Q1. Describe the decision tree classifier algorithm and how it works to make predictions.

Ans:Decision tree classsifier algorithm,is a tree-like structure,where it works by splitting the data into subset based on the input features.It works like:

- Begin with the root node,which is the top of the decision tree.
- Choosing the best feature to split the data based on some criteria,This feature will help to create a decison node.
- Based on the feature value again divide the dataset for creating branches for each outcome.
- Until it reaches the leaf nodes,repeat the above steps.
- Once the dataset reach the leafnode it will determine the predicted class

Q2. Provide a step-by-step explanation of the mathematical intuition behind decision tree classification.

Ans:

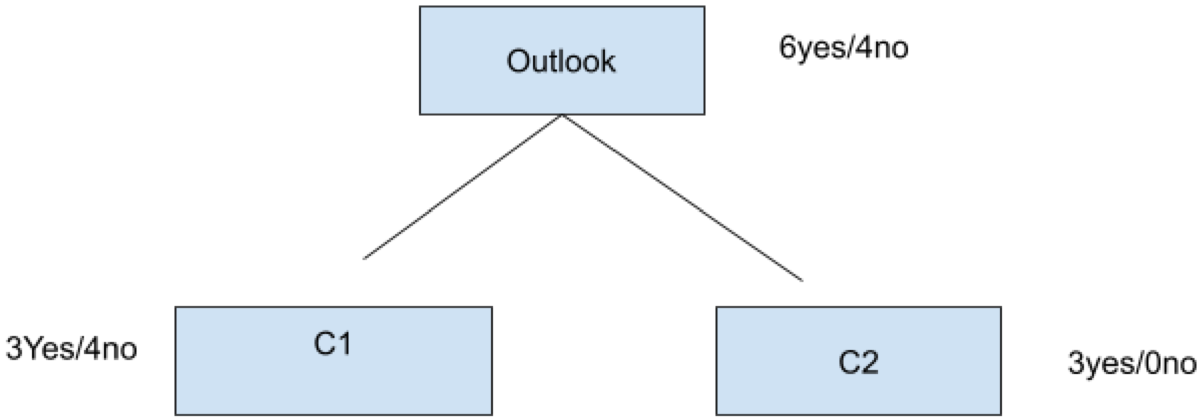
- Entropy:It is used to measure the disorder in the dataset.
- Gini impurity:It is the summation of all the probability.Lower the gini impurity more purer will be the split.
- Information gain:It is the reduction in the entropy or impurity achieved by splitting a dataset based on particular feature.

Q3. Explain how a decision tree classifier can be used to solve a binary classification problem.

Ans:In binary classification, a decision tree classifier separates the data into two classes by making a series of decisions. Each decision node represents a test on a feature, leading to a branch for each possible outcome, and the leaves of the tree represent the predicted classes.

Q4. Discuss the geometric intuition behind decision tree classification and how it can be used to make predictions.

Ans:



Q5. Define the confusion matrix and describe how it can be used to evaluate the performance of a classification model.

Ans:Confusion matrix is the table used to evaluate the performance of classification model.It can be be evaluated using the four metrics.

True positive(TP),True negative(TN),False Positive(FP),False Negative(FN)

Q6. Provide an example of a confusion matrix and explain how precision, recall, and F1 score can be calculated from it.

Lets give an example:

	Actual positive	Actual Negative
Predicted Positive	80	20
Predicted negative	10	15

Precision:TP/(TP+FP)=80/80+20=0.8

Recall:TP/(TP+FN)=80/80+10=0.88

F1Score:2*(precision*recall)/precison+recall=2*(0.8*0.88)/(0.8+0.88)=0.84

Q7.Discuss the importance of choosing an appropriate evaluation metric for a classification problem and explain how this can be done.

Ans:Precision, recall, and F1 score offer insights into different aspects of model performance, and the choice should align with the desired balance between false positives and false negatives.

Q8. Provide an example of a classification problem where precision is the most important metric, and explain why.
Ans:In spam email detection, precision is crucial because falsely classifying a legitimate email as spam (false positive) can be more problematic than missing some spam emails (false negatives).

Q9. Provide an example of a classification problem where recall is the most important metric, and explain why.
In a medical diagnosis scenario, recall is more important because it's crucial to identify all positive cases (disease), even if it means having some false positives, to avoid missing potentially critical diagnoses.