R script:

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# MIS 545 Section 02
# Lab09DineshA.R
# to import a dataset of Indonesian rice farms and generate a decision
tree
# model that will predict a farm's ownership status (farmer-owned or
sharecropped)
# based on other farm data.

# install.packages("tidyverse")
# install.packages("rpart.plot")

library(tidyverse)
library(rpart)
library(rpart.plot)

# set the working directory
setwd("~/MIS/Classes/MIS545/Assignments/Lab09")

riceFarms <- read_csv(file = "IndonesianRiceFarms.csv",
                      col_types = "fniiinf",
                      col_names = TRUE)

# print the riceFarms tibble
print(riceFarms)

# print the structure of riceFarms
print(str(riceFarms))

# print the summary of riceFarms
print(summary(riceFarms))

# set the seed to 370
set.seed(370)
sampleSet <- sample(nrow(riceFarms),
                    round(nrow(riceFarms)*0.75),
                    replace = FALSE)
# loading 75% of the training dataset
riceFarmsTraining <- riceFarms[sampleSet, ]

# loading the remaining 25% of the dataset for testing
riceFarmsTesting <- riceFarms[-sampleSet, ]

# create the decsion tree model for farm ownership with cp = 0.01
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farmOwnershipModel <- rpart(formula = FarmOwnership ~.,
                            method = "class",
                            cp = 0.01,
                            data = riceFarmsTraining)
# display the decsion tree plot
rpart.plot(farmOwnershipModel)

# predict the classes for each record
riceFarmsPrediction <- predict(farmOwnershipModel,
                               riceFarmsTesting,
                               type = "class")

# display the predictions from riceFarmsPrediction
print(riceFarmsPrediction)

# create the confusion matrix
riceFarmsConfusionMatrix <- table(riceFarmsTesting$FarmOwnership,
                                  riceFarmsPrediction)
# display the confusion matrix
print(riceFarmsConfusionMatrix)

# displaying the predictive accuracy of the decision tree model
predictiveAccuracy <- sum(diag(riceFarmsConfusionMatrix)) /
  nrow(riceFarmsTesting)
print(predictiveAccuracy)

# create the decsion tree model for farm ownership with cp = 0.007
farmOwnershipModel2 <- rpart(formula = FarmOwnership ~.,
                            method = "class",
                            cp = 0.007,
                            data = riceFarmsTraining)

# display the decsion tree plot
rpart.plot(farmOwnershipModel2)

# predict the classes for each record
riceFarmsPrediction2 <- predict(farmOwnershipModel2,
                               riceFarmsTesting,
                               type = "class")

# display the predictions from riceFarmsPrediction
print(riceFarmsPrediction2)

# create the confusion matrix
riceFarmsConfusionMatrix2 <- table(riceFarmsTesting$FarmOwnership,
                                  riceFarmsPrediction2)
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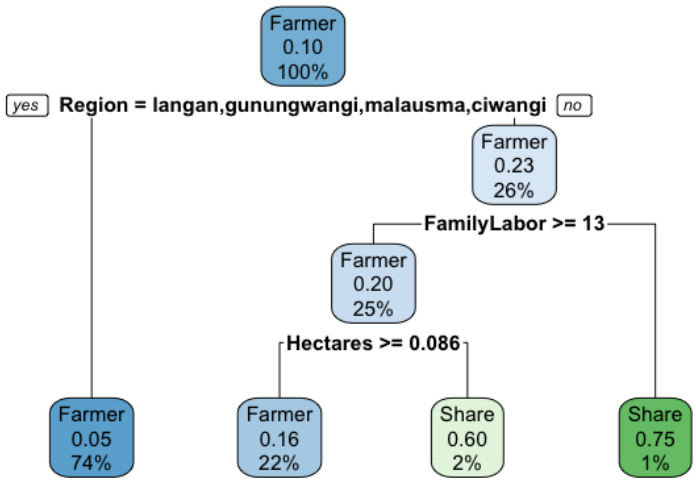
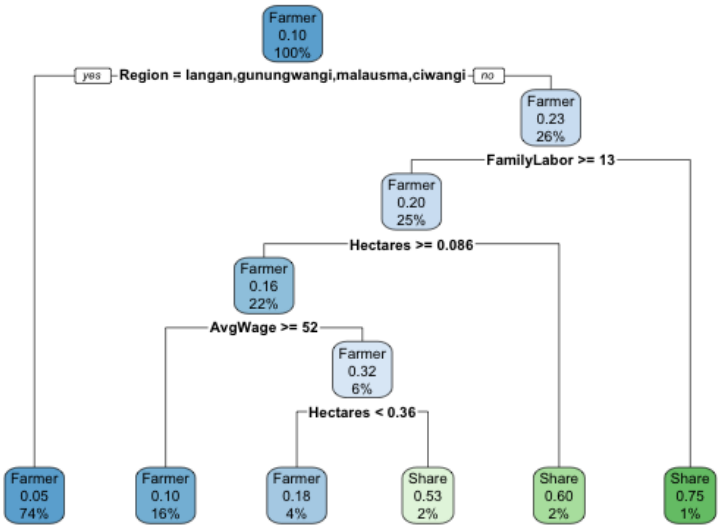
# display the confusion matrix
print(riceFarmsConfusionMatrix2)

# displaying the predictive accuracy of the decision tree model
predictiveAccuracy2 <- sum(diag(riceFarmsConfusionMatrix2)) /
  nrow(riceFarmsTesting)
print(predictiveAccuracy2)
```

Decision tree visualization for cp = 0.01



Decision tree visualization for cp = 0.007



Answer:
Increasing the complexity counter-intuitively reduced the accuracy in this case from 0.877451 to 0.872549. This is because as we increase the complexity, we tend to over-fit our model for the training set and the model wouldn’t be able to predict the classes for an unknown testing set.