

② Use an appropriate data set for building the decision tree (ID3) and apply that knowledge to classify a new sample.

Step 1: Import necessary libraries.

```
import pandas as pd.  
from sklearn.model_selection import train_test_split.  
from sklearn.preprocessing import LabelEncoder  
from sklearn.tree import DecisionTreeClassifier, plot_tree  
from sklearn import metrics.  
import matplotlib.pyplot as plt.
```

Step 2: Load the weather dataset from the CSV file.

```
df = pd.read_csv("/content/tennis.csv")
```

Step 3: Display the first few rows of the dataset to understand its structure.

```
print("First 5 rows of the dataset:")  
print(df.head())
```

Step 4: Pre processing

```
le_outlook = LabelEncoder()  
le_temp = LabelEncoder()  
le_humidity = LabelEncoder()  
le_windy = LabelEncoder()  
le_play = LabelEncoder()
```

Encoding the relevant column (call `converter` at your dataset)

```
df['outlook'] = le_outlook.fit_transform(df['outlook'])  
df['temp'] = le_temp.fit_transform(df['temp'])  
df['humidity'] = le_humidity.fit_transform(df['humidity'])  
df['windy'] = le_windy.fit_transform(df['windy'])  
df['play'] = le_play.fit_transform(df['play'])
```

Step 5: Define features (X) and the target variable (y).

```
X = df[['outlook', 'temp', 'humidity', 'windy']]
```

```
y = df['play']
```

Step 6: Split the dataset.

```
X_train, X_test, y_train, y_test = train_test_split(X, y,  
                                                    test_size=0.2, random_state=42)
```

Step 7: Create a Decision tree classifier.

```
clf = DecisionTreeClassifier(criterion='entropy', random_state=42)
```

Step 8: Train the classifier

```
clf.fit(X_train, y_train)
```

Step 9: Predict the labels.

```
y_pred = clf.predict(X_test)
```

Step 10: Evaluate the model's accuracy.

```
accuracy = metrics.accuracy_score(y_test, y_pred)
```

```
print(f"Accuracy: {accuracy * 100:.2f}%")
```

Step 11: Classify a new weather sample.

```
new_sample = [[le_outlook.transform(['Sunny'])[0],  
               le_temp.transform(['cool'])[0],  
               le_humidity.transform(['high'])[0],  
               le_windy.transform(['false'])[0]]]
```

predicted_class = clf.predict(new_sample)

output the predicted class.

print(f"predicted class for the new sample: {'yes' if
le_play.inverse_transform([predicted_class[0]])
[0] == 'yes' else 'no'})

Step 12: Visualize the decision tree.

plt.figure(figsize=(12,8))

plot_tree(clf, feature_names=['outlook', 'temp', 'humidity',
'windy'], class_names=le_play.classes_,
filled=True, rounded=True)

plt.title("Decision tree for weather data")

plt.show()

Output:

First 5 rows of the dataset:

	Outlook	temp	humidity	windy	play
0	Sunny	hot	high	False	no
1	Sunny	hot	high	True	no
2	Overcast	hot	high	False	yes
3	rainy	mild	high	False	yes
4	rainy	cool	high normal	False	yes

Accuracy: 100.00%

predicted class for the new sample: no

Decision tree:

Outlook
├ Sunny
├ humidity
│ └ high
│ └ no
└ normal
└ yes

L overcast

→ yes

L rainy

windy

L False

→ yes

L True

→ no

Ag 11/13

0	low	high	low	high	low
1	low	high	low	high	low
2	low	high	low	high	low
3	low	high	low	high	low
4	low	high	low	high	low
5	low	high	low	high	low