



UTHM

Universiti Tun Hussein Onn Malaysia

UNIVERSITI TUN HUSSEIN ONN MALAYSIA

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY

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DATA MINING

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SECTION 03

LAB ASSIGNMENT 07

TITLE

CLASSIFICATION WITH NEURAL NETWORK IN R

LECTURER'S NAME

DR. ROZITA BINTI ABDUL JALIL

NAME	TUAN KHALIDAH SYAZWANA BINTI TUAN MOHD KASMAWI
MATRIC NUMBER	AI220118
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Topic: Classification with Neural Network in R

Objectives:

1. Learn how to preprocess data and prepare packages for neural network classification in R.
2. Develop a neural network classification model using the neuralnet package.
3. Evaluate model performance using confusion matrix and metrics like accuracy, precision, recall, and F-score.
4. Visualize the architecture of the trained neural network.

Duration: 2 hours

Assessment Question:

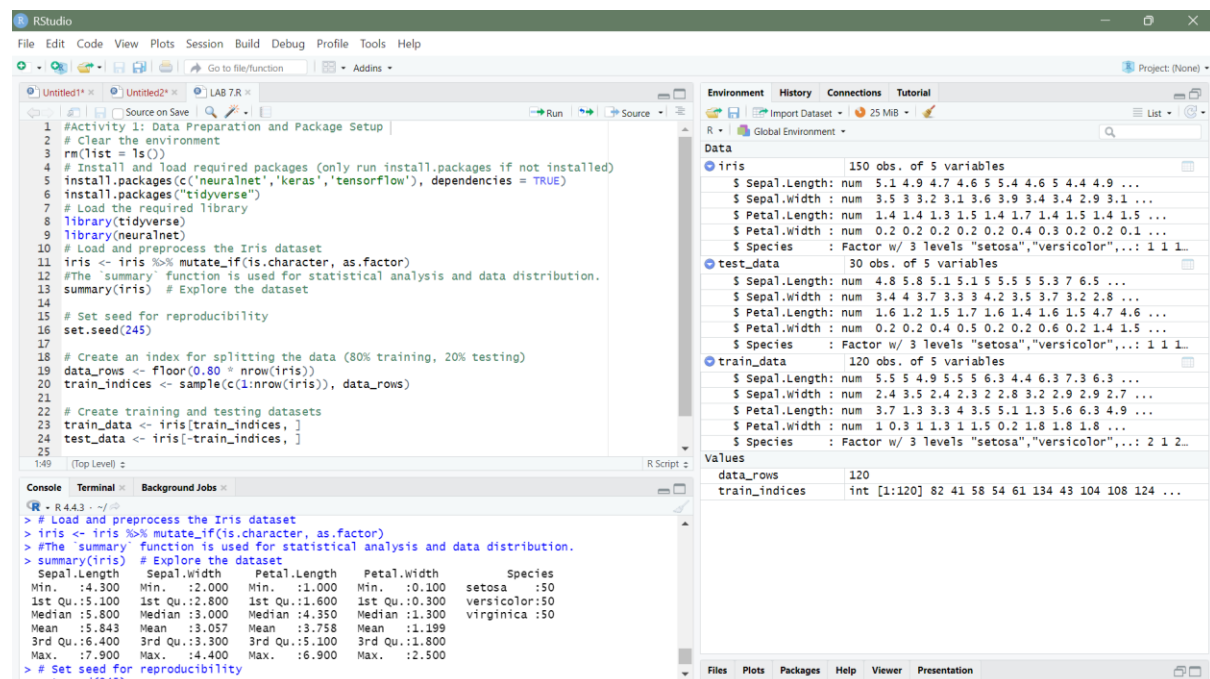
1. Run the provided code in R (Activity 1-4) and understanding the classification using Neural Network.
2. Submit the visualizations as image/data snapshots for each activity along with a brief explanation of the insights gained.

Activity 1: Data Preparation and Package Setup

Instruction:

In this activity, you will prepare your R environment by installing and loading necessary packages. You will also load and inspect the Iris dataset, then split it into training and testing sets (80:20 ratio)

Source code:



```
1 #Activity 1: Data Preparation and Package Setup
2 # Clear the environment
3 rm(list = ls())
4 # Install and load required packages (only run install.packages if not installed)
5 install.packages(c('neuralnet','keras','tensorflow'), dependencies = TRUE)
6 install.packages("tidyverse")
7 # Load the required library
8 library(tidyverse)
9 library(neuralnet)
10 # Load and preprocess the Iris dataset
11 iris <- iris %>% mutate_if(is.character, as.factor)
12 #The 'summary' function is used for statistical analysis and data distribution.
13 summary(iris) # Explore the dataset
14
15 # Set seed for reproducibility
16 set.seed(245)
17
18 # Create an index for splitting the data (80% training, 20% testing)
19 data_rows <- floor(0.80 * nrow(iris))
20 train_indices <- sample(c(1:nrow(iris)), data_rows)
21
22 # Create training and testing datasets
23 train_data <- iris[train_indices, ]
24 test_data <- iris[-train_indices, ]
25
```

The screenshot shows the RStudio interface with the source code editor on the left, the console on the bottom left, and the environment pane on the right. The console output shows the summary of the iris dataset, and the environment pane shows the loaded objects: iris, test_data, and train_data.

Justification:

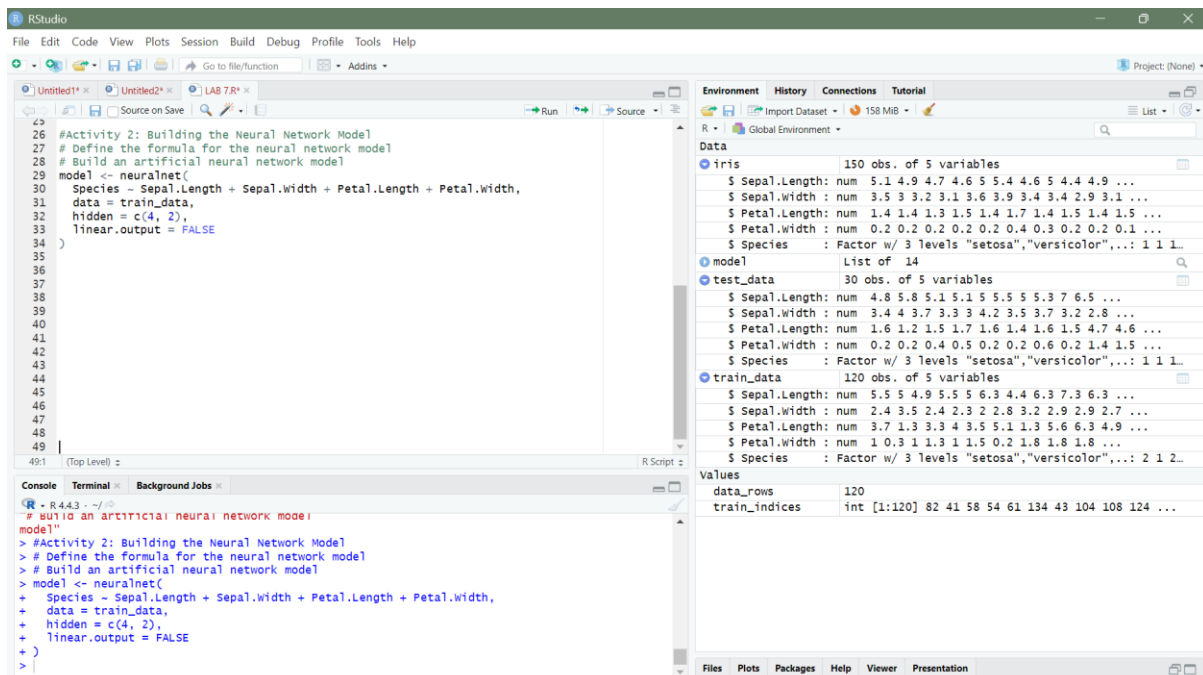
This activity is important because it gets everything ready before we build a model. We start by cleaning the R environment to avoid errors. Then we install and load the needed libraries like neuralnet and tidyverse. We use the iris dataset, which is popular for testing classification models. To make sure the model works properly, we convert character columns to factor type. Finally, we split the data into training and testing sets. This allows us to train the model with one part of the data and test its accuracy using the other part later.

Activity 2: Building the Neural Network Model

Instruction:

Now you will build a feedforward neural network with two hidden layers. You will use the training dataset created earlier to train the model.

Source code:



```
26 #Activity 2: Building the Neural Network Model
27 # Define the formula for the neural network model
28 # Build an artificial neural network model
29 model <- neuralnet(
30   Species ~ Sepal.Length + Sepal.Width + Petal.Length + Petal.Width,
31   data = train_data,
32   hidden = c(4, 2),
33   linear.output = FALSE
34 )
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
```

The screenshot shows the RStudio interface. The source editor on the left contains the R code for building a neural network model using the `neuralnet` package. The code defines a formula for the neural network, splits the data into training and test sets, and builds the model with two hidden layers. The environment pane on the right shows the objects in the global environment, including the `iris` dataset, the `model` object, and the `train_data` and `test_data` datasets. The console at the bottom shows the execution of the code.

Justification:

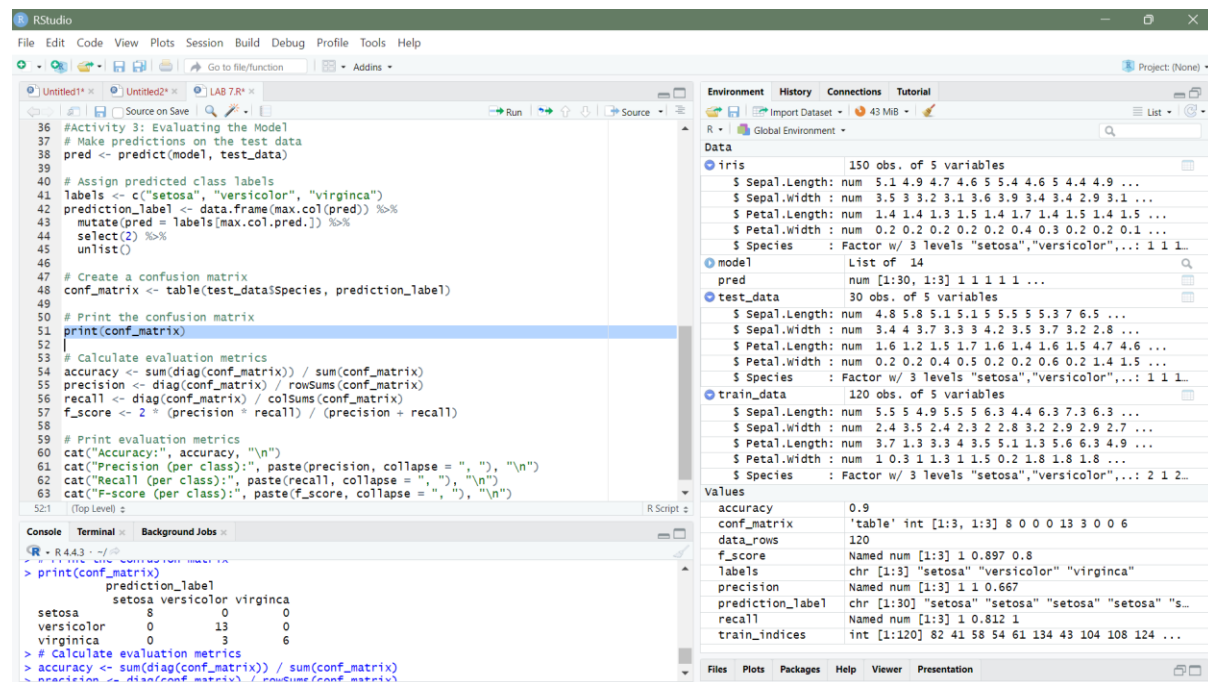
In this activity, we build a neural network model using the training data. This model tries to learn the relationship between the flower measurements (like petal and sepal length) and the flower species. The `neuralnet()` function builds this model with two hidden layers. Hidden layers help the model understand complex patterns. This step is very important because it teaches the computer how to predict the species based on the input data. The better the model learns from the training data, the more accurate it will be when making predictions on new, unseen data.

Activity 3: Evaluating the Model

Instruction:

In this activity, you will evaluate the performance of your trained neural network using the testing dataset. You will generate predictions and compute the confusion matrix along with key classification metrics.

Source code:



```
#Activity 3: Evaluating the Model
# Make predictions on the test data
pred <- predict(model, test_data)

# Assign predicted class labels
labels <- c("setosa", "versicolor", "virginica")
prediction_label <- data.frame(max.col(pred)) %>%
  mutate(pred = labels[max.col(pred)]) %>%
  select(2) %>%
  unlist()

# Create a confusion matrix
conf_matrix <- table(test_data$Species, prediction_label)

# Print the confusion matrix
print(conf_matrix)

# Calculate evaluation metrics
accuracy <- sum(diag(conf_matrix)) / sum(conf_matrix)
precision <- diag(conf_matrix) / rowSums(conf_matrix)
recall <- diag(conf_matrix) / colSums(conf_matrix)
f_score <- 2 * (precision * recall) / (precision + recall)

# Print evaluation metrics
cat("Accuracy:", accuracy, "\n")
cat("Precision (per class):", paste(precision, collapse = ", "), "\n")
cat("Recall (per class):", paste(recall, collapse = ", "), "\n")
cat("F-score (per class):", paste(f_score, collapse = ", "), "\n")
```

Environment

Object	Class	Attributes
iris	data.frame	150 obs. of 5 variables
model	list	14
pred	matrix	num [1:30, 1:3] 1 1 1 1 ...
test_data	data.frame	30 obs. of 5 variables
train_data	data.frame	120 obs. of 5 variables
accuracy	numeric	0.9
conf_matrix	table	'table' int [1:3, 1:3] 8 0 0 0 13 3 0 0 6
data_rows	integer	120
f_score	numeric	Named num [1:3] 1 0.897 0.8
labels	character	chr [1:3] "setosa" "versicolor" "virginica"
precision	numeric	Named num [1:3] 1 1 0.667
prediction_label	character	chr [1:30] "setosa" "setosa" "setosa" "setosa" "s...
recall	numeric	Named num [1:3] 1 0.812 1
train_indices	integer	int [1:120] 82 41 58 54 61 134 43 104 108 124 ...

```
> # Print evaluation metrics
> cat("Accuracy:", accuracy, "\n")
Accuracy: 0.9
> cat("Precision (per class):", paste(precision, collapse = ", "), "\n")
Precision (per class): 1, 1, 0.666666666666667
> cat("Recall (per class):", paste(recall, collapse = ", "), "\n")
Recall (per class): 1, 0.8125, 1
> cat("F-score (per class):", paste(f_score, collapse = ", "), "\n")
F-score (per class): 1, 0.896551724137931, 0.8
> |
```

Justification:

After building the model, we need to check how well it performs. In this activity, we use the test data to make predictions and compare them with the actual labels. We create a confusion matrix to see where the model was right and where it was wrong. Then, we calculate the accuracy, precision, recall, and F-score to understand the performance in more detail. These values help us know if the model is good or needs improvement. Evaluation is necessary to make sure the model is reliable before using it in real-world tasks.

Activity 4: Visualizing the Neural Network Architecture

Instruction:

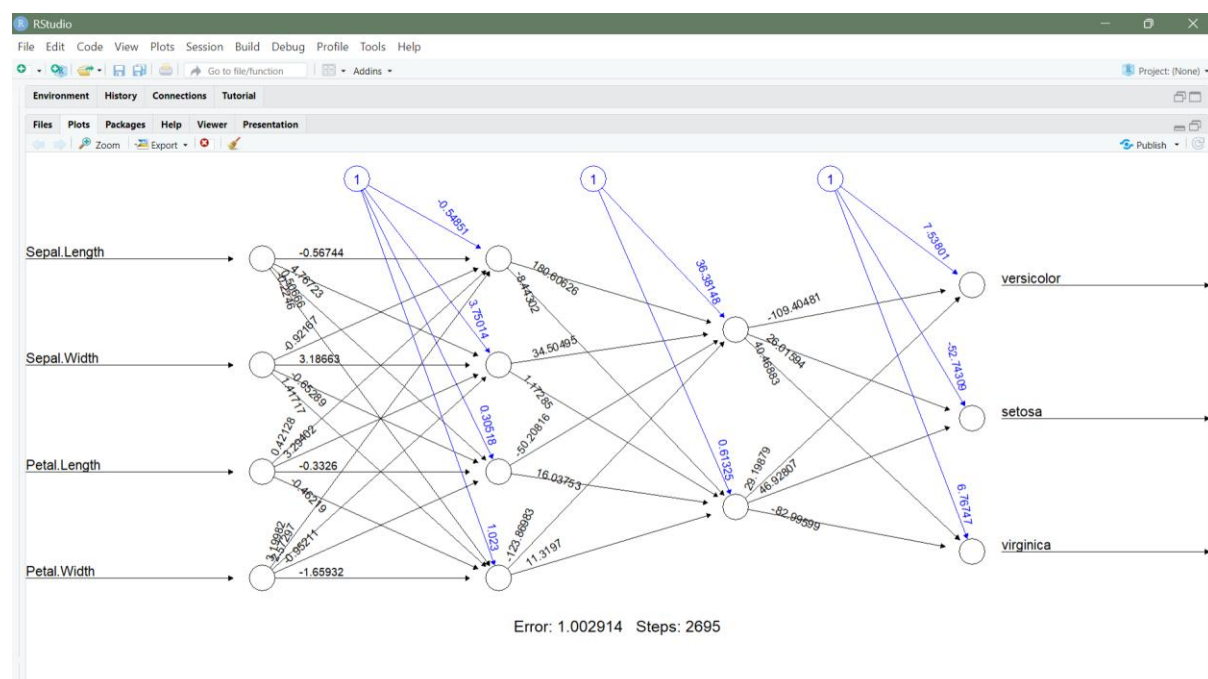
Lastly, you will visualize the structure of the trained neural network. The `plot()` function helps you see how many nodes and connections the model has.

Source code:

```
65 #Activity 4: Visualizing the Neural Network Architecture
66 # Visualize the neural network architecture
67 plot(model, rep = "best")
68
69:1 (Top Level) ▾
```

Console Terminal Background Jobs

```
R • R 4.4.3 • ~/
> #Activity 4: Visualizing the Neural Network Architecture
> # Visualize the neural network architecture
> plot(model, rep = "best")
>
```



Justification:

This activity helps us see the structure of the neural network we built. By using the `plot()` function, we can visualize how the input values connect to hidden layers and how those connect to the output. This makes it easier to understand what's happening inside the model. It also helps in identifying if the network has too many or too few layers or nodes. Visualization is useful for both learning and debugging, and it can help us explain the model to others more easily. It's a helpful step for better understanding and presentation of the model.

3. Using the iris dataset in R, perform a classification task using the Neural Network algorithm with the following steps:
 1. Split the data into 70% training and 30% testing. Make sure to use `set.seed()` so your result is reproducible.

```

1 #1. Install and load required packages
2 install.packages("nnet")      # For neural networks
3 install.packages("caret")    # For data splitting and confusion matrix
4 install.packages("e1071")    # Required for confusionMatrix
5
6 library(nnet)
7 library(caret)
8 library(e1071)
9
10 #2. Split the data into 70% training and 30% testing
11 set.seed(123) # Makes the result the same each time you run
12
13 data(iris)
14 split <- createDataPartition(iris$Species, p = 0.7, list = FALSE)
15 trainData <- iris[split, ]
16 testData <- iris[-split, ]

```

2. Build a Neural Network classifier using the training set to predict the flower species.

```

18 #3. Build a Neural Network model
19 # Normalize data (neural networks work best with scaled inputs)
20 trainData_scaled <- trainData
21 testData_scaled <- testData
22 trainData_scaled[,1:4] <- scale(trainData[,1:4])
23 testData_scaled[,1:4] <- scale(testData[,1:4])
24
25 # Train the model
26 nn_model <- nnet(Species ~ ., data = trainData_scaled,
27                 size = 5, decay = 5e-4, maxit = 200)

```

Environment pane details:

- `confMatrix`: List of 6
- `iris`: 150 obs. of 5 variables
- `model`: List of 14
- `nn_model`: List of 19
 - `pred`: num [1:30, 1:3] 1 1 1 1 1 ...
 - `split`: int [1:105, 1] 3 4 5 7 8 9 10 11 12 13 ...
- `test_data`: 30 obs. of 5 variables
 - `$ Sepal.Length`: num 4.8 5.8 5.1 5.1 5.5 5.5 5.3 7 6.5 ...
 - `$ Sepal.Width`: num 3.4 4 3.7 3.3 4.2 3.5 3.7 3.2 2.8 ...
 - `$ Petal.Length`: num 1.6 1.2 1.5 1.7 1.6 1.4 1.6 1.5 4.7 4.6 ...
 - `$ Petal.Width`: num 0.2 0.2 0.4 0.5 0.2 0.2 0.6 0.2 1.4 1.5 ...
 - `$ Species`: Factor w/ 3 levels "setosa","versicolor",...: 1 1 1 1 1 1 1 ...
- `testData`: 45 obs. of 5 variables
- `testData_scaled`: 45 obs. of 5 variables
- `train_data`: 120 obs. of 5 variables
 - `$ Sepal.Length`: num 5.5 5 4.9 5.5 5 6.3 4.4 6.3 7.3 6.3 ...
 - `$ Sepal.Width`: num 2.4 3.5 2.4 2.3 2 2.8 3.2 2.9 2.9 2.7 ...
 - `$ Petal.Length`: num 3.7 1.3 3.3 4 3.5 5.1 1.3 5.6 6.3 4.9 ...
 - `$ Petal.Width`: num 1 0.3 1 1.3 1 1.5 0.2 1.8 1.8 1.8 ...
 - `$ Species`: Factor w/ 3 levels "setosa","versicolor",...: 2 1 2 2 3 1 3 ...
- `trainData`: 105 obs. of 5 variables
- `trainData_scaled`: 105 obs. of 5 variables
- `Values`:
 - `accuracy`: 0.9
 - `conf_matrix`: 'table' int [1:3, 1:3] 8 0 0 0 13 3 0 0 6
 - `data_rows`: 120
 - `f_score`: Named num [1:3] 1 0.897 0.8
 - `labels`: chr [1:3] "setosa" "versicolor" "virginica"
 - `precision`: Named num [1:3] 1 1 0.667
 - `prediction_label`: chr [1:30] "setosa" "setosa" "setosa" "setosa" "setosa" ...

3. Evaluate your model using the testing set and report:
 1. Confusion matrix
 2. Accuracy
 3. Precision, Recall, and F-score for each class

4. Plot the Neural Network and observe its structure.

```

11 set.seed(123) # Makes the result the same each time you run
12
13 data(iris)
14 split <- createDataPartition(iris$Species, p = 0.7, list = FALSE)
15 trainData <- iris[split, ]
16 testData <- iris[-split, ]
17
18 #3. Build a Neural Network model
19 # Normalize data (neural networks work best with scaled inputs)
20 trainData_scaled <- trainData
21 testData_scaled <- testData
22 trainData_scaled[,1:4] <- scale(trainData[,1:4])
23 testData_scaled[,1:4] <- scale(testData[,1:4])
24
25 # Train the model
26 nn_model <- nnet(Species ~ ., data = trainData_scaled,
27                 size = 5, decay = 5e-4, maxit = 200)
28
29 #4. Predict using the testing set
30 predictions <- predict(nn_model, testData_scaled[,1:4], type = "class")
31
32 #5. Evaluate the model
33 # Make sure both are factors
34 predictions <- as.factor(predictions)
35 testData_scaled$Species <- as.factor(testData_scaled$Species)
36
37 # Align the factor levels
38 levels(predictions) <- levels(testData_scaled$Species)
39
40 # Create confusion matrix
41 confMatrix <- confusionMatrix(predictions, testData_scaled$Species)
42 print(confMatrix)
43
44 #6. Plot the Neural Network
45 install.packages("NeuralNetTools")
46 library(NeuralNetTools)
47 plotnet(nn_model)
48

```

Environment

- Global Environment
- Data
 - confMatrix: List of 6
 - iris: 150 obs. of 5 variables
 - model: List of 14
 - nn_model: List of 19
 - pred: num [1:30, 1:3] 1 1 1 1 1 ...
 - split: int [1:105, 1] 3 4 5 7 8 9 10 11 12 13 ...
 - test_data: 30 obs. of 5 variables
 - \$ Sepal.Length: num 4.8 5.8 5.1 5.1 5.5 5.5 5.3 7 6.5 ...
 - \$ Sepal.Width: num 3.4 4 3.7 3.3 3 4.2 3.5 3.7 3.2 2.8 ...
 - \$ Petal.Length: num 1.6 1.2 1.5 1.7 1.6 1.4 1.6 1.5 4.7 4.6 ...
 - \$ Petal.Width: num 0.2 0.2 0.4 0.5 0.2 0.2 0.6 0.2 1.4 1.5 ...
 - \$ Species: Factor w/ 3 levels "setosa","versicolor",...: 1 1 1 1 1 1 1 ...
 - testData: 45 obs. of 5 variables
 - testData_scaled: 45 obs. of 5 variables
 - train_data: 120 obs. of 5 variables
 - \$ Sepal.Length: num 5.5 5.4 9 5.5 5 6.3 4.4 6.3 7.3 6.3 ...
 - \$ Sepal.Width: num 2.4 3.5 2.4 2.3 2 2.8 3.2 2.9 2.9 2.7 ...
 - \$ Petal.Length: num 3.7 1.3 3.3 4 3.5 5.1 1.3 5.6 6.3 4.9 ...
 - \$ Petal.Width: num 1 0.3 1 1.3 1 1.5 0.2 1.8 1.8 1.8 ...
 - \$ Species: Factor w/ 3 levels "setosa","versicolor",...: 2 1 2 2 2 3 1 3...
 - trainData: 105 obs. of 5 variables
 - trainData_scaled: 105 obs. of 5 variables
- Values
 - accuracy: 0.9
 - conf_matrix: 'table' int [1:3, 1:3] 8 0 0 13 3 0 0 6
 - data_rows: 120
 - f_score: Named num [1:3] 1 0.897 0.8
 - labels: chr [1:3] "setosa" "versicolor" "virginica"
 - precision: Named num [1:3] 1 1 0.667
 - prediction_label: chr [1:30] "setosa" "setosa" "setosa" "setosa" "setosa"

```

> print(confMatrix)
Confusion Matrix and Statistics

          Reference
Prediction setosa versicolor virginica
setosa      15             0             0
versicolor   0            15             3
virginica    0             0            12

Overall Statistics

          Accuracy : 0.9333
          95% CI   : (0.8173, 0.986)
    No Information Rate : 0.3333
    P-Value [Acc > NIR] : < 2.2e-16

          Kappa : 0.9

McNemar's Test P-Value : NA

Statistics by class:

          Class: setosa Class: versicolor Class: virginica
Sensitivity      1.0000      1.0000      0.8000
Specificity      1.0000      0.9000      1.0000
Pos Pred Value   1.0000      0.8333      1.0000
Neg Pred Value   1.0000      1.0000      0.9091
Prevalence       0.3333      0.3333      0.3333
Detection Rate   0.3333      0.3333      0.2667
Detection Prevalence 0.3333      0.4000      0.2667
Balanced Accuracy 1.0000      0.9500      0.9000

> #6. Plot the Neural Network
> install.packages("NeuralNetTools")
WARNING: Rtools is required to build R packages but is not currently installed. Please
download and install the appropriate version of Rtools before proceeding:
https://cran.rstudio.com/bin/windows/Rtools/
Installing package into 'C:/Users/user/AppData/Local/R/win-library/4.4'
(as 'lib' is unspecified)

```

Environment

- Global Environment
- Files
 - Length: I1, I2, I3, I4
 - I.Width: I2, I4
 - H1, H2, H3, H4, H5
 - B1, B2
 - O1: setosa
 - O2: versico
 - O3: virginic

Self-Assessment/Study (No need to submit your answers):

- 1. Why we need to convert the character columns in the Iris dataset using `mutate_if` before training the model.**

Neural networks need numbers, not text. So, we convert character data to factor (category) format that can be used in training.

- 2. What does the parameter `hidden = c(4, 2)` represent in the `neuralnet` function?**

This sets the structure of the neural network. It means 2 hidden layers: one with 4 neurons and one with 2 neurons.

- 3. From the confusion matrix output, identify which species is most accurately predicted.**

Look at the confusion matrix. The species with the highest correct predictions (diagonal) is predicted the best.

- 4. How can we improve the neural network's performance further (in terms of accuracy or generalization)?**

You can tune the hidden layers, train with more data, normalize the data, or try other machine learning methods.

- 5. Interpret the F-score result for each class. what does it tell us about model reliability?**

F-score shows how balanced precision and recall are. A higher F-score means the model is more reliable for that class.