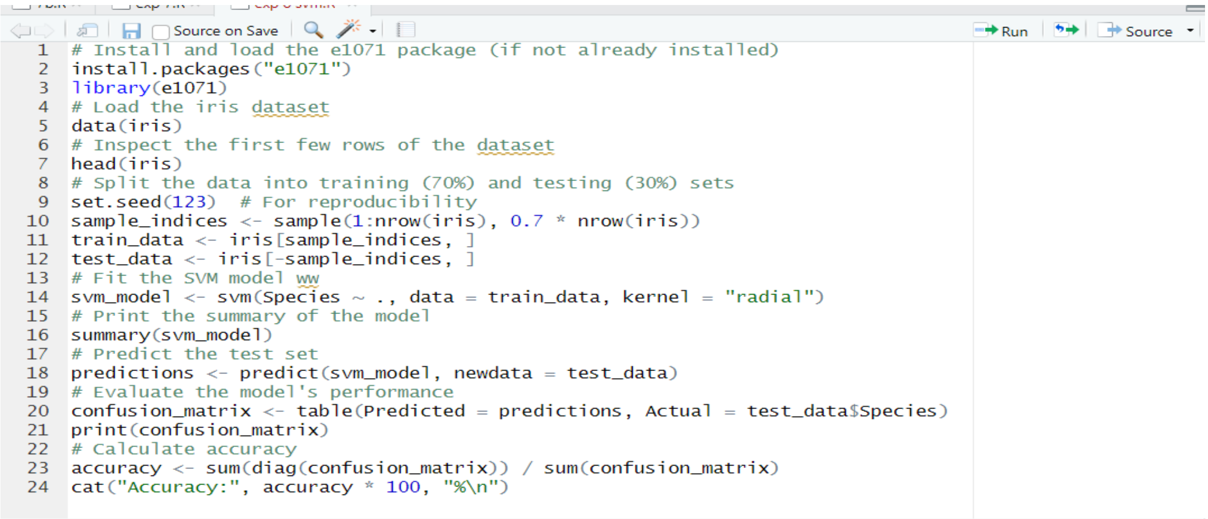
Exp8:

Implement SVM/Decision tree classification techniques

a) SVM IN R

```
# Install and load the e1071 package (if not already installed)
install.packages("e1071")
library(e1071)

# Load the iris dataset
data(iris)

# Inspect the first few rows of the dataset
head(iris)

# Split the data into training (70%) and testing (30%) sets
set.seed(123)  # For reproducibility
sample_indices <- sample(1:nrow(iris), 0.7 * nrow(iris))
train_data <- iris[sample_indices, ]
test_data <- iris[-sample_indices, ]

# Fit the SVM model
svm_model <- svm(Species ~ ., data = train_data, kernel = "radial")

# Print the summary of the model
summary(svm_model)

# Predict the test set
predictions <- predict(svm_model, newdata = test_data)

# Evaluate the model's performance
confusion_matrix <- table(Predicted = predictions, Actual = test_data$Species)
print(confusion_matrix)

# Calculate accuracy
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
cat("Accuracy:", accuracy * 100, "%\n")
```



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# Inspect the first few rows of the dataset
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print(confusion_matrix)
# Calculate accuracy
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
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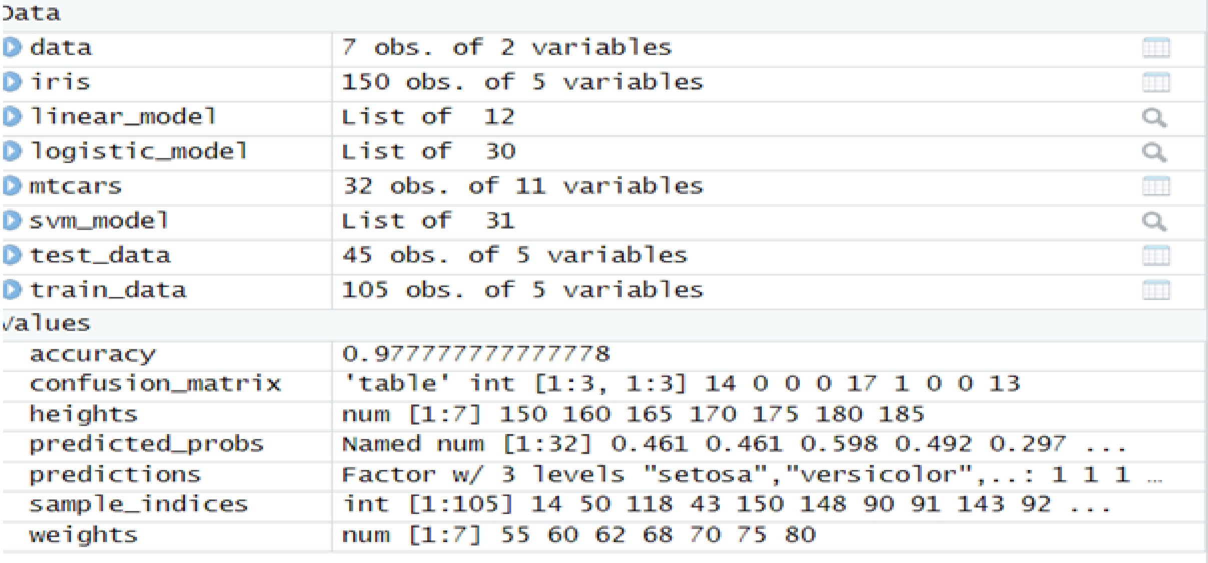
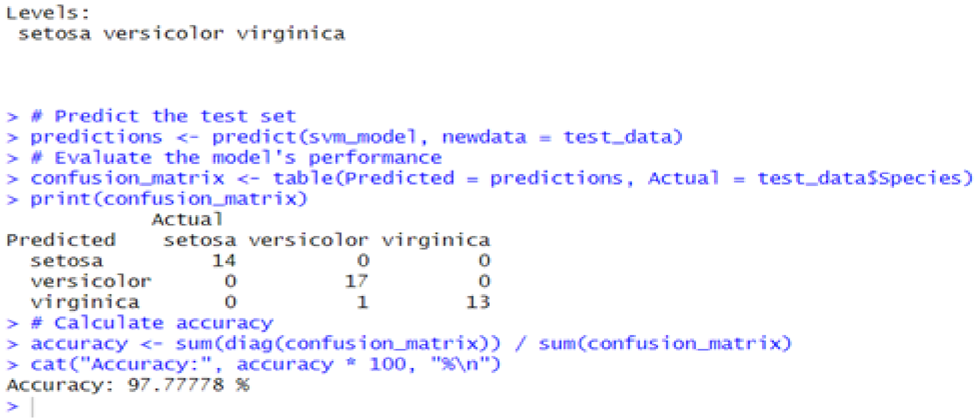


Data	
data	7 obs. of 2 variables
iris	150 obs. of 5 variables
linear_model	List of 12
logistic_model	List of 30
mtcars	32 obs. of 11 variables
svm_model	List of 31
test_data	45 obs. of 5 variables
train_data	105 obs. of 5 variables
Values	
accuracy	0.977777777777778
confusion_matrix	'table' int [1:3, 1:3] 14 0 0 0 17 1 0 0 13
heights	num [1:7] 150 160 165 170 175 180 185
predicted_probs	Named num [1:32] 0.461 0.461 0.598 0.492 0.297 ...
predictions	Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 ...
sample_indices	int [1:105] 14 50 118 43 150 148 90 91 143 92 ...
weights	num [1:7] 55 60 62 68 70 75 80

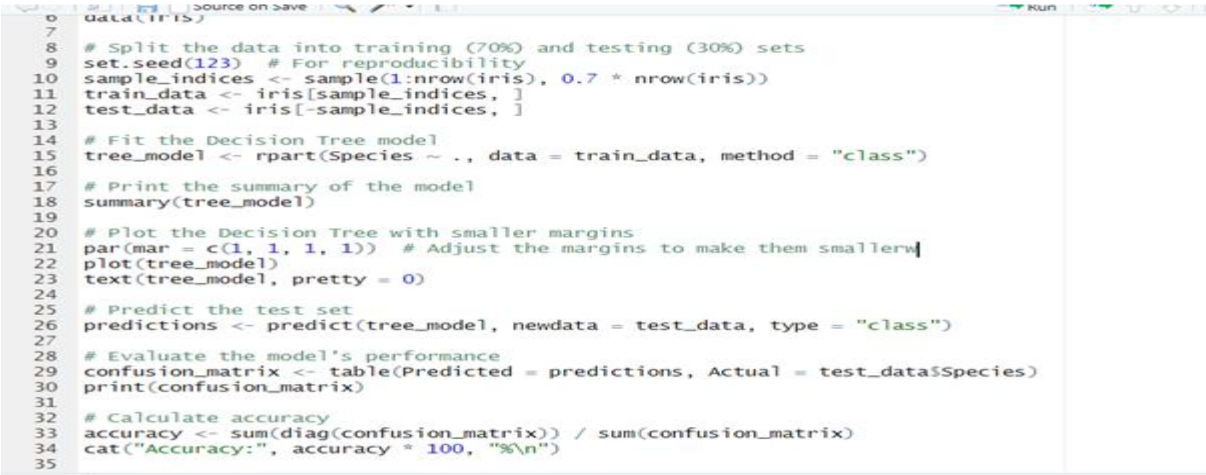


```
Levels:
 setosa versicolor virginica


> # Predict the test set
> predictions <- predict(svm_model, newdata = test_data)
> # Evaluate the model's performance
> confusion_matrix <- table(Predicted = predictions, Actual = test_data$Species)
> print(confusion_matrix)
               Actual
Predicted     setosa versicolor virginica
  setosa          14          0         0
  versicolor       0         17         0
  virginica        0          1        13
> # Calculate accuracy
> accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
> cat("Accuracy:", accuracy * 100, "%\n")
Accuracy: 97.77778 %
> |
```

b) Decision tree in R

```
# Install and load the rpart package (if not already installed)
install.packages("rpart")
library(rpart)

# Load the iris dataset
data(iris)

# Split the data into training (70%) and testing (30%) sets
set.seed(123)  # For reproducibility
sample_indices <- sample(1:nrow(iris), 0.7 * nrow(iris))
train_data <- iris[sample_indices, ]
test_data <- iris[-sample_indices, ]

# Fit the Decision Tree model
tree_model <- rpart(Species ~ ., data = train_data, method = "class")

# Print the summary of the model
summary(tree_model)

# Plot the Decision Tree
plot(tree_model)
text(tree_model, pretty = 0)

# Predict the test set
predictions <- predict(tree_model, newdata = test_data, type = "class")

# Evaluate the model's performance
confusion_matrix <- table(Predicted = predictions, Actual = test_data$Species)
print(confusion_matrix)
```

```
# Calculate accuracy
  accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
  cat("Accuracy:", accuracy * 100, "%\n")
```



```
data(iris)

# Split the data into training (70%) and testing (30%) sets
set.seed(123)  # For reproducibility
sample_indices <- sample(1:nrow(iris), 0.7 * nrow(iris))
train_data <- iris[sample_indices, ]
test_data <- iris[-sample_indices, ]

# Fit the Decision Tree model
tree_model <- rpart(Species ~ ., data = train_data, method = "class")

# Print the summary of the model
summary(tree_model)

# Plot the Decision Tree with smaller margins
par(mar = c(1, 1, 1, 1))  # Adjust the margins to make them smallerw
plot(tree_model)
text(tree_model, pretty = 0)

# Predict the test set
predictions <- predict(tree_model, newdata = test_data, type = "class")

# Evaluate the model's performance
confusion_matrix <- table(Predicted = predictions, Actual = test_data$Species)
print(confusion_matrix)

# Calculate accuracy
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
cat("Accuracy:", accuracy * 100, "%\n")
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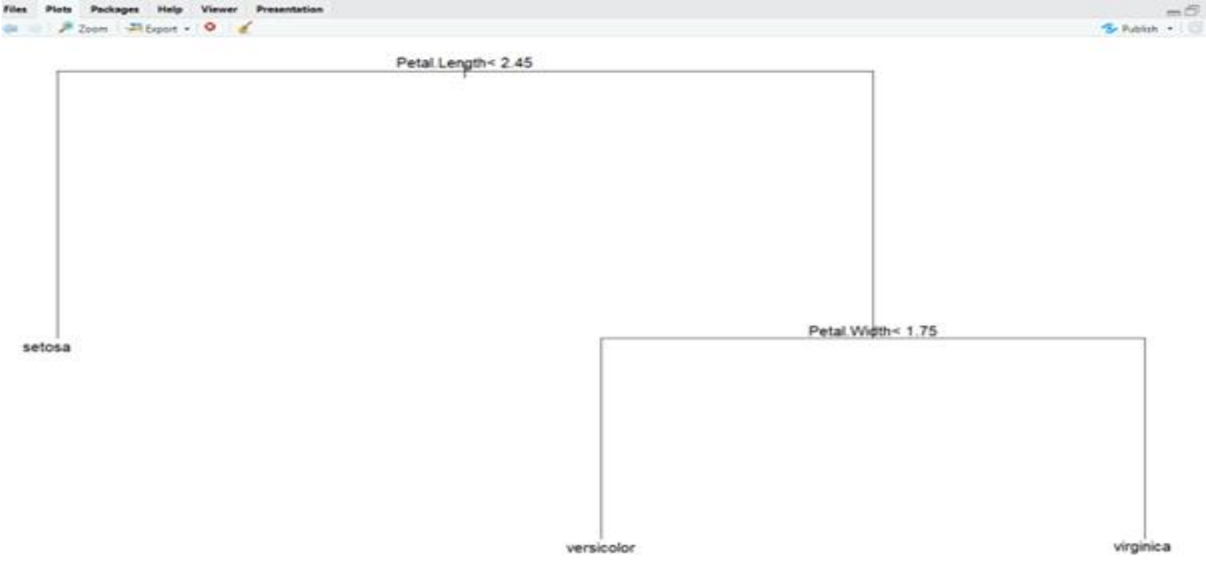

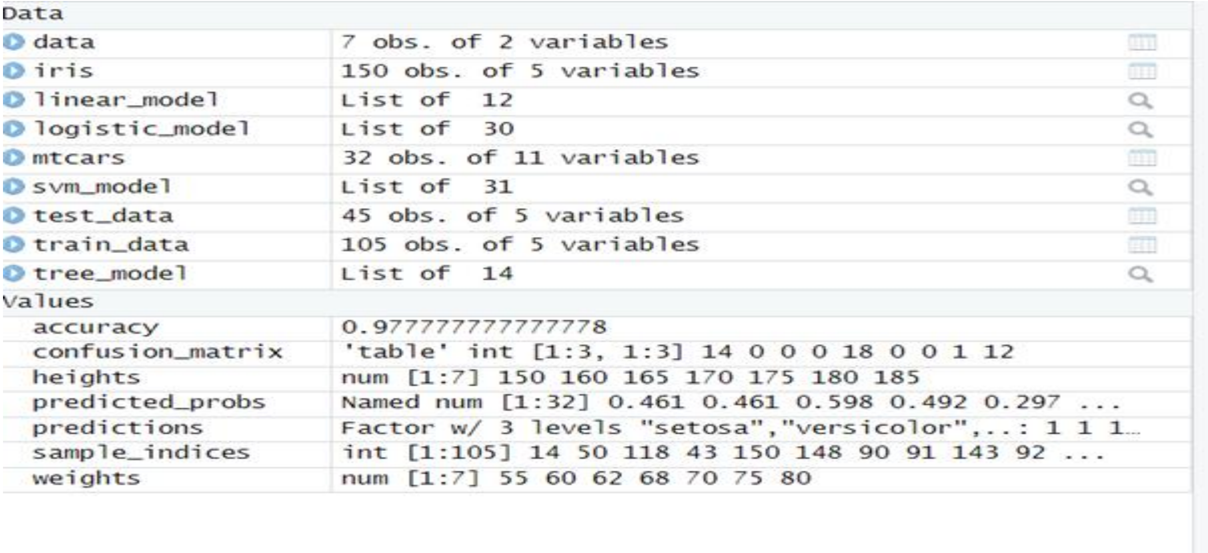

```
Data
data               7 obs. of 2 variables
iris               150 obs. of 5 variables
linear_model       List of 12
logistic_model     List of 30
mtcars             32 obs. of 11 variables
svm_model          List of 31
test_data          45 obs. of 5 variables
train_data         105 obs. of 5 variables
tree_model         List of 14
Values
accuracy           0.977777777777778
confusion_matrix   'table' int [1:3, 1:3] 14 0 0 0 18 0 0 1 12
heights            num [1:7] 150 160 165 170 175 180 185
predicted_probs    Named num [1:32] 0.461 0.461 0.598 0.492 0.297 ...
predictions        Factor w/ 3 levels "setosa","versicolor",..: 1 1 1…
sample_indices     int [1:105] 14 50 118 43 150 148 90 91 143 92 ...
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