solution

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1 Decision Tree Implelentation

- 1.1 Step-1: Importing Dataset
- 1.2 Step-2: Parsing the Dataset

```
[2]: from ucimlrepo import fetch_ucirepo

# fetch dataset
lenses = fetch_ucirepo(id=58)

# data (as pandas dataframes)
X = lenses.data.features
y = lenses.data.targets

# variable information
# print(lenses.variables)

dataframe = lenses.data['original']
print(lenses.data['original'])
```

	id	age	spectacle_prescription	astigmatic	class
1	1	1	1	1	3
2	1	1	1	2	2
3	1	1	2	1	3
4	1	1	2	2	1
5	1	2	1	1	3
6	1	2	1	2	2
7	1	2	2	1	3
8	1	2	2	2	1
9	2	1	1	1	3
10	2	1	1	2	2
11	2	1	2	1	3
12	2	1	2	2	1
13	2	2	1	1	3
14	2	2	1	2	2
15	2	2	2	1	3
16	2	2	2	2	3
17	3	1	1	1	3

```
18
    3
         1
                                1
                                            2
                                                   3
19 3
                                2
                                                   3
         1
                                            1
                                2
                                            2
20 3
         1
                                                   1
21
    3
         2
                                1
                                            1
                                                   3
                                                   2
22
    3
         2
                                1
                                            2
                                2
23
    3
         2
                                            1
                                                   3
24
    3
         2
                                            2
                                                   3
```

1.3 Step-3: Visual Representations

```
[]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

sns.pairplot(dataframe, hue='class', palette='viridis')
plt.show()

corr = dataframe.corr()
sns.heatmap(corr, annot=True, cmap='viridis', fmt='.2f')
plt.title('Feature Correlation Heatmap')
plt.show()
```

1.4 Step-4: Train the Classifier

1.5 Step-5: Write a function to descend the tree for a given instance

```
[]: class TreeNode:
         def __init__(self, feature_index=None, threshold=None, left=None,_
      ⇒right=None, value=None):
             self.feature_index = feature_index # Index of the feature to check (e.
      \hookrightarrow g., 0 for 'age')
             self.threshold = threshold
                                                # Threshold value for the feature
             self.left = left
                                                # Left child node
             self.right = right
                                                # Right child node
             self.value = value
                                                 # Predicted class (for leaf nodes_
      ⇔only)
     def descend_tree(node, instance):
         Descends the decision tree for a given instance and returns the prediction.
        Parameters:
         - node (TreeNode): The root node of the decision tree.
         - instance (list): A list of feature values for a single instance (e.g., \Box
      \hookrightarrow [1, 2, 1]).
         Returns:
         - The predicted class at the leaf node.
         while node.left is not None and node.right is not None: # Traverse until a_
      → leaf
             feature_value = instance[node.feature_index] # Get feature value from_
      →instance
             # Check the threshold to determine the next branch
             if feature value <= node.threshold:</pre>
                 node = node.left
             else:
                 node = node.right
         return node.value # Return prediction at the leaf node
     # Example decision tree setup (this would normally be constructed by a training_
      →algorithm)
     leaf1 = TreeNode(value=1) # For example, "Class 1"
     leaf2 = TreeNode(value=2) # For example, "Class 2"
     root = TreeNode(feature_index=0, threshold=1.5, left=leaf1, right=leaf2) #__
     →Root node checks 'age'
     # Instance to classify (e.g., age=2, spectacle_prescription=1, astigmatic=1)
```

```
instance = [2, 1, 1]

# Predict by descending the tree
prediction = descend_tree(root, instance)
print("Predicted class:", prediction)
```

Predicted class: 2

1.6 Step-6: Persist the tree data structure so it can be recalled without building the tree; then use it in any application.

```
[]: import pickle
     def save_tree(tree, filename):
         Saves the decision tree to a file.
         Parameters:
         - tree (TreeNode): The root node of the decision tree.
         - filename (str): The name of the file to save the tree.
         with open(filename, 'wb') as f:
             pickle.dump(tree, f)
         print(f"Tree saved to {filename}")
     def load_tree(filename):
         Loads the decision tree from a file.
         Parameters:
         - filename (str): The name of the file to load the tree from.
         - TreeNode: The root node of the loaded decision tree.
         with open(filename, 'rb') as f:
            tree = pickle.load(f)
         print(f"Tree loaded from {filename}")
         return tree
     # Save the tree to a file
     save_tree(root, 'decision_tree.pkl')
     # Later in your application, load the tree
     loaded_tree = load_tree('decision_tree.pkl')
```

1.7 Step-7: Information Gain Function

```
[]: import pandas as pd
     import numpy as np
     import math
     def entropy(column):
         Calculate the entropy of a column of values.
         Parameters:
         - column (list): A list of values in a column (e.g., [1, 0, 0, 1, 1]).
         Returns:
         - float: The entropy of the column.
         # Count the frequency of each value
         counts = np.bincount(column)
         probabilities = counts / len(column)
         # Calculate entropy
         return -np.sum(prob * np.log2(prob) for prob in probabilities if prob > 0)
     def info_gain(left_column, right_column, parent_entropy):
         Calculate the information gain from splitting a parent column into two \sqcup
      ⇔child columns.
         Parameters:
         - left_column (list): The values in the left child column.
         - right_column (list): The values in the right child column.
         - parent_entropy (float): The entropy of the parent column.
         Returns:
         - float: The information gain of making the split.
         total_instances = len(left_column) + len(right_column)
         left_weight = len(left_column) / total_instances
         right_weight = len(right_column) / total_instances
         left_entropy = entropy(left_column)
         right_entropy = entropy(right_column)
         # Weighted average of the child entropies
```