Data Preprocessing:

Load dataset and split data into training, validation, and testing data

```
import sklearn
import numpy as np
from operator import index
from numpy import number
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import seaborn as sn
from sklearn.metrics import classification_report, confusion_matrix

# Load breast cancer dataset
data = sklearn.datasets.load_breast_cancer()

label = data.target
data = data.data

# Divide data into training, validation, and testing data. Data is d
trainingFeatures, remainingFeatures, trainingLabels, remainingLabels
validationFeatures, testingFeatures, validationLabels, testingLabels
```

Creating a "Node" class, which creates the nodes found in the tree

```
class Node:
  def __init__(self, featureChosen=None, threshold=None, left=None,
    # Intializing each node with the values provided to it from the
    # Each node would contain the information gain associated with
    self.featureChosen = featureChosen
    self.threshold = threshold
    self.left = left
    self.right = right
    self.informationGain = informationGain
    self.entropy = entropy
    self.value = value
```

Creating a "Tree" class, which handles the logic for the implementation of the entire tree

```
class DecisionTree:
```

```
    def __init__(self, minSamplesSplit=2, maxDepth=2):
      # Intializes the root of the tree. Placed as None as the tree o
      self.root = None
      # Identifies the stopping condition for the tree.
      self.minSamplesSplit = minSamplesSplit
      self.maxDepth = maxDepth

    def makeTree(self, trainingFeatures, trainingLabels, currentDepth
      numberofSamples = trainingLabels.shape[0]
      numberofFeatures = trainingFeatures.shape[1]
      pureSplit = len(np.unique(trainingLabels)) == 1

      # Account for stopping conditions
      if currentDepth <= self.maxDepth and numberofSamples >= self.mi
        # Get optimal split
        optimalSplit = self.getOptimalSplit(trainingFeatures, trainin

        # Ensure current optimal split has a positive information gai
        if optimalSplit["informationGain"] > 0:
          # Build left subtree
          leftSubtree = self.makeTree(optimalSplit["leftFeatures"], o

          # Build right subtree
          rightSubtree = self.makeTree(optimalSplit["rightFeatures"],

          return Node(optimalSplit["featureChosen"], optimalSplit["th

      # If stopping conditions are met, then this is currently a leaf
      leaf = self.makeLeafNode(trainingLabels)
      return Node(value=leaf)

    def getOptimalSplit(self, trainingFeatures, trainingLabels, numbe
      # Create dictionary to store best split
      bestSplit = {}
      # Intialize the maximum information gain with minus infinity
      # This is crucial as the greedy algorithm must intially start f
      maxInformationGain = -float("inf")

      # Loop over all possible features to determine which feature wi
      for featureIndex in range(numberofFeatures):
        featureValues = trainingFeatures[:, featureIndex]
        possibleThresholds = np.unique(featureValues)
        for threshold in possibleThresholds:
          # Split according to current given values
          dataLeft, dataRight, labelsLeft, labelsRight = self.split(t
          # Ensure both left and right children are not null
          if len(dataLeft) > 0 and len(dataRight) > 0:
            informationGain = self.informationGain(trainingLabels, la
```

```
                # Update current split if the information gain obtained f
                if informationGain > maxInformationGain:
                  bestSplit["featureChosen"] = featureIndex
                  bestSplit["threshold"] = threshold
                  bestSplit["leftFeatures"] = dataLeft
                  bestSplit["leftLabels"] = labelsLeft
                  bestSplit["rightFeatures"] = dataRight
                  bestSplit["rightLabels"] = labelsRight
                  bestSplit["informationGain"] = informationGain
                  maxInformationGain = informationGain

          # Return the current best split
          return bestSplit

        def split(self, trainingFeatures, trainingLabels, featureIndex, t
          dataLeft = np.array([row for row in trainingFeatures if row[fea
          dataRight = np.array([row for row in trainingFeatures if row[fe
          labelsLeft = trainingLabels[trainingFeatures[:, featureIndex] <
          labelsRight = trainingLabels[trainingFeatures[:, featureIndex]
          return dataLeft, dataRight, labelsLeft, labelsRight

        def makeLeafNode(self, trainingLabels):
          trainingLabels = np.array(trainingLabels)
          return max(set(trainingLabels), key=list(trainingLabels).count)

        def getEntropy(self,trainingLabels):
          labels = np.unique(trainingLabels)
          # Intialize entropy with zero
          entropy = 0
          for label in labels:
            # Calculate the probability of occurence of the label
            probability = len(trainingLabels[trainingLabels == label]) /
            entropy += -probability * np.log2(probability)
          return entropy

        def informationGain(self, labelCurrent, labelLeft, labelRight):
          # Get the weight of the left and right children from the total
          weightedLeft = len(labelLeft) / len(labelCurrent)
          weightedRight = len(labelRight) / len(labelCurrent)

          # Calculate the information gain
          infoGain = self.getEntropy(labelCurrent) - (weightedLeft * self
          return infoGain

        def printTree(self, tree=None, indent=" "):
          if not tree:
            tree = self.root
          if tree.value is not None:
```

```
        if tree.value == 1:
          print("Malignant")
        elif tree.value == 0:
          print("Benign")
        else:
          print(tree.value)
      else:
        print("X"+str(tree.featureChosen), "<=", tree.threshold, "?")
        print("%sInformation Gain: " % (indent),tree.informationGain)
        print("%sleft:" % (indent), end="")
        self.printTree(tree.left, indent + indent)
        print("%sright:" % (indent), end="")
        self.printTree(tree.right, indent + indent)

    def fit(self, trainingFeatures, trainingLabels):
      self.root = self.makeTree(trainingFeatures, trainingLabels)

    def predict(self, testingFeatures):
      predictions = [self.makePredictions(row, self.root) for row in
      return predictions

    def makePredictions(self, testingFeatures, tree):
      if tree.value != None:
        return tree.value
      featureValue = testingFeatures[tree.featureChosen]
      if featureValue <= tree.threshold:
        return self.makePredictions(testingFeatures, tree.left)
      else:
        return self.makePredictions(testingFeatures, tree.right)

    def accuracy(self, testingFeatures, testingLabels):
      predictions = self.predict(testingFeatures)
      return np.mean(np.array(predictions) == np.array(testingLabels)
```

```
tree = DecisionTree(minSamplesSplit=3,maxDepth=3)
tree.fit(trainingFeatures, trainingLabels)
tree.printTree()
```

```
X22 <= 105.9 ?
 Information Gain:  0.645947668978021
 left:X27 <= 0.1423 ?
  Information Gain:  0.09557508006087603
  left:X3 <= 690.2 ?
    Information Gain:  0.03145500992451482
    left:X14 <= 0.00328 ?
        Information Gain:  0.023338451601787248
        left:Malignant
        right:Malignant
    right:Benign
  right:X13 <= 18.15 ?
    Information Gain:  0.6394725269414906
    left:X1 <= 20.22 ?
        Information Gain:  0.6500224216483541
        left:Malignant
        right:Benign
    right:Benign
 right:X27 <= 0.1489 ?
  Information Gain:  0.2080739414679902
  left:X21 <= 19.31 ?
    Information Gain:  0.29469601591956374
    left:Malignant
    right:X20 <= 16.76 ?
        Information Gain:  0.3515358797217579
        left:Malignant
        right:Benign
  right:Benign
```

```
# Testing the tree
print("Tree Accuracy on Validation Data:", tree.accuracy(validation
```

```
Tree Accuracy on Validation Data: 0.9176470588235294
```

Fine Tuning the Hyperparameters:

Maximum Tree Depth and Minimum Samples Per Split

```
def tuning(minSamplesSplit, maxDepth):
  trainingTree = DecisionTree(minSamplesSplit=minSamplesSplit,maxDe
  trainingTree.fit(trainingFeatures, trainingLabels)
  return trainingTree.accuracy(validationFeatures, validationLabels

def multipleRuns(minSamplesSplit=[2,5,10], maxDepth=[2,4,6,8,10]):
  optimalSampleSplit = 0
  optimalMaxDepth = 0
  maxAccuracy = 0

  for sampleSplit in minSamplesSplit:
    for depth in maxDepth:
      accuracy = tuning(sampleSplit, depth)
      if accuracy > maxAccuracy:
        maxAccuracy = accuracy
        optimalSampleSplit = sampleSplit
        optimalMaxDepth = depth
  print("Hyperparameter Tuning:")
  print("Minimum Samples Per Split:", optimalSampleSplit)
  print("Maximum Tree Depth:", optimalMaxDepth)
  print("Maximum Accuracy:", maxAccuracy)
  return optimalSampleSplit, optimalMaxDepth, maxAccuracy

minSampleSplit, maxDepth, maxAccuracy = multipleRuns()
```

```
Hyperparameter Tuning:
Minimum Samples Per Split: 2
Maximum Tree Depth: 4
Maximum Accuracy: 0.8941176470588236
```

```
tree = DecisionTree(minSamplesSplit=minSampleSplit,maxDepth=maxDept
tree.fit(trainingFeatures, trainingLabels)
# Test optimal minSamplesSplit and maxDepth on testing data
predictions = tree.predict(testingFeatures)
print("Tree Accuracy on Testing Data:", tree.accuracy(testingFeatur
```

```
Tree Accuracy on Testing Data: 0.9302325581395349
```

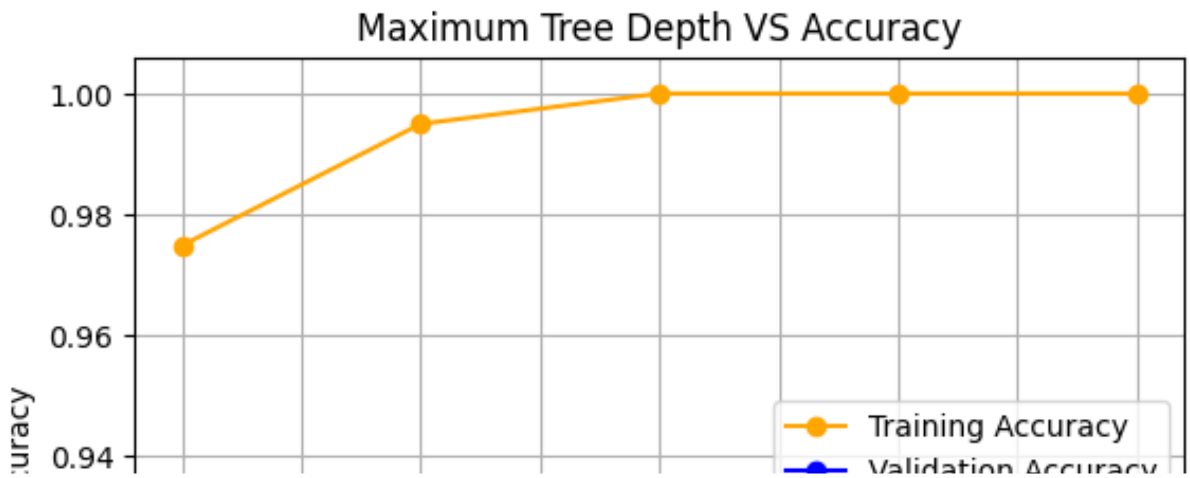
```
# Examining training and validation accuracy change with maximum de
samples=[2,4,6,8,10]
trainingAccuracyData=[]
validationAccuracyData=[]
def accuracyChange(samples=[2,4,6,8,10]):
  for depth in samples:
    trainingTree = DecisionTree(minSamplesSplit=2,maxDepth=depth)
    trainingTree.fit(trainingFeatures, trainingLabels)
```

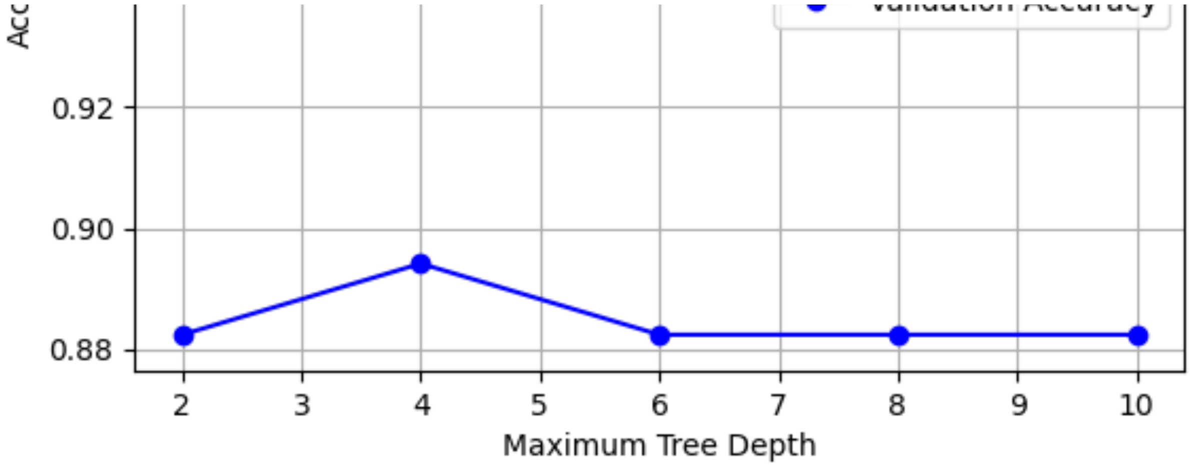
```
        trainingAccuracy = trainingTree.accuracy(trainingFeatures, trai
        validationAccuracy = trainingTree.accuracy(validationFeatures,
        print("Maximum Tree Depth:", depth)
        print("Training Accuracy:", trainingAccuracy)
        print("Validation Accuracy:", validationAccuracy)
        trainingAccuracyData.append(trainingAccuracy)
        validationAccuracyData.append(validationAccuracy)

    def plotAccuracyChange(samples, trainingAccuracyData, validationAcc
      plt.plot(samples, trainingAccuracyData, label='Training Accuracy'
      plt.plot(samples, validationAccuracyData, label='Validation Accur
      plt.xlabel('Maximum Tree Depth')
      plt.ylabel('Accuracy')
      plt.legend()
      plt.grid()
      plt.title('Maximum Tree Depth VS Accuracy')
      plt.show()

    accuracyChange()
    plotAccuracyChange(samples, trainingAccuracyData, validationAccurac
```

```
Maximum Tree Depth: 2
Training Accuracy: 0.9748743718592965
Validation Accuracy: 0.8823529411764706
Maximum Tree Depth: 4
Training Accuracy: 0.9949748743718593
Validation Accuracy: 0.8941176470588236
Maximum Tree Depth: 6
Training Accuracy: 1.0
Validation Accuracy: 0.8823529411764706
Maximum Tree Depth: 8
Training Accuracy: 1.0
Validation Accuracy: 0.8823529411764706
Maximum Tree Depth: 10
Training Accuracy: 1.0
Validation Accuracy: 0.8823529411764706
```






```
tree = DecisionTree(minSamplesSplit=minSampleSplit,maxDepth=maxDepth
tree.fit(trainingFeatures, trainingLabels)
# Test optimal minSamplesSplit and maxDepth on testing data
predictions = tree.predict(testingFeatures)

numpyPredictions = np.array(predictions)
numpyActualLabels = np.array(testingLabels)

# Performance Metrics

# Calculating the precision, recall, and f-score
# Precision: How many positively predicted instances the model predi
# Recall: Out of all of the positive instances, how many did the mod
# F1-Score: Harmonic mean of both the precision and the recall. Heav
true_positives = np.sum(np.logical_and(numpyPredictions == 0, numpyA
true_negatives = np.sum(np.logical_and(numpyPredictions == 1, numpyA
false_positives = np.sum(np.logical_and(numpyPredictions == 0, numpy
false_negatives = np.sum(np.logical_and(numpyPredictions == 1, numpy

precision = true_positives / (true_positives + false_positives)
recall = true_positives / (true_positives + false_negatives)
f1_score = 2 * ((precision * recall) / (precision + recall))

print("Classification Report for Testing Data:")
print("------------")
print("Benign: Positive || Malignant: Negative")
print("Precision: ",precision)
print("Recall: ",recall)
print("F1-Score: ",f1_score)
print("------------")

# Confusion Matrix

print("Confusion Matrix for Testing Data:")
print("------------")
```

```python
confusionMatrix = confusion_matrix(testingLabels, predictions)
plt.figure()
sn.heatmap(confusionMatrix, annot=True, fmt="d", cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix for Testing Data:')
plt.show()
```

```
Classification Report for Testing Data:
------------
Benign: Positive || Malignant: Negative
Precision:  0.8823529411764706
Recall:  0.9375
F1-Score:  0.9090909090909091
------------
Confusion Matrix for Testing Data:
------------
```