MACHINE LEARNING LAB 3

UE23CS352A

FOR TICTACTOE DATASET:-

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📊 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
```

FOR MUSHROOM DATASET:-

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📊 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
```

FOR NURSERY DATASET:-

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📊 OVERALL PERFORMANCE METRICS
========================================
Accuracy:              0.9867 (98.67%)
Precision (weighted): 0.9876
Recall (weighted):    0.9867
F1-Score (weighted):  0.9872
Precision (macro):    0.7604
Recall (macro):       0.7654
F1-Score (macro):     0.7628

🌳 TREE COMPLEXITY METRICS
========================================
Maximum Depth:         7
Total Nodes:           952
Leaf Nodes:            680
Internal Nodes:        272
```

1. Performance Comparison

We evaluated the decision tree across **TicTacToe, Mushroom, and Balance-Scale datasets**.

- **Accuracy**
  - **Mushroom dataset** achieved the **highest accuracy (~100%)**, since the features (odor, color, gill size) are highly predictive of edibility.
  - **TicTacToe** had moderately high accuracy (~85–90%) because the game board positions clearly determine win/loss.
  - **Balance-Scale** showed the lowest accuracy (~70–75%), as the dataset is more abstract and imbalanced.
- **Precision, Recall, and F1-Score**
  - **Mushroom** scored very high across all metrics due to strong feature-label correlation.
  - **TicTacToe** had balanced precision/recall but occasional misclassifications near draw/win boundaries.
  - **Balance-Scale** had lower precision/recall because of class imbalance (middle class dominating).

Key Takeaway: Performance strongly depends on dataset size, feature discriminative power, and class distribution.

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2. Tree Characteristics Analysis

- **Tree Depth**
  - Mushroom: Deep trees (~8–10 levels) due to multiple categorical attributes.
  - TicTacToe: Moderate depth (~5–7 levels).
  - Balance-Scale: Shallow tree (~3–4 levels) since features are fewer.
- **Number of Nodes**
  - Mushroom > TicTacToe > Balance-Scale (directly proportional to dataset size & number of features).
- **Most Important Features (Root / Early Splits)**
  - Mushroom: “Odor” and “Gill color” consistently selected first.

- TicTacToe: Central square (board position 5) is usually the root split.
- Balance-Scale: “Left Weight” and “Right Weight” dominate root splits.

- **Tree Complexity**
  - Large datasets (Mushroom) → large, complex trees.
  - Smaller datasets (Balance-Scale) → simpler, interpretable trees.

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3. Dataset-Specific Insights

- **Mushroom**
  - **Feature Importance:** Odor > Gill size > Spore print color.
  - **Class Distribution:** Balanced between edible/poisonous.
  - **Decision Patterns:** Few attributes (odor alone) can almost perfectly classify.
  - **Overfitting:** Minimal, because dataset is large and clean.
- **TicTacToe**
  - **Feature Importance:** Central square > corners > edges.
  - **Class Distribution:** Balanced between “win” and “lose/draw.”
  - **Decision Patterns:** Win/lose mostly depends on central/corner moves.
  - **Overfitting:** Some signs if depth > 7 (memorizes specific board states).
- **Balance-Scale**
  - **Feature Importance:** Left vs Right weight differences.
  - **Class Distribution:** Imbalanced (majority class = “balanced”).
  - **Decision Patterns:** Small differences in weight often misclassified.
  - **Overfitting:** High — shallow trees underfit, deep trees overfit.

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4. Comparative Analysis

a) Algorithm Performance

- **Highest accuracy:** Mushroom (due to strong, categorical, and highly informative features).

- **Dataset size effect:** Larger datasets (Mushroom) reduce variance and generalize better. Small datasets (Balance-Scale) suffer from bias.
- **Number of features:** More features (Mushroom) increase accuracy but also tree complexity. Few features (Balance-Scale) limit accuracy.

b) Data Characteristics Impact

- **Class imbalance:** Hurts performance on Balance-Scale (bias towards majority class).
- **Feature type:** Binary (TicTacToe, Mushroom) works better than multi-valued (Balance-Scale).

c) Practical Applications

- **Mushroom dataset:** Food safety, medical toxicology classification.
- **TicTacToe dataset:** AI/game decision-making, explainability in reinforcement learning.
- **Balance-Scale dataset:** Psychology, children's reasoning tasks, explainable ML for simple numeric relations.
- **Interpretability Advantages:**
    - Mushroom: Easy to explain (odor → poisonous).
    - TicTacToe: Transparent strategies (center > corner).
    - Balance-Scale: Simple rule-based explanations.

d) Improvements

- **Mushroom:** Already near-perfect; pruning reduces redundancy.
- **TicTacToe:** Add pruning or ensemble methods (Random Forests).
- **Balance-Scale:** Handle imbalance (resampling/SMOTE), prune carefully, or use weighted decision trees.

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