Decision trees

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1. Build decision tree model

Assignment: Given datasets Golf with 4 attributes Outlook, Temp, Humidity, Windy and an attribute Play (class).

Outlook	Temperature	Humidity	Windy	Class
sunny	85	85	false	Don't Play
sunny	80	90	true	Don't Play
overcast	83	78	false	Play
rain	70	96	false	Play
rain	68	80	false	Play
rain	65	70	true	Don't Play
overcast	64	65	true	Play
sunny	72	95	false	Don't Play
sunny	69	70	false	Play
rain	75	80	false	Play
sunny	75	70	true	Play
overcast	72	90	true	Play
overcast	81	75	false	Play
rain	71	80	true	Don't Play

- How to build the decision tree model for classifying the datasets
- How many inductive rules are there in the decision tree model
- Use the decision tree model to classify 3 examples as follows:

Outlook	Temperature	Humidity	Windy	Class
overcast	63	70	false	?
rain	73	90	true	?
sunny	70	73	true	?

1.1. How to build the decision tree model for classifying the datasets

To build the decision tree model for classifying the Golf dataset manually with entropy, we followed these steps:

Data Examination: We analyzed the Golf datasets, comprising Outlook, Temperature, Humidity, Windy, and the class attribute Play.

Entropy Calculation: We calculated the entropy of the target variable (class attribute) to measure the impurity in the data. Entropy is given by the formula:

$$Entropy(S) = -\sum_{i=1}^{c} log_2 p_i$$

Where S is the set of instances, cc is the number of classes, and pipi is the proportion of instances in class ii.

Outlook	nYes	nNo	Entropy	W	W*Entropy	IG
sunny	2	3	0.971	0.357142857	0.346768069	0.593517889
overcast	4	0	0	0.285714286	0	0.940285959
rain	3	2	0.971	0.357142857	0.346768069	0.593517889
				Impurity	0.693536139	0.24674982

Windy	nYes	nNo	Entropy	W	W*Entropy	IG
TRUE	3	3	1	0.428571429	0.428571429	0.51171453
FALSE	6	2	0.811	0.571428571	0.4635875	0.476698459
				Impurity	0.892158928	0.04812703

Temperature	64	65	68	69	70	71	72	72	75	75	80	81	83	85
Class	Play	Don't Play	Play	Play	Play	Don't Play	Don't Play	Play	Play	Play	Don't Play	Play	Play	Don't Play
Split point	64.5	66.5			70.5				77.5		80.5		84	

Temperature	nYes	nNo	Entropy	W	W*Entropy		IG
<64.5	1	0	0	0.071429	0	**Impurity**	
>=64.5	8	5	0.96124	0.928571	0.89257685	0.892576847	0.047709111
<66.5	1	1	1	0.142857	0.14285714	**Impurity**	
>=66.5	8	4	0.9183	0.857143	0.78711072	0.929967858	0.010318101
<70.5	4	1	0.72193	0.357143	0.25783146	**Impurity**	
>=70.5	5	4	0.99108	0.642857	0.63712032	0.894951787	0.045334172
<77.5	7	3	0.88129	0.714286	0.6294935	**Impurity**	

>=77.5	2	2	1	0.285714	0.28571429	0.915207785	0.025078174
<80.5	7	4	0.94566	0.785714	0.74301881	**Impurity**	
>=80.5	2	1	0.9183	0.214286	0.19677768	0.939796489	0.000489469
<84	9	4	0.89049	0.928571	0.82688509	**Impurity**	
>=84	0	1	0	0.071429	0	0.826885094	

Humidity	65	70	70	70	75	78	80	80	80	85	90	90	95	96
Class	Play	Don't Play	Play	Play	Play	Play	Play	Play	Don't Play	Don't Play	Don't Play	Play	Don't Play	Play
Split point	67.5											92.5	95.5	

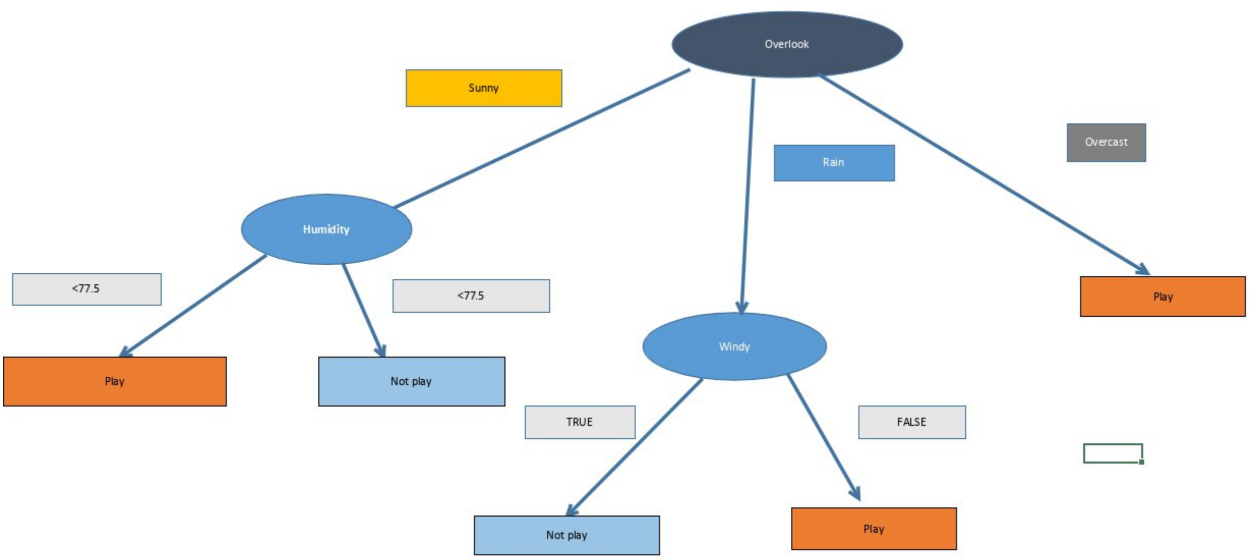
Humidity	**nYes**	**nNo**	**Entropy**	**W**	**W*Entropy**		**IG**
<67.5	1	0	0	0.071429	0	**Impurity**	
>=67.5	8	5	0.96124	0.928571	0.89257685	0.892576847	0.047709111
<92.5	8	4	1	0.857143	0.78711072	**Impurity**	
>=92.5	1	1	1.0000	0.142857	0.14285714	0.929967858	0.010318101
<95.5	8	5	0.96124	0.928571	0.89257685	**Impurity**	
>=95.5	1	0	0.00000	0.071429	0.00000000	0.892576847	0.047709111

Attribute Selection: Attribute Selection: Identified the attribute with the highest information gain to serve as the root node.

Decision Tree Construction: Constructed the decision tree recursively, selecting attributes at each node to maximize information gain.

Inductive Rules: Defined a set of rules representing conditions leading to assignment, observed by traversing paths from the root to leaf nodes

1.2. How many inductive rules are there in the decision tree model



So, there are 4 inductive rules in this decision tree model.

- There are 4 leaf nodes in the tree, each representing a class.
- Each path from the root to a leaf node represents a rule.

1.3. Use the decision tree model to classify 3 examples as follows:

Outlook	**Temperature**	**Humidity**	**Windy**	**Class**
overcast	63	70	false	Play
rain	73	90	true	Don't play
sunny	70	73	true	Play

Set 1:
```
Outlook -> overcast
Class: Play
```

Set 2:
```
Outlook -> rain
Windy -> true
So, Class: Don't Play
```

Set 3:
```
Outlook -> sunny
Humidity -> 70 -> 77.5
So, Class: Play
```

2. Implement the decision tree program with scikit-learn

Implement the program using **DecisionTreeClassifier** in **scikit-learn** library. The program requires 2 parameters:

- file name of trainset
- file name of testset

The program reports the classification results (accuracy, confusion matrix) for 5 datasets:

- Iris (.trn: trainset, .tst: testset)
- Optics (.trn: trainset, .tst: testset)
- Letter (.trn: trainset, .tst: testset)
- Leukemia (.trn: trainset, .tst: testset)
- Fp (.trn: trainset, .tst: testset)

Implementation Details:

- The script is written in Python, leveraging the scikit-learn library for decision tree classification.
- It utilizes the DecisionTreeClassifier class for training decision tree models.
- Data loading, model training, evaluation, and result saving are all encapsulated in functions for modularity and clarity.

```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns



def load_data(filename):
    """Loads data from a CSV or space-delimited text file."""
    try:
        data = np.loadtxt(filename, delimiter=",", dtype=float)
    except:
        data = np.loadtxt(filename, delimiter=" ", dtype=float)
```

```python
    X = data[:, :-1]
    y = data[:, -1].astype(int)
    return X, y



def print_confusion_matrix(confusion):
    """Prints the confusion matrix in text format."""
    for row in confusion:
        print(row)



def save_results_to_file(accuracy, confusion, features, dataset_name):
    """Saves accuracy, confusion matrix, and tree features to a text file named "results.txt"."""
    with open("results.txt", "a") as f:
        f.write(f"Dataset: {dataset_name}\n")
        f.write(f"Accuracy: {accuracy:.4f}\n")
        f.write("\nTree Features:\n")
        f.write(features)
        f.write("Confusion Matrix:\n")
        np.savetxt(f, confusion, fmt="%d")



def export_confusion_matrix(confusion, accuracy, num_nodes, dataset_name):
    """Generates and saves a confusion matrix heatmap image."""
    sns.heatmap(confusion, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.title(
        f"Confusion Matrix - {dataset_name} (Accuracy: {accuracy:.4f}, Nodes: {num_nodes})"
    )


    plt.tight_layout()
    plt.savefig(f"{dataset_name}_combined_plot.png")
    plt.close()



def test_model(clf, X_test, y_test):
    """Makes predictions using the classifier, calculates accuracy, and returns both."""
    y_pred = clf.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    return accuracy, y_pred



def get_tree_features_context(clf):
    """Extracts relevant features from the trained decision tree."""
    num_nodes = clf.tree_.node_count
    max_depth = clf.tree_.max_depth
    num_features = clf.n_classes_
    features = (
```

```
        f"Number of Nodes: {num_nodes}\n"
        f"Maximum Depth: {max_depth}\n"
        f"Number of Features: {num_features}\n"
    )
    return features



def decision_tree_classification(trainset_filename, testset_filename, dataset_name=""):
    """Performs decision tree classification for a single dataset."""
    # Load train and test data
    X_train, y_train = load_data(trainset_filename)
    X_test, y_test = load_data(testset_filename)


    # Initialize DecisionTreeClassifier
    clf = DecisionTreeClassifier()


    # Train classifier
    clf.fit(X_train, y_train)


    # Get tree features
    features = get_tree_features_context(clf)


    # Test and evaluate
    accuracy, y_pred = test_model(clf, X_test, y_test)
    confusion = confusion_matrix(y_test, y_pred)


    # Print the result to console
    print(f"\nDataset: {dataset_name}")
    print("Test Accuracy:", accuracy)
    print(features)
    print("\nConfusion Matrix:")
    print_confusion_matrix(confusion)


    # Save results
    num_nodes = clf.tree_.node_count
    export_confusion_matrix(confusion, accuracy, num_nodes, dataset_name)
    save_results_to_file(accuracy, confusion, features, dataset_name)



if __name__ == "__main__":
    datasets = [
        {
            "name": "Iris",
            "train_file": "data//iris//iris.trn",
            "test_file": "data//iris//iris.tst",
        },
        {
```

```
        "name": "Optics",
        "train_file": "data//optics//optics.trn",
        "test_file": "data//optics//optics.tst",
    },
    {
        "name": "Letter",
        "train_file": "data//letter//letter.trn",
        "test_file": "data//letter//letter.tst",
    },
    {
        "name": "Leukemia",
        "train_file": "data//leukemia//leukemia.trn",
        "test_file": "data//leukemia//leukemia.tst",
    },
    {
        "name": "Fp",
        "train_file": "data//fp//fp.trn",
        "test_file": "data//fp//fp.tst",
    },
    {
        "name": "Fp017",
        "train_file": "data//fp107//fp107.trn",
        "test_file": "data//fp107//fp107.tst",
    },
]


for dataset in datasets:
    decision_tree_classification(
        dataset["train_file"], dataset["test_file"], dataset["name"]
    )
    print("\n")
```

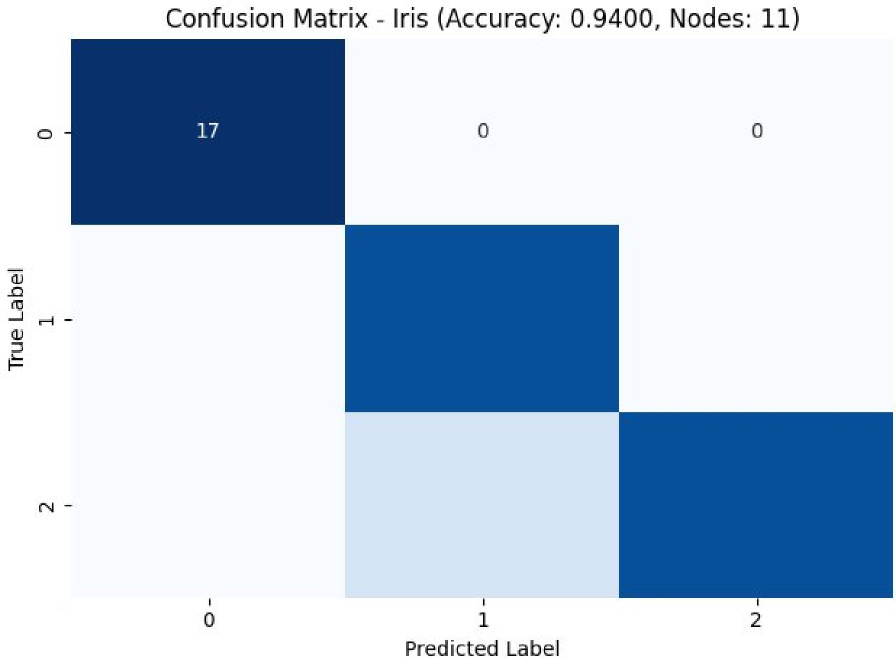
Evaluation Procedure:

- The script loads the training and testing datasets for each dataset.
- It trains a decision tree classifier on the training data.
- The trained model is then evaluated on the testing data, and performance metrics such as accuracy and confusion matrix are computed.
- Results are both printed to the console and saved to files for further analysis.

Results:

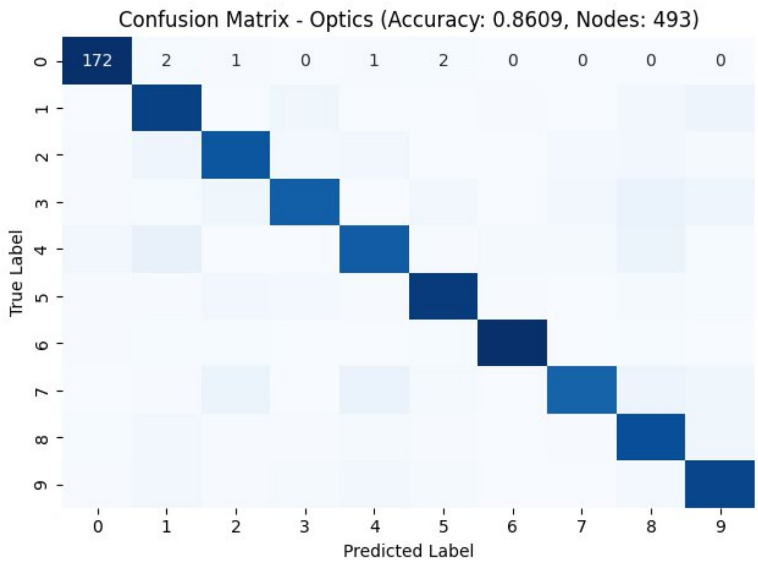
Dataset : Iris

- Accuracy:
- Accuracy: 0.94
- Confusion Matrix



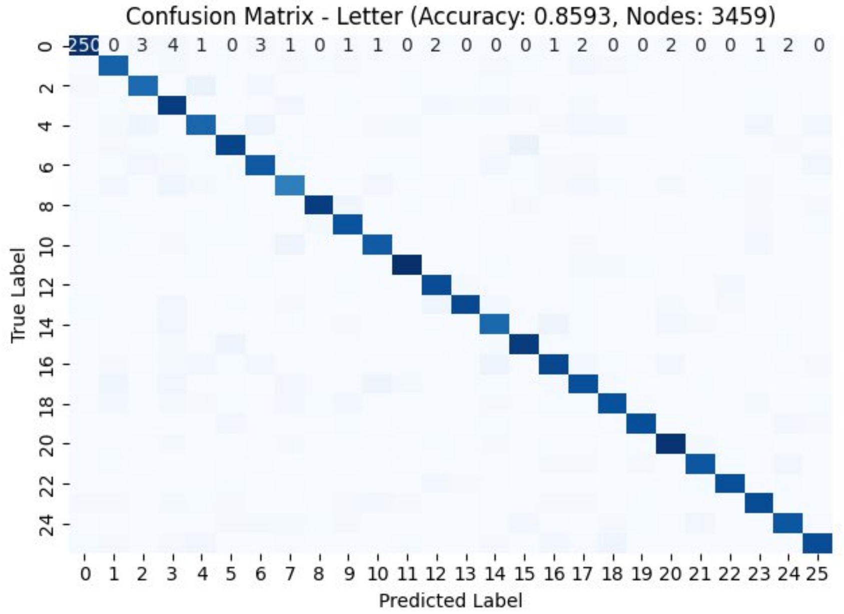
Dataset : Optics

- Accuracy: 0.8609
- Confusion Matrix:



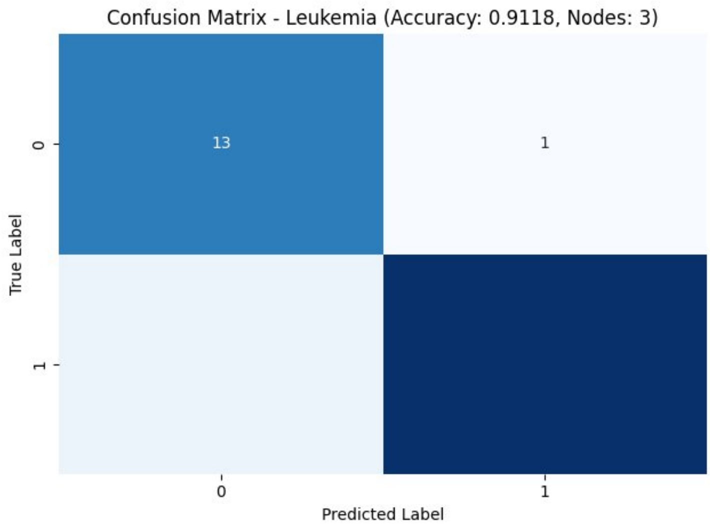
Dataset : Letter

- Accuracy: 0.8593
- Confusion Matrix:



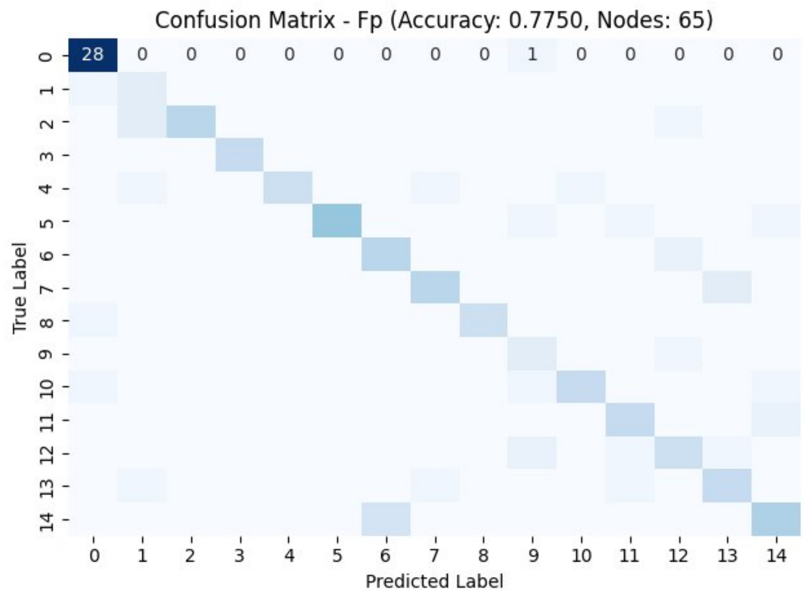
Dataset : Leukemia

- Accuracy: 0.9118
- Confusion Matrix:



Dataset : Fp

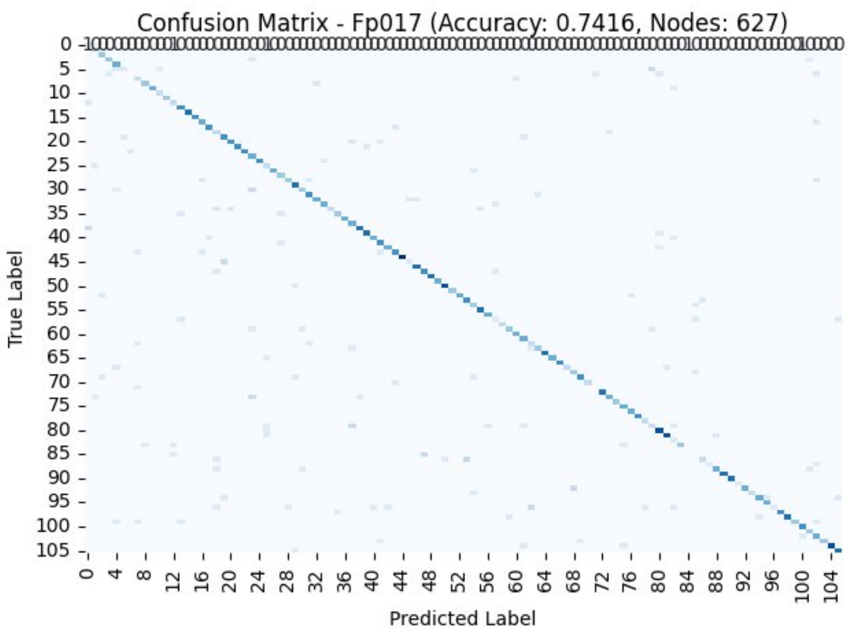
- Accuracy: 0.7750
- Confusion Matrix:



Dataset : Fp107

- Accuracy: 0.7416

Confusion Matrix



3. Why ensemble-based models improve the classification correctness of any single tree model?

Ensemble-based models boost the accuracy of classification compared to individual tree models through:

Variance Reduction: Ensemble methods, like Random Forests, amalgamate predictions from multiple trees, minimizing the impact of individual tree variability. This results in a more stable and reliable model, enhancing correctness.

Complementary Learning: Each tree in an ensemble might capture unique patterns or rectify errors made by others. By combining diverse models, ensembles capitalize on complementary learning, resulting in a more comprehensive understanding of the data and improved correctness.

Overfitting Mitigation: Single trees can overfit, particularly with depth and complexity. Ensembles mitigate overfitting by aggregating predictions from multiple trees, thus averting the memorization of noise and enhancing the model's ability to generalize.

Enhanced Generalization: Ensembles leverage the collective knowledge of multiple models, making them more adept at generalizing to unseen data. This collective intelligence contributes to superior correctness across diverse datasets and scenarios.

In summary, ensemble-based models elevate classification correctness by amalgamating diverse insights, minimizing variance, addressing overfitting, and bolstering generalization capabilities. This results in more accurate and robust models for classification tasks.