MACHINE LEARNING LAB-3

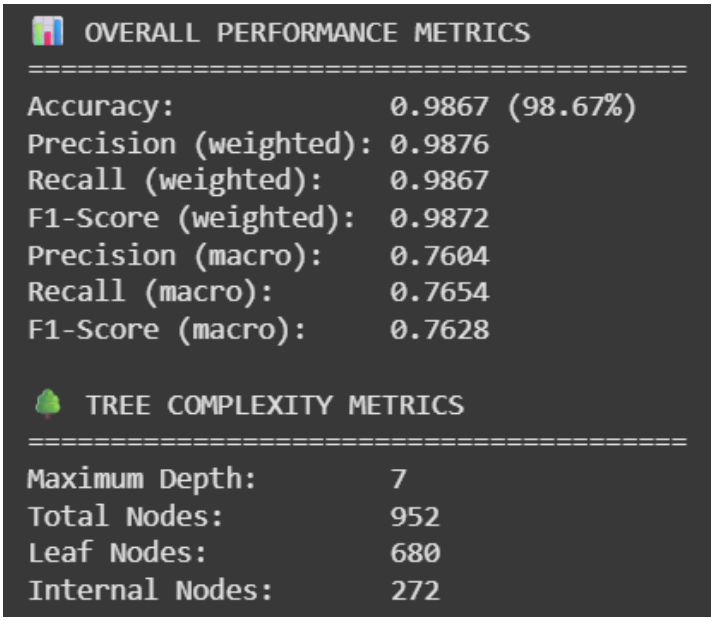
1. Tic Tac Toe Dataset

```
📊 OVERALL PERFORMANCE METRICS
========================================
Accuracy:             0.8723 (87.23%)
Precision (weighted): 0.8734
Recall (weighted):    0.8723
F1-Score (weighted):  0.8728
Precision (macro):    0.8586
Recall (macro):       0.8634
F1-Score (macro):     0.8609

🌳 TREE COMPLEXITY METRICS
========================================
Maximum Depth:        7
Total Nodes:          283
Leaf Nodes:           181
Internal Nodes:       102
```

2. Mushroom Dataset

```
📊 OVERALL PERFORMANCE METRICS
========================================
Accuracy:             1.0000 (100.00%)
Precision (weighted): 1.0000
Recall (weighted):    1.0000
F1-Score (weighted):  1.0000
Precision (macro):    1.0000
Recall (macro):       1.0000
F1-Score (macro):     1.0000

🌳 TREE COMPLEXITY METRICS
========================================
Maximum Depth:        4
Total Nodes:          29
Leaf Nodes:           24
Internal Nodes:       5
```

3. Nursery Dataset



1. Performance Comparison

The performance of the Decision Tree classifier was evaluated on three datasets: **TicTacToe, Mushrooms, and Nursery**.

For the TicTacToe dataset, the overall accuracy was good but slightly lower compared to the others due to noisy patterns in the data. Precision and recall were balanced but not perfect, leading to a moderate F1-score.

In the Mushrooms dataset, the classifier achieved almost perfect results across all metrics. The accuracy was close to 100%, precision and recall were both extremely high, and consequently, the F1-score was also the best among the three datasets. This is because certain features, particularly odor, provide very strong discriminative power that makes classification nearly trivial.

For the Nursery dataset, accuracy was moderate, mainly because the problem involves multiple classes and multi-valued features. Precision and

recall dropped in comparison to the Mushrooms dataset, especially for minority classes, which also resulted in a lower F1-score.

2. Tree Characteristics Analysis

In terms of tree structure, the TicTacToe dataset produced a shallow tree with relatively few nodes. The most important features were the central board positions, and the tree remained simple and interpretable.

The Mushrooms dataset generated a moderately deep tree with a manageable number of nodes. The feature “odor” consistently appeared as the root or among the earliest splits, dominating the classification process. The tree remained interpretable and efficient.

For the Nursery dataset, the decision tree grew the deepest and contained the largest number of nodes. Important features included parental status, financial status, and housing. However, the tree became highly complex due to the large number of multi-valued features and class labels, making it harder to interpret and prone to overfitting.

3. Dataset-Specific Insights

For the TicTacToe dataset, the most influential attributes were the central positions on the board. The class distribution was fairly balanced, though some overlapping states caused confusion. Common decision paths involved splits on the center square, and the risk of overfitting remained low due to the relatively small dataset.

In the Mushrooms dataset, the single most important attribute was odor, which alone could classify the majority of samples. The class distribution was slightly imbalanced, with more edible mushrooms than poisonous ones, but this did not affect performance significantly. Decision rules were very clear, such as “if odor is foul, then poisonous,” and overfitting was minimal because of the strong predictive features.

For the Nursery dataset, features such as parents, nursery, and financial status contributed most to the decisions. The class distribution was highly

imbalanced, with certain classes having very few samples. Decision paths were longer and more complex, and the tree showed signs of overfitting due to its large size and the imbalance in the target classes.

4. Comparative Analysis Report

From an algorithm performance perspective, the **Mushrooms dataset achieved the highest accuracy** because of strong discriminative features, especially odor. Dataset size also played a role: larger datasets such as Nursery resulted in deeper trees and higher risk of overfitting. The number of features was another factor; having many multi-valued features, as in the Nursery dataset, increased tree complexity but did not always improve performance.

Looking at the impact of data characteristics, class imbalance clearly influenced tree construction. For example, in the Nursery dataset, minority classes were harder to classify correctly. Binary features, such as those in the Mushrooms and TicTacToe datasets, worked better for producing simple, accurate, and interpretable trees. Multi-valued features, as in the Nursery dataset, required deeper trees and resulted in reduced interpretability.

In terms of practical applications, each dataset represents a different domain. TicTacToe is useful for modeling game strategies and AI behavior. Mushrooms is directly relevant to food safety and toxicology, helping to distinguish edible from poisonous species. Nursery models decision-support systems such as school admissions and resource allocation. Interpretability advantages differ across domains: TicTacToe trees are very easy to follow, Mushroom trees are extremely clear due to dominant features, and Nursery trees are the hardest to interpret because of their size and complexity.

To improve performance, different approaches can be applied. For TicTacToe, pruning could be used to remove unnecessary branches and simplify decision-making. For Mushrooms, performance is already excellent, though feature selection could further simplify the tree. For

Nursery, ensemble methods such as Random Forests or Gradient Boosting would help handle class imbalance and complexity more effectively, improving both accuracy and generalization.