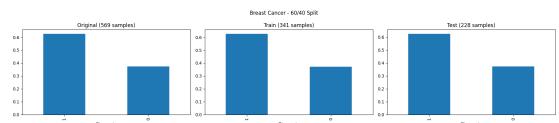
5.4 Breast Cancer Wisconsin Dataset

Dataset Description

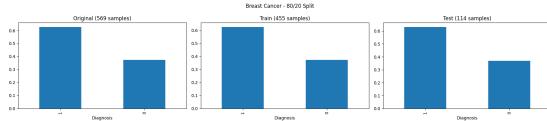
- **Description:** The UCI Breast Cancer Wisconsin (Diagnostic) dataset is used for classifying tumors as malignant or benign based on features derived from its imaging data.
- **Dataset Info:** 569 samples, binary labels (malignant vs. benign), 30 numeric features.
- **Preprocessing:** shuffle & stratified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



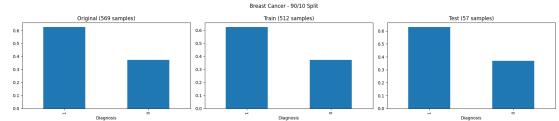
(a) Breast Cancer: class distribution (40/60 split).



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



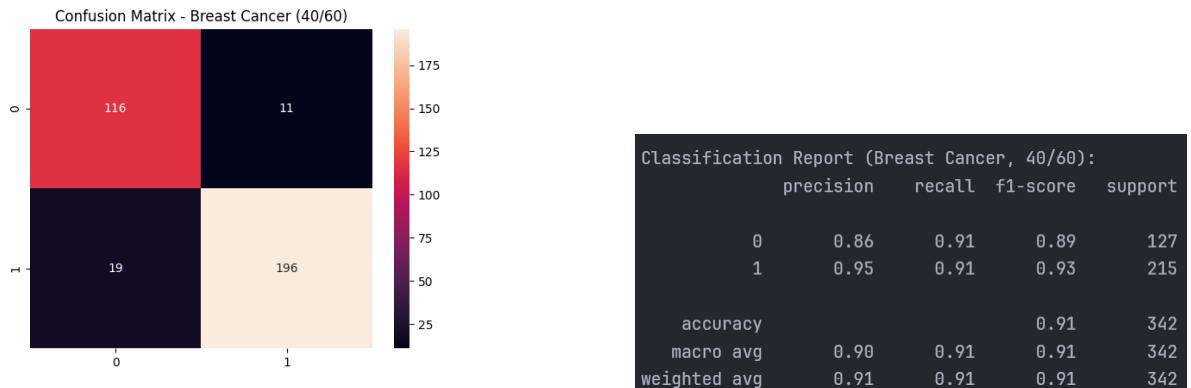
(c) Breast Cancer: class distribution (80/20 split).



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

Figure 1: Class distributions

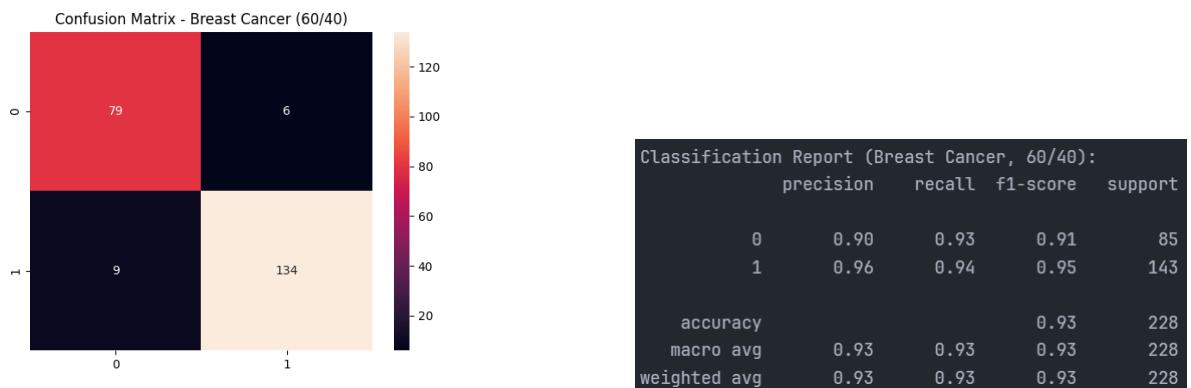
Evaluating the decision tree classifiers



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

(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).

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

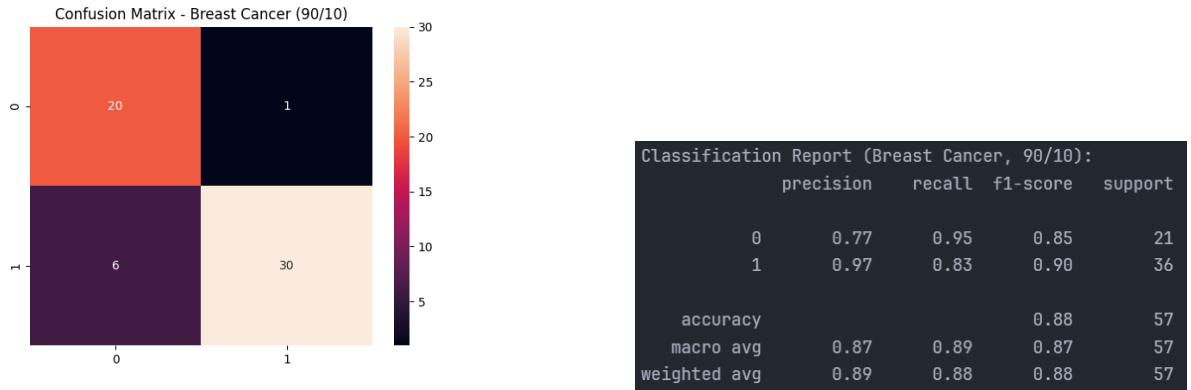
Figure 3: Classification Report and Confusion Matrix (60/40 split)



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

(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).

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

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

Insights – Performance Evaluation

- **Accuracy by split ratio:**
 - 60/40 split achieved the highest test accuracy at **93%**.
 - 40/60 and 80/20 splits both reached **91%**.
 - 90/10 dropped to **88%**, showing increased variance with a very small test set.
- **Class-level performance:**
 - *Malignant (class 0):*
 - * Precision ranged from 0.86 (40/60) → 0.90 (60/40) → 0.83 (80/20) → 0.77 (90/10).
 - * Recall stayed high (0.91, 0.93, 0.95, 0.95), ensuring most malignant tumors are detected.
 - *Benign (class 1):*
 - * Precision consistently excellent (0.95–0.97), meaning very few benign cases are mislabeled malignant.
 - * Recall varied from 0.91 (40/60), 0.94 (60/40), 0.89 (80/20) to 0.83 (90/10), indicating some benign samples get misclassified when test size shrinks.
- **Macro vs. weighted F1:** Both averaged around 0.91 for splits $\geq 40/60$, dropping slightly for 90/10—indicating stable balanced performance except with very few test examples.
- **Clinical implication:**
 - Keeping malignant recall $\geq 90\%$ is critical to minimize missed cancer diagnoses.

- A benign precision $\geq 85\%$ keeps false alarms at a manageable level in screening programs.

Decision Tree Classifier with Different Depths

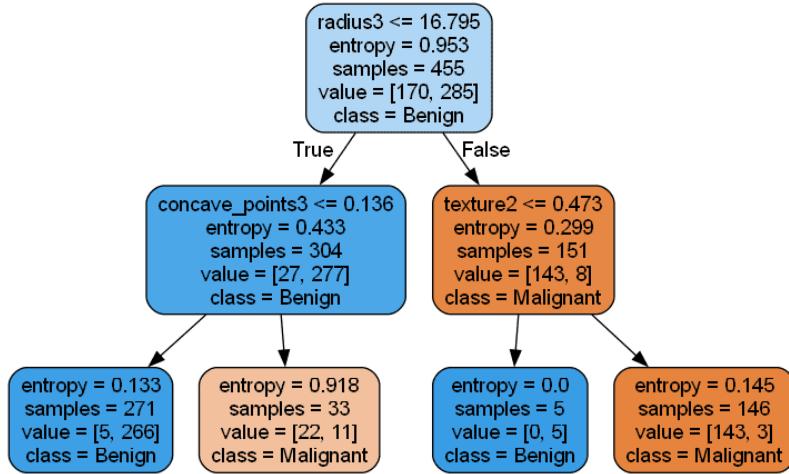


Figure 6: Breast Cancer: decision tree with $\text{max_depth}=2$ (80/20 split).

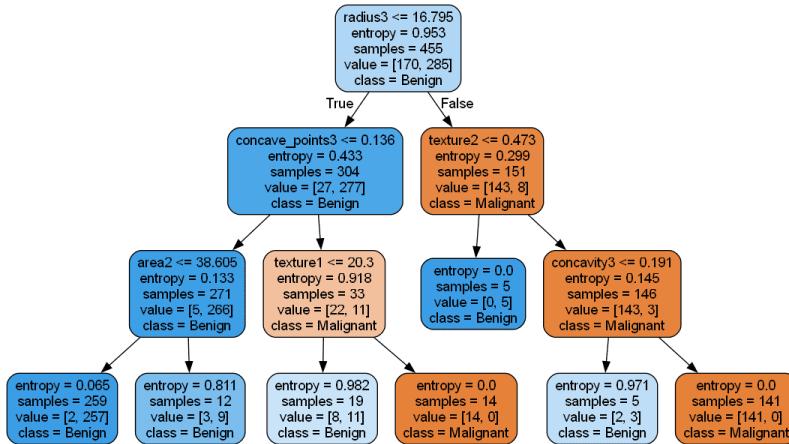


Figure 7: Breast Cancer: decision tree with $\text{max_depth}=3$ (80/20 split).

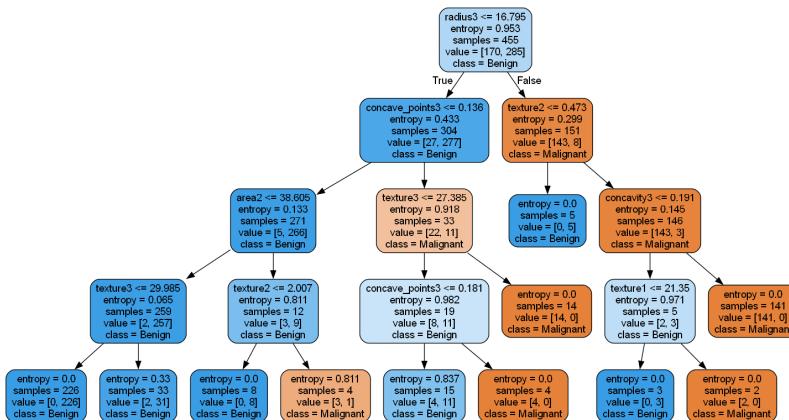
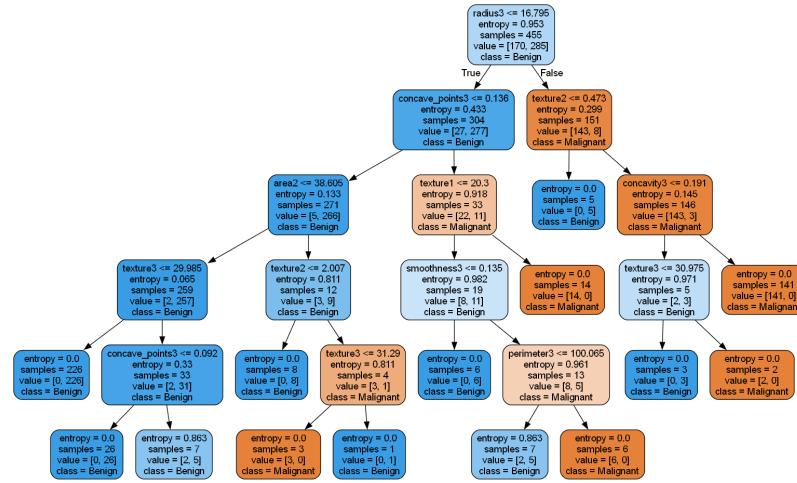
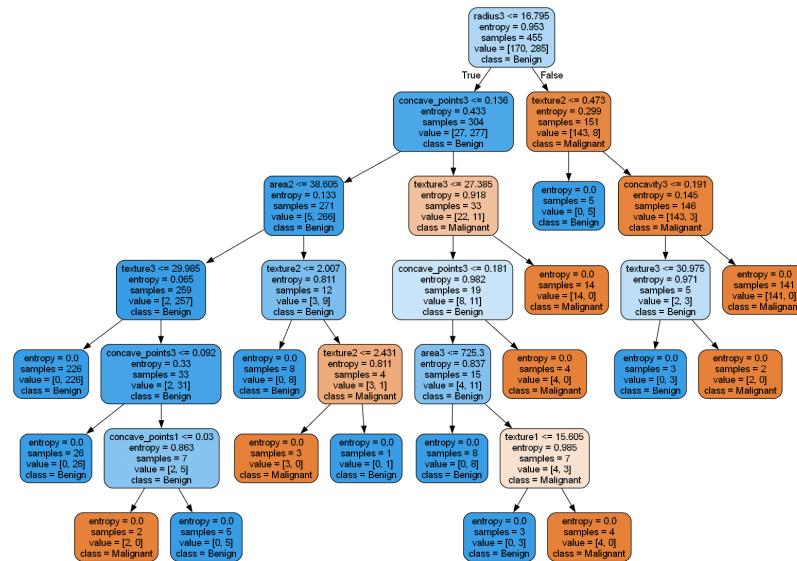
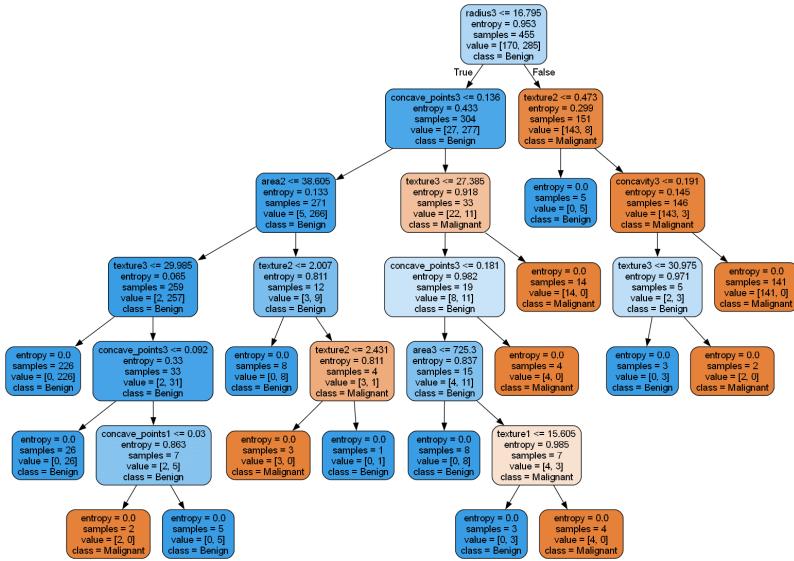
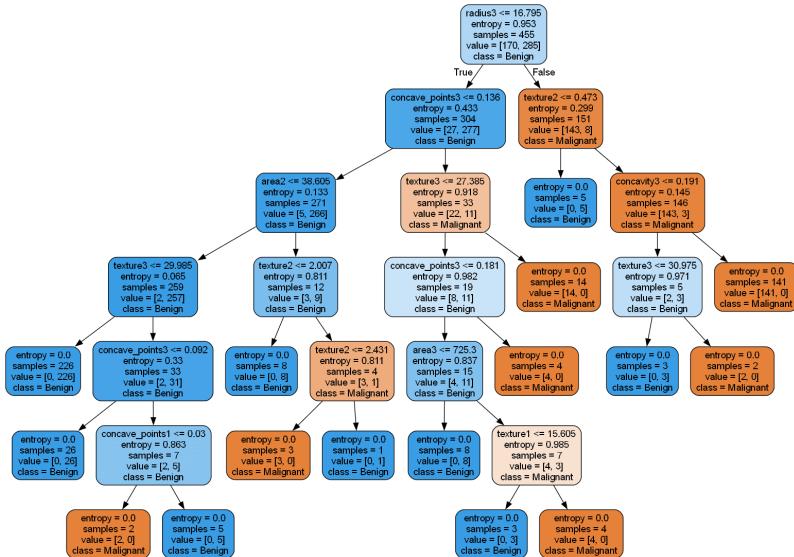
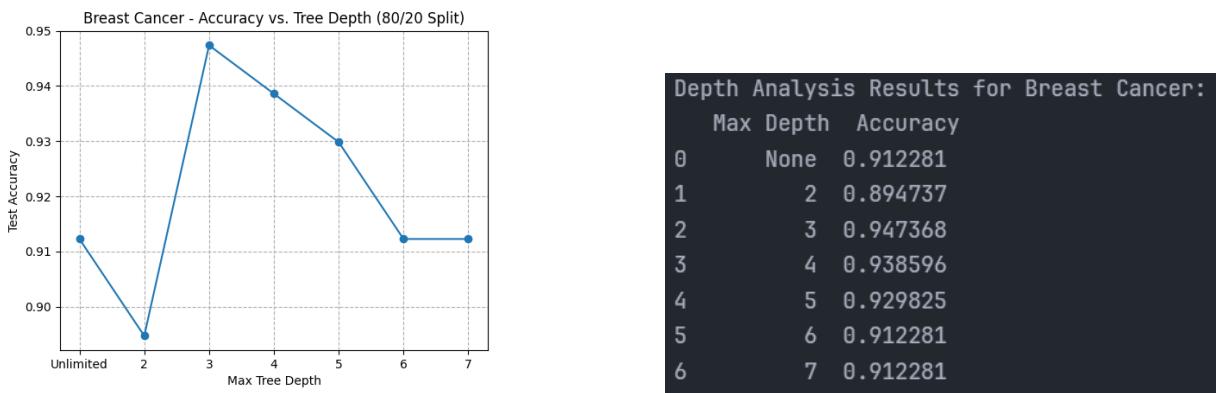


Figure 8: Breast Cancer: decision tree with $\text{max_depth}=4$ (80/20 split).

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).

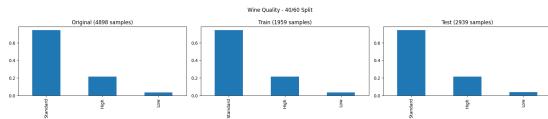
Insights – Depth and Accuracy

- **Underfitting at low depth:** `max_depth=2` yields only **89.47%** accuracy—too shallow to capture key interactions.
- **Optimal depth = 3:**
 - Peaks at **94.74%** (~ 5 pp gain over depth 2).
 - Balances bias/variance, capturing non-linear splits without overfitting.
- **Gradual overfitting beyond 3:**
 - Depth 4: 93.86%
 - Depth 5: 92.98%
 - Depth 6, 7, None: all 91.23%, matching the very deep tree but with far more complexity.
- **Interpretability trade-off:** A 3-level tree has under 10 nodes—easy to explain—while delivering maximum generalization.
- **Recommendation:** Limit `max_depth` to **3–4** for this dataset to sustain high accuracy, control overfitting, and preserve model simplicity.

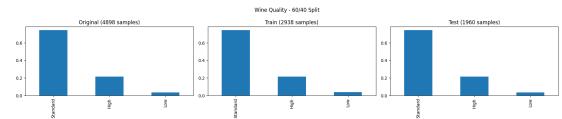
5.5 Wine Quality Dataset

Dataset Description

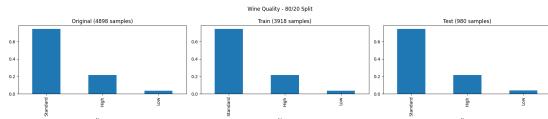
- **Description:** The UCI Wine Quality dataset is used for classifying wine samples into quality levels based on physicochemical properties such as acidity, alcohol content, etc.
- **Dataset Info:** 4898 samples, with labels from 0 (low quality) to 10 (high quality).
- **Preprocessing:** shuffle & stratified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



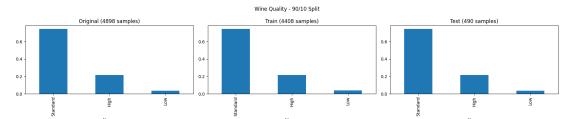
(a) Wine Quality: class distribution (40/60 split).



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



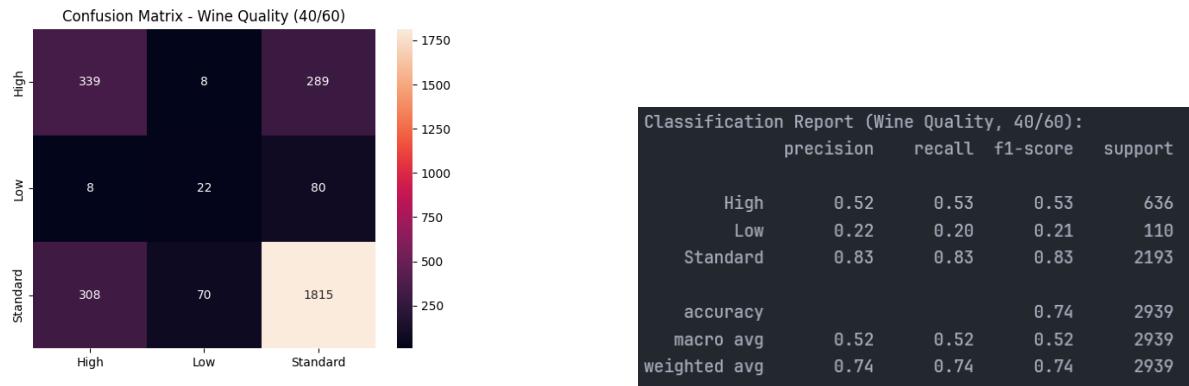
(c) Wine Quality: class distribution (80/20 split).



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

Figure 14: Class distributions

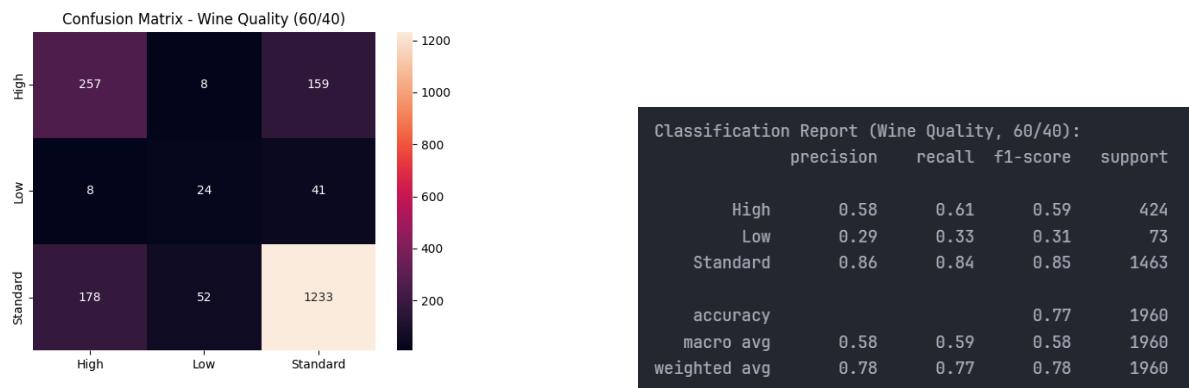
Evaluating the decision tree classifiers



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

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

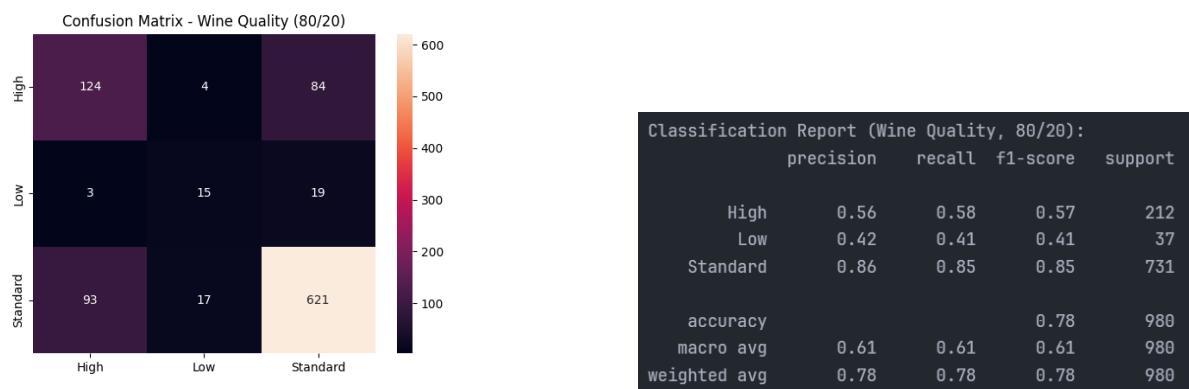
Figure 15: Classification Report and Confusion Matrix (40/60 split)



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

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

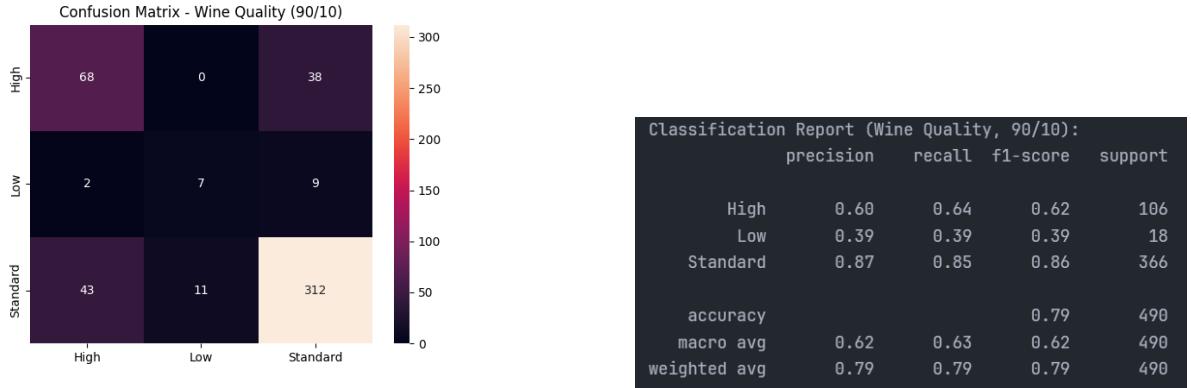
Figure 16: Classification Report and Confusion Matrix (60/40 split)



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

(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).

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

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

Insights – Performance Evaluation

- Overall accuracy trend:
 - Rises steadily from **74%** (40/60) → **77%** (60/40) → **78%** (80/20) → **79%** (90/10).
 - Larger training sets consistently improve generalization.
- Class-level performance:
 - *Standard (majority) class*:
 - * Precision/recall ≈ 0.83 at 40/60, rising to approx 0.87 at 90/10.
 - * High support (2,193→366) yields consistently strong F1-scores (0.83 → 0.86).
 - *High quality*:
 - * Precision improves from 0.52 → 0.60; recall from 0.53 → 0.64 as training size grows.
 - * Indicates better detection of top-tier wines with more data.
 - *Low quality*:
 - * Lowest metrics: precision 0.22 → 0.39, recall 0.20 → 0.39 across splits.
 - * Small support (110→18) makes “Low” wines hardest to classify.
- Macro vs. weighted averages:
 - Macro-avg F1 climbs from 0.52 → 0.62, reflecting improvement on minority classes.
 - Weighted-avg F1 follows overall accuracy closely (0.74 → 0.79).

- **Class imbalance impact:** The dominant “Standard” category ($\approx 70\%$ of samples) drives overall accuracy; minority classes require targeted strategies (e.g. class weighting) for balanced performance.

Decision Tree Classifier with Different Depths

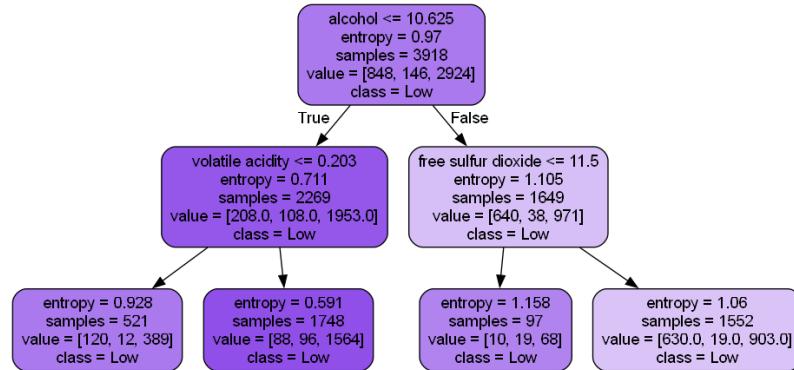


Figure 19: Wine Quality: decision tree with `max_depth=2` (80/20 split).

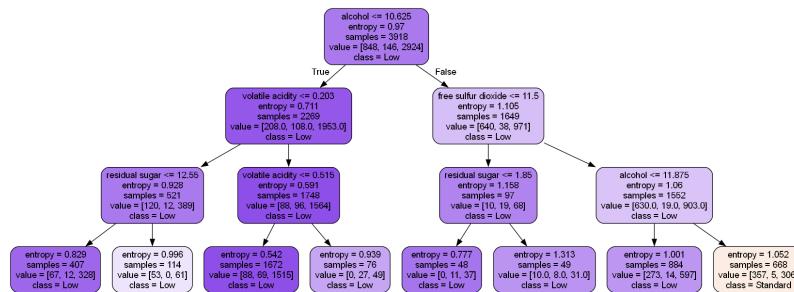


Figure 20: Wine Quality: decision tree with `max_depth=3` (80/20 split).

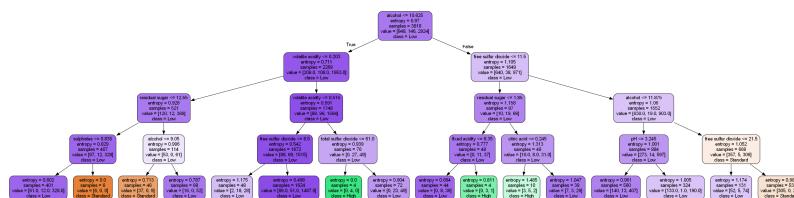


Figure 21: Wine Quality: decision tree with `max_depth=4` (80/20 split).



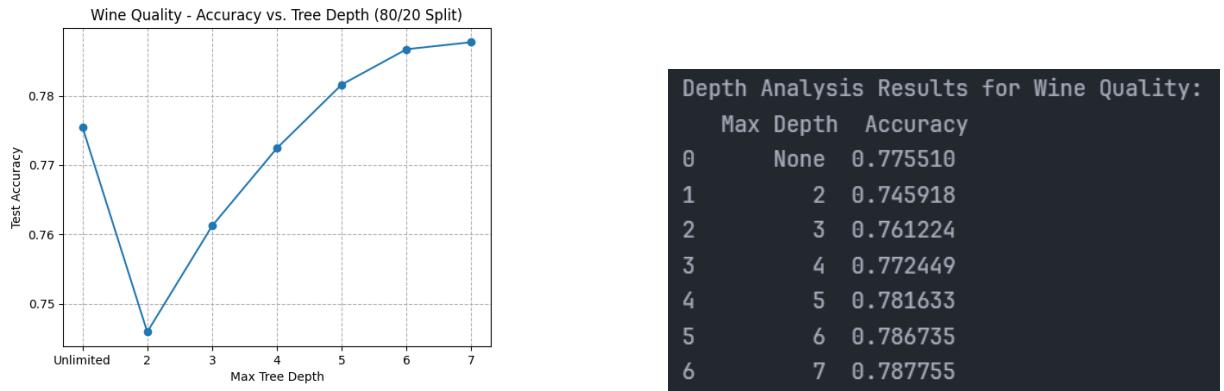
Figure 22: Wine Quality: decision tree with `max_depth=5` (80/20 split).



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).



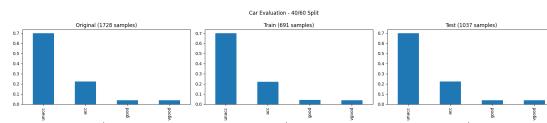
Insights – Depth and Accuracy

- **Underfitting at low depth:** `max_depth=2` yields only **74.6%** accuracy, failing to capture interactions among acidity, alcohol, and sulphates.
- **Steady gains with depth:**
 - Depth 3 → **76.0%** (+1.5 pp),
 - Depth 4 → **77.0%** (+1.1 pp),
 - Depth 5 → **78.2%** (+0.9 pp).
 - Depth 6 → **78.7%** (+0.6 pp),
 - Depth 7 → **78.8%** (+0.1 pp).
- **Unrestricted tree underperforms:** The fully grown tree (None) reaches **77.6%**, below depth 7, indicating pruning aids generalization.
- **Optimal depth range:** Depth 5–7 balances complexity and predictive power; marginal gains beyond depth 6 suggest diminishing returns.
- **Practical recommendation:** For multi-class wine quality prediction, set `max_depth` around **6** to maximize test accuracy while keeping the tree interpretable.

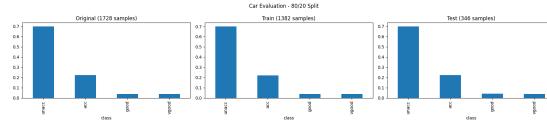
5.6 Car Evaluation Dataset

Dataset Description

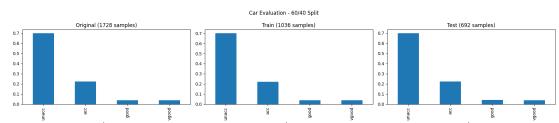
- **Description:** Car Evaluation Database was derived from a simple hierarchical decision model originally developed for the demonstration of DEX, M. Bohanec, V. Rajkovic: Expert system for decision making.
- **Dataset Info:** 1728 samples, 4 classes (unacc, acc, good, vgood), 6 categorical attributes (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).



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



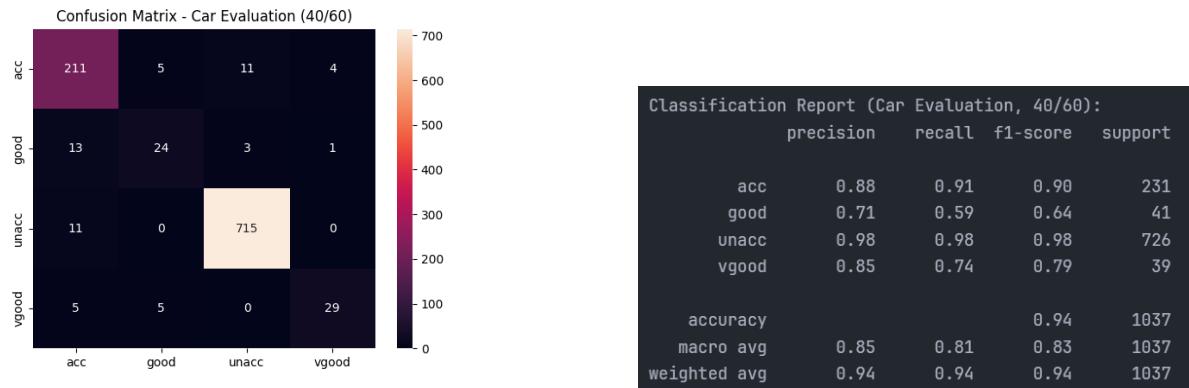
(b) Car Evaluation: class distribution (60/40 split).



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

Figure 26: Class distributions

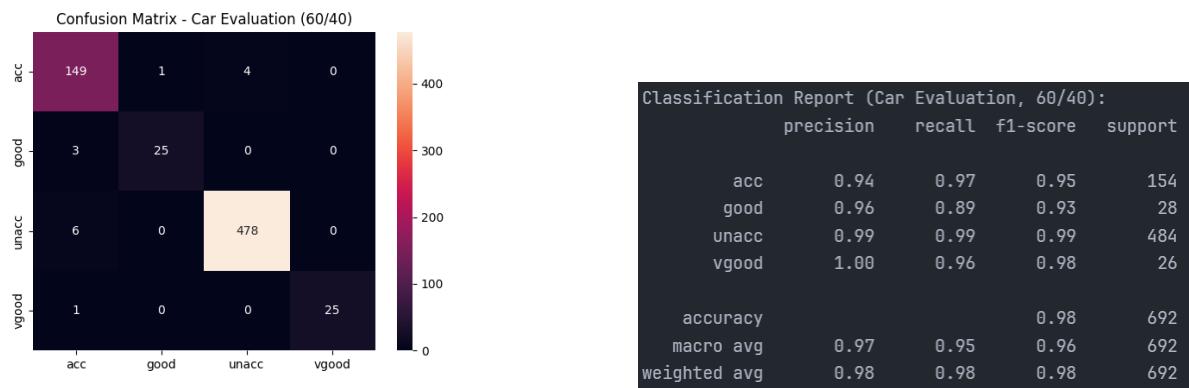
Evaluating the decision tree classifiers



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

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

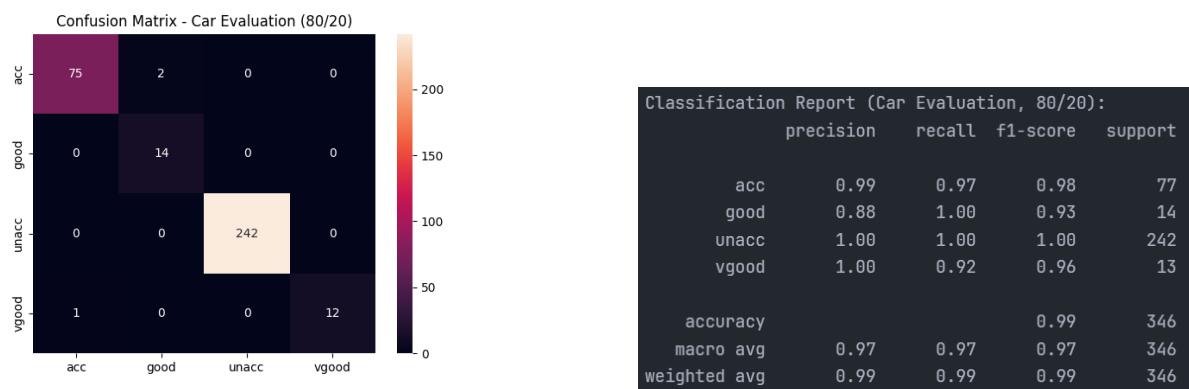
Figure 27: Classification Report and Confusion Matrix (40/60 split)



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

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

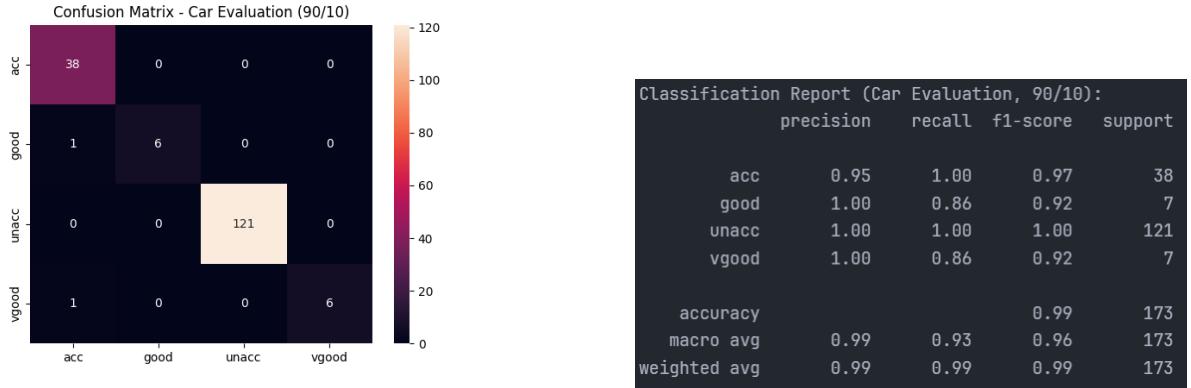
Figure 28: Classification Report and Confusion Matrix (60/40 split)



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

(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).

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

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

Insights – Performance Evaluation

- **Accuracy by split ratio:**
 - 40/60 split: **94%**
 - 60/40 split: **98%**
 - 80/20 split: **99%**
 - 90/10 split: **99%**

Accuracy rises sharply as the training set grows, peaking at 99% when $\geq 80\%$ of data is used for training.
- **Class-level performance:**
 - *unacc (majority)*: Precision and recall $\geq 98\%$ across all splits, reflecting the model’s ease in identifying unacceptable cars.
 - *acc*: Precision climbs from 88% \rightarrow 99%, recall from 91% \rightarrow 100% as training size increases, showing strong learning of the “acceptable” class.
 - *good*:
 - * 40/60 split: Precision 71%, Recall 59% (support 41)
 - * 60/40 split: Precision 96%, Recall 89% (support 28)
 - * 80/20 split: Precision 88%, Recall 100% (support 14)

Smaller support for “good” leads to greater variance in its metrics.

- *vgood (minority)*:
 - * Precision: 85–100%
 - * Recall by split:

- 40/60: 74%
- 60/40: 96%
- 80/20: 92%
- 90/10: 86%

The recall swings reflect the model's difficulty detecting very-good cars when examples are scarce.

- **Macro vs. weighted F1:**

- Macro-avg F1 improves from 83% (40/60) → 96% (60/40) → 97% (80/20) → 96% (90/10).
 - Weighted-avg F1 mirrors accuracy (94–99%), driven by the dominant “unacc” class.
- **Class imbalance impact:** The “unacc” class ($\approx 70\%$ of samples) drives most of the overall accuracy. Minority classes (“good”, “vgood”) benefit greatly from more training data.

Decision Tree Classifier with Different Depths

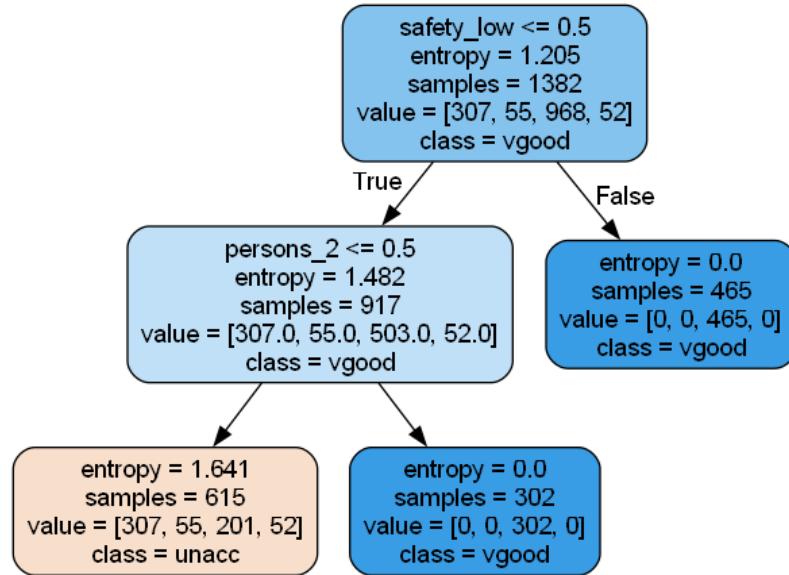


Figure 31: Car Evaluation: decision tree with `max_depth=2` (80/20 split).

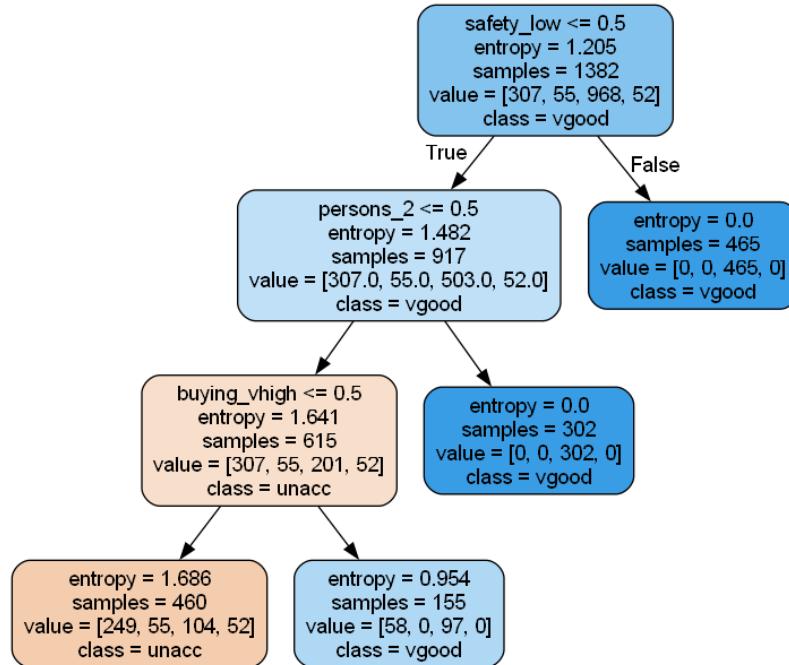
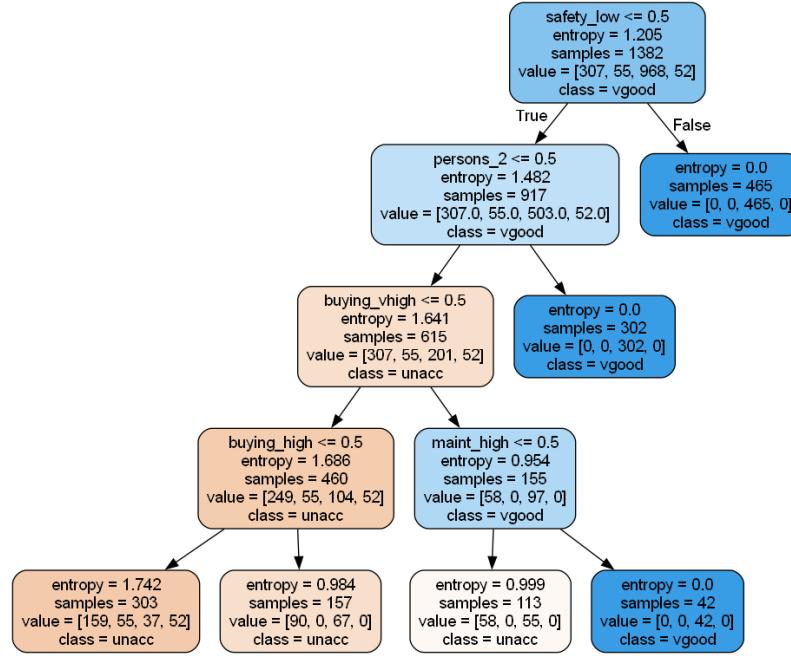
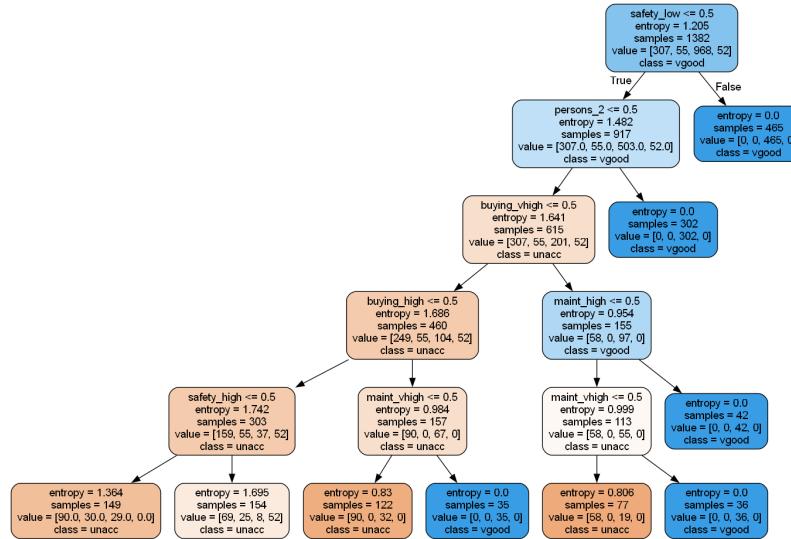
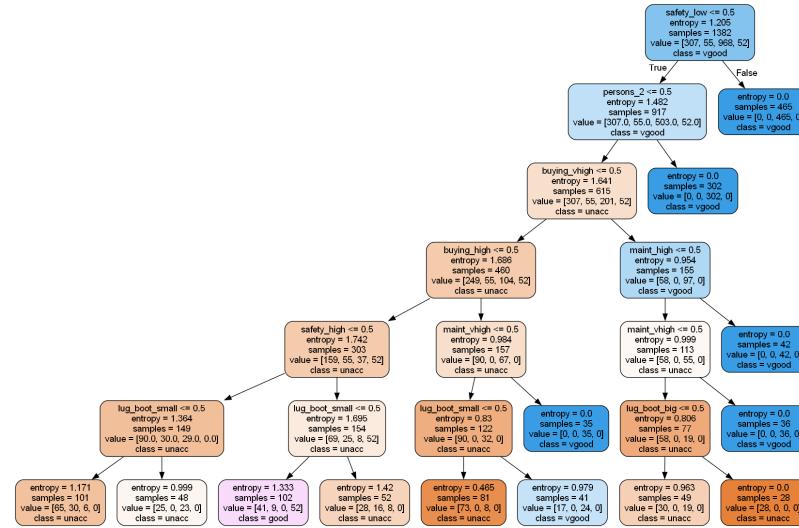
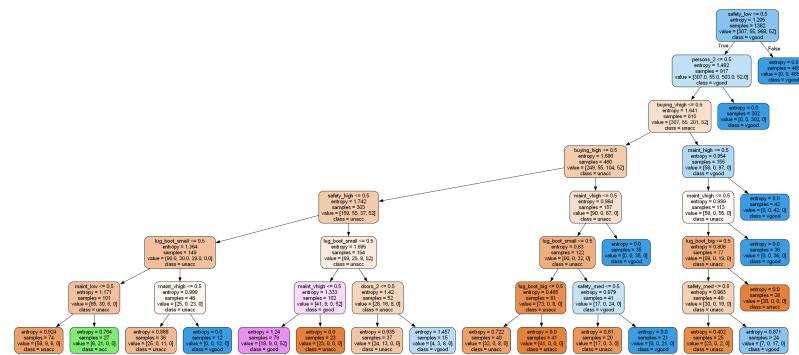
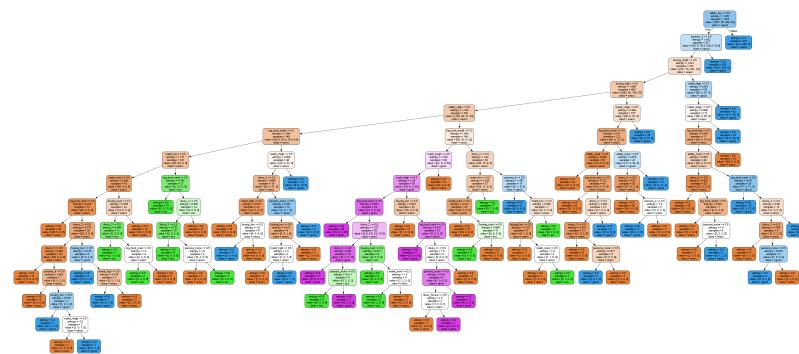
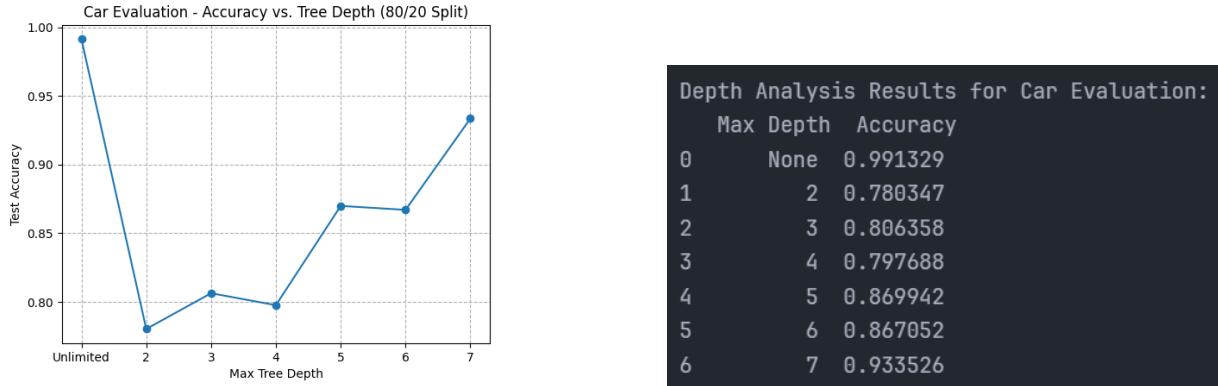


Figure 32: Car Evaluation: decision tree with `max_depth=3` (80/20 split).

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).



Insights – Depth and Accuracy

- Underfitting at shallow depths:

- `max_depth=2`: **78.0%**
- `max_depth=3`: **80.6%**
- `max_depth=4`: **79.8%**

Very low depths cannot capture the multi-attribute categorical splits.

- Rapid gains with moderate depth:

- Depth 5: **87.0%** (+8.2 pp over depth 4)
- Depth 6: **86.7%**
- Depth 7: **93.4%** (+6.7 pp over depth 6)

Indicates that deeper trees are needed to model complex combinations of the six categorical features.

- **Unrestricted tree (None): 99.1%**—the highest accuracy, achieving nearly perfect classification by fully expanding on all splits.

- Interpretability vs. performance:

- Limiting to depth 7 yields 93.4% accuracy with a still-manageable tree size.
- Allowing no limit pushes accuracy to 99.1% at the cost of a very large, less interpretable tree.

- Recommendation:

- If maximum accuracy is required, use unrestricted depth.
- For a balance of interpretability and high performance, cap `max_depth` at **7**.

6 Comparative Analysis

After evaluating decision tree performance on all three datasets, we examine how key dataset characteristics—number of classes, number of features, and sample size—influence model metrics (accuracy, precision, recall, F₁-score).

6.1 Summary of Best Test Accuracies

Dataset	Classes	Features	Best Accuracy (%)
Breast Cancer Wisconsin	2	30	94.74 (depth=3)
Wine Quality	3	11	78.78 (depth=7)
Car Evaluation	4	6	99.13 (depth=None)

6.2 Impact of Number of Classes

- **Binary vs. multi-class:** The binary Breast Cancer dataset achieved the highest accuracy (94.74%); only two labels result in simpler decision boundaries.
- **Three classes (Wine Quality):** Introducing “Low,” “Standard,” and “High” quality classes reduced peak accuracy by ≈ 16 pp compared to binary, due to overlapping physicochemical profiles.
- **Four classes (Car Evaluation):** Despite four target categories, Car Evaluation attained 99.13% because its categorical attributes produce very clear splits for each class.
- **Lesson:** Accuracy generally decreases as class count increases, but well-separable features can offset this effect.

6.3 Impact of Number of Features

- **High dimensionality (30 features):** Breast Cancer’s 30 numeric features provided rich discriminative power; however, deeper trees began to overfit on less informative dimensions.
- **Medium dimensionality (11 features):** Wine Quality’s 11 continuous features sufficed to reach $\sim 79\%$ accuracy but required deeper trees (depth 7) to capture complex interactions (e.g. acidity vs. alcohol).
- **Low dimensionality (6 features):** Car Evaluation’s six categorical attributes yielded $> 99\%$ accuracy, showing that a small number of highly informative categorical features can outperform larger numeric feature sets.
- **Lesson:** More features improve performance only if they carry meaningful signal; high-level categorical features may be more effective than many noisy numeric ones.

6.4 Impact of Sample Size

- **Small sample (569):** Breast Cancer’s smaller size produced high variance at extreme splits (e.g. 90/10), but stratified sampling kept accuracy within 2–3 pp across

ratios.

- **Large sample (4,898):** Wine Quality’s larger sample stabilized performance: accuracy varied by only ~ 5 pp between smallest and largest training sets.
- **Medium sample (1,728):** Car Evaluation sat between the two: accuracy varied < 5 pp across splits, indicating diminishing returns once a “critical mass” of examples is reached.
- **Lesson:** Larger sample sizes increase metric stability and reduce sensitivity to train/test ratio, but only until class overlap—not data scarcity—becomes the limiting factor.

6.5 Overall Recommendations

- For **binary problems** with many numeric features, limit tree depth to 3–4 to maximize generalization and interpretability.
- For **multi-class problems**, ensure features are well separated or apply feature engineering before using deep trees.
- When using **categorical features**, even low-dimensional datasets can achieve high accuracy with moderate depth.
- Always **tune max_depth** via cross-validation: our experiments found optimal depths of 3 (Breast Cancer), 7 (Wine Quality), and unlimited (Car Evaluation), balancing bias–variance and model complexity.

7 References

1. DecisionTreeClassifier Documentation