Neural Network Project - Lung Cancer Pred

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Setup and Data Loading

1.1 Load Necessary Libraries

```
# Load necessary libraries
library(nnet)
library(neuralnet)
library(caret)
```

```
## Loading required package: ggplot2

## Loading required package: lattice
```

```
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
library(readr)  # For loading CSV files
library(NeuralNetTools)
library(reticulate)
library(magrittr)
library(ggplot2)
library(lattice)
library(smotefamily)
```

1.2 Load and Inspect Data

```
# Load the dataset
data <- read_csv("survey_lung_cancer.csv")
```

```
## Rows: 309 Columns: 16
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (2): GENDER, LUNG_CANCER
## dbl (14): AGE, SMOKING, YELLOW_FINGERS, ANXIETY, PEER_PRESSURE, CHRONIC DISE...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
# Displaying the first few rows of data
head(data)
```

```
## # A tibble: 6 x 16
##   GENDER   AGE SMOKING YELLOW_FINGERS ANXIETY PEER_PRESSURE `CHRONIC DISEASE`
##   <chr>  <dbl>   <dbl>          <dbl>   <dbl>         <dbl>             <dbl>
## 1 M         69       1              2       2             1                 1
## 2 M         74       2              1       1             1                 2
## 3 F         59       1              1       1             2                 1
## 4 M         63       2              2       2             1                 1
## 5 F         63       1              2       1             1                 1
## 6 F         75       1              2       1             1                 2
## # i 9 more variables: FATIGUE <dbl>, ALLERGY <dbl>, WHEEZING <dbl>,
## #   `ALCOHOL CONSUMING` <dbl>, COUGHING <dbl>, `SHORTNESS OF BREATH` <dbl>,
## #   `SWALLOWING DIFFICULTY` <dbl>, `CHEST PAIN` <dbl>, LUNG_CANCER <chr>
```

GENDER: Categorical variable indicating the gender (M or F). AGE: Numeric variable representing the age of the individual. SMOKING: Ordinal variable indicating the level of smoking. YELLOW_FINGERS: Ordinal variable indicating the presence of yellow fingers. ANXIETY: Ordinal variable indicating the level of anxiety. PEER_PRESSURE: Ordinal variable indicating the influence of peer pressure. CHRONIC DISEASE: Ordinal variable indicating the presence of chronic disease. FATIGUE: Ordinal variable indicating the level of fatigue. ALLERGY: Ordinal variable indicating the presence of allergy. WHEEZING: Ordinal variable indicating the presence of wheezing. ALCOHOL CONSUMING: Ordinal variable indicating alcohol consumption. COUGHING: Ordinal variable indicating the presence of coughing. SHORTNESS OF BREATH: Ordinal variable indicating shortness of breath. SWALLOWING DIFFICULTY: Ordinal variable indicating difficulty in swallowing. CHEST PAIN: Ordinal variable indicating the presence of chest pain. LUNG_CANCER: Categorical variable indicating whether the individual has lung cancer (YES or NO).

1.3 Data Preprocessing

```r
# Convert categorical variables to numeric
data$GENDER <- ifelse(data$GENDER == "M", 1, 0)
data$LUNG_CANCER <- ifelse(data$LUNG_CANCER == "YES", 1, 0)

# Normalize numeric variables
normalize <- function(x) {
  return ((x - min(x)) / (max(x) - min(x)))
}
data_normalized <- as.data.frame(lapply(data, normalize))
```

```r
# Checking for missing values
sum(is.na(data_normalized))
```

```
## [1] 0
```

```r
# Display the first few rows of the preprocessed data
head(data_normalized)
```

```
##   GENDER       AGE SMOKING YELLOW_FINGERS ANXIETY PEER_PRESSURE CHRONIC.DISEASE
## 1      1 0.7272727       0              1       1             0               0
## 2      1 0.8030303       1              0       0             0               1
## 3      0 0.5757576       0              0       0             1               0
## 4      1 0.6363636       1              1       1             0               0
## 5      0 0.6363636       0              1       0             0               0
## 6      0 0.8181818       0              1       0             0               1
##   FATIGUE ALLERGY WHEEZING ALCOHOL.CONSUMING COUGHING SHORTNESS.OF.BREATH
## 1       1       0        1                 1        1                   1
## 2       1       1        0                 0        0                   1
## 3       1       0        1                 0        1                   1
## 4       0       0        0                 1        0                   0
## 5       0       0        1                 0        1                   1
## 6       1       1        1                 0        1                   1
##   SWALLOWING.DIFFICULTY CHEST.PAIN LUNG_CANCER
## 1                     1          1           1
## 2                     1          1           1
## 3                     0          1           0
## 4                     1          1           0
## 5                     0          0           0
## 6                     0          0           1
```

Missing Values:

The result of the sum(is.na(data_normalized)) indicates that there are no missing values in the data_normalized dataframe, meaning that the dataset is complete and ready for modeling.

First Few Rows of Data:

The output of head(data_normalized) shows the first six rows of the preprocessed data. Each column represents a feature that has been normalized to a range between 0 and 1. The columns include various features like GENDER, AGE, SMOKING, YELLOW_FINGERS, etc. The rows represent individual records with normalized values for these features.

1.4 Train/Test Split

```r
# Setting a seed for reproducibility
set.seed(123)

# Split the data into training (70%) and testing (30%) sets
trainIndex <- createDataPartition(data_normalized$LUNG_CANCER, p = 0.7, list = FALSE, times = 1)
dataTrain <- data_normalized[ trainIndex,]
dataTest  <- data_normalized[-trainIndex,]
```

##2. Exploratory Data Analysis

2.1 Summary and Descriptive Statistics

```r
# Viewing summary statistic of the data set before proceeding
summary(dataTrain)
```

```
##      GENDER           AGE            SMOKING       YELLOW_FINGERS
##  Min.   :0.00   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.00   1st Qu.:0.5606   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :1.00   Median :0.6364   Median :1.0000   Median :1.0000
##  Mean   :0.53   Mean   :0.6342   Mean   :0.5484   Mean   :0.5484
##  3rd Qu.:1.00   3rd Qu.:0.7273   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.00   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##     ANXIETY       PEER_PRESSURE    CHRONIC.DISEASE     FATIGUE
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000   Median :0.0000   Median :1.0000   Median :1.0000
##  Mean   :0.4931   Mean   :0.4885   Mean   :0.5069   Mean   :0.6636
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##     ALLERGY          WHEEZING      ALCOHOL.CONSUMING    COUGHING
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000    Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000    1st Qu.:0.0000
##  Median :1.0000   Median :1.0000   Median :1.0000    Median :1.0000
##  Mean   :0.5668   Mean   :0.5576   Mean   :0.5899    Mean   :0.5806
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000    3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000    Max.   :1.0000
##  SHORTNESS.OF.BREATH SWALLOWING.DIFFICULTY   CHEST.PAIN      LUNG_CANCER
##  Min.   :0.0000      Min.   :0.0000        Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000      1st Qu.:0.0000        1st Qu.:0.0000   1st Qu.:1.0000
##  Median :1.0000      Median :0.0000        Median :1.0000   Median :1.0000
##  Mean   :0.6452      Mean   :0.4562        Mean   :0.5438   Mean   :0.8756
##  3rd Qu.:1.0000      3rd Qu.:1.0000        3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.0000      Max.   :1.0000        Max.   :1.0000   Max.   :1.0000
```

GENDER: The gender variable is binary, with a minimum of 0 (representing one gender) and a maximum of 1 (representing the other gender). The mean is 0.53, indicating a slightly higher proportion of individuals coded as 1.

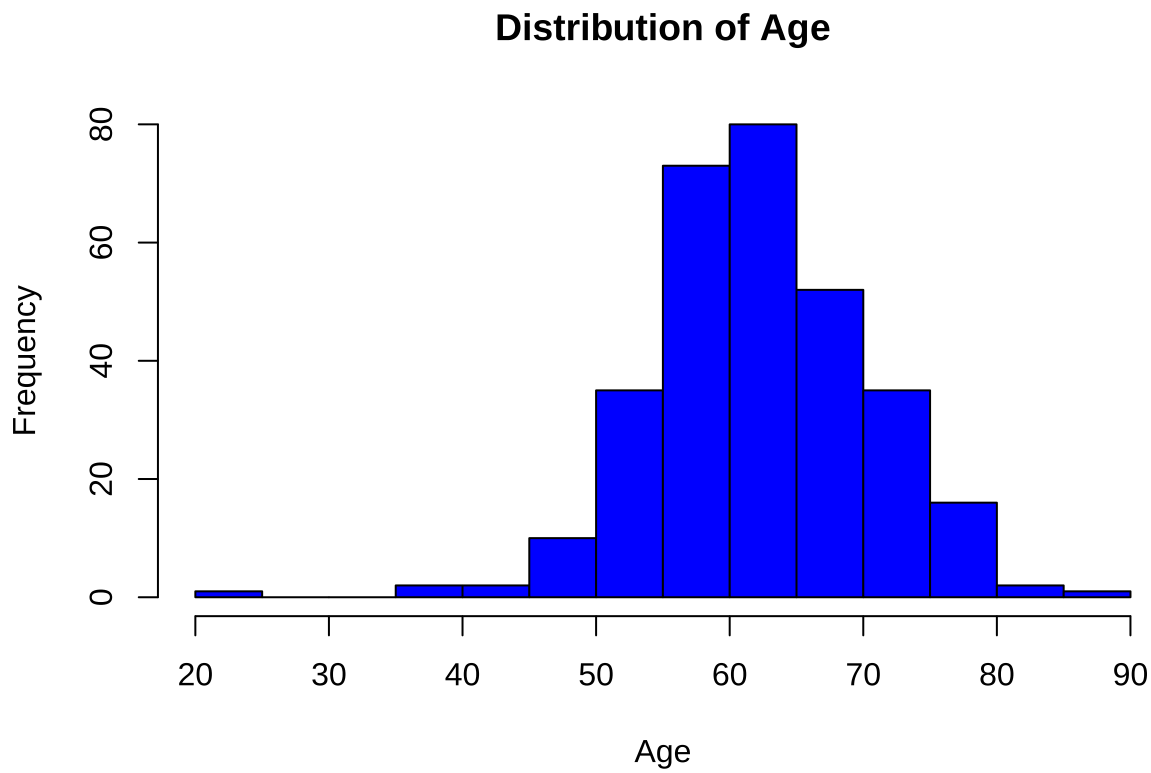
AGE: The age variable has been normalized, with values ranging from 0 to 1. The mean age is around 0.63, with the first quartile at 0.56 and the third quartile at 0.73.

SMOKING to CHEST.PAIN: These variables are all binary, with values either 0 or 1. The summary shows that many of these features have a mean close to 0.5, indicating a relatively balanced distribution between the two categories.

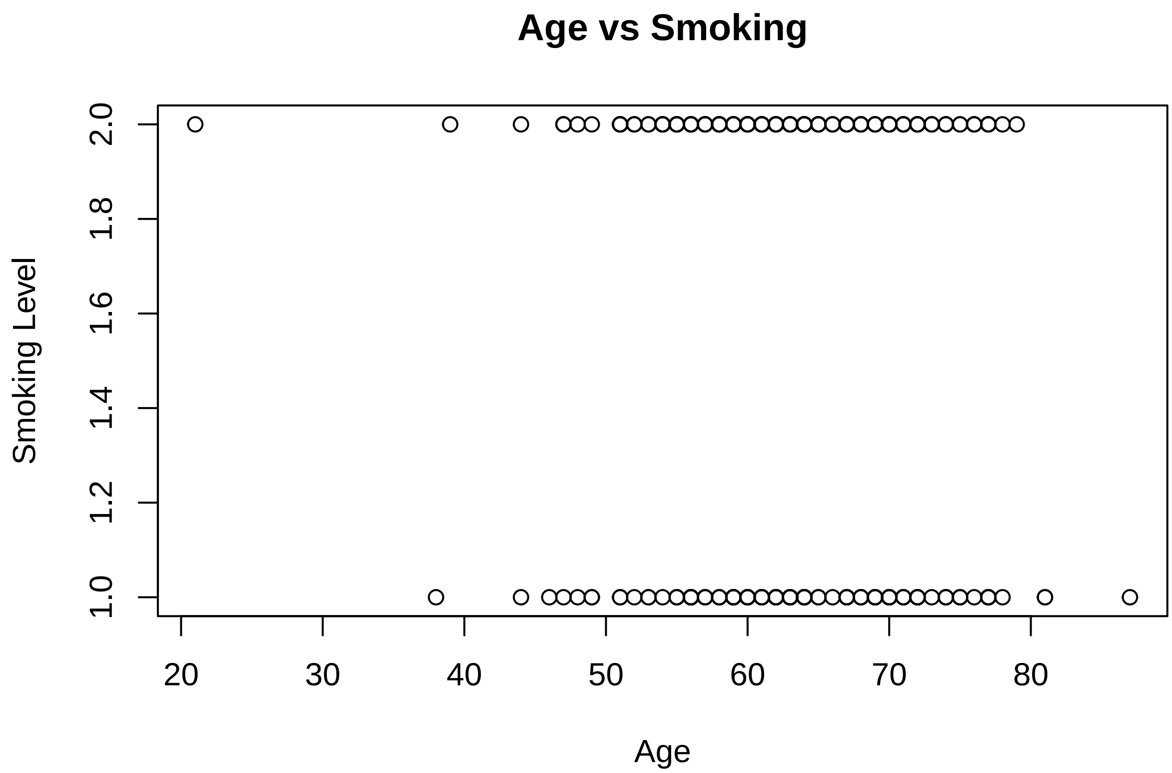
LUNG_CANCER: The target variable is also binary, with a mean of 0.8756, suggesting that a large proportion of the training data consists of individuals with lung cancer (coded as 1).

2.2 Visualizations

```r
# Histogram of Age distribution
hist(data$AGE, main="Distribution of Age", xlab="Age", col="blue")
```




```r
# Scatter plot: Age vs Smoking
plot(data$AGE, data$SMOKING, main="Age vs Smoking", xlab="Age", ylab="Smoking Level")
```



The histogram of Age (hist(data$AGE)) shows the distribution of the AGE variable within the dataset. The majority of individuals in the dataset fall within the age range of 50 to 70, with a peak around 60-65 years old.

The scatter plot (plot(data$AGE, data$SMOKING)) visualizes the relationship between AGE and SMOKING. The plot shows that smoking levels are either 0 or 1 across all age groups, with some individuals aged between 50 and 80 showing a smoking level of 2.

3. Model Building and Evaluation

3.1 Neural Network with neuralnet Library

Using Sigmoid Activation

```r
# Checking column names before training the neural network
names(dataTrain)
```

```
##  [1] "GENDER"                "AGE"                   "SMOKING"
##  [4] "YELLOW_FINGERS"        "ANXIETY"               "PEER_PRESSURE"
##  [7] "CHRONIC.DISEASE"       "FATIGUE"               "ALLERGY"
## [10] "WHEEZING"              "ALCOHOL.CONSUMING"     "COUGHING"
## [13] "SHORTNESS.OF.BREATH"   "SWALLOWING.DIFFICULTY" "CHEST.PAIN"
## [16] "LUNG_CANCER"
```

```r
# Define the formula for the neural network
formula <- LUNG_CANCER ~ GENDER + AGE + SMOKING + YELLOW_FINGERS + ANXIETY +
```

```r
           PEER_PRESSURE + `CHRONIC.DISEASE` + FATIGUE + ALLERGY + WHEEZING +
           `ALCOHOL.CONSUMING` + COUGHING + `SHORTNESS.OF.BREATH` +
           `SWALLOWING.DIFFICULTY` + `CHEST.PAIN`

# Train the neural network
set.seed(123)
nn <- neuralnet(formula, data=dataTrain, hidden=5, linear.output=FALSE)

#summary of the model
summary(nn)
```

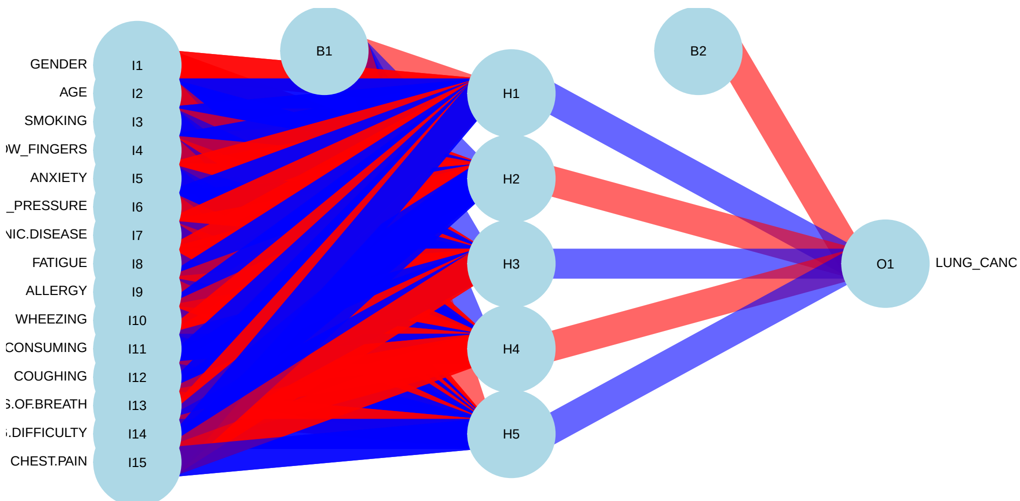
```
##                     Length Class      Mode
## call                   5   -none-     call
## response             217   -none-     numeric
## covariate           3255   -none-     numeric
## model.list             2   -none-     list
## err.fct                1   -none-     function
## act.fct                1   -none-     function
## linear.output          1   -none-     logical
## data                  16   data.frame list
## exclude                0   -none-     NULL
## net.result             1   -none-     list
## weights                1   -none-     list
## generalized.weights    1   -none-     list
## startweights           1   -none-     list
## result.matrix         89   -none-     numeric
```

```r
# Plot the neural network
png("neuralnetwork_plot.png", width = 2400, height = 1500, res = 200)

# Seting up margins to prevent labels from being cut off
par(mar = c(7, 7, 7, 7))  # bottom, left, top, right

plotnet(nn,
        circle_col = "lightblue",   # Color of the nodes
        circle_cex = 6,             # Increase the size of the nodes
        pos_col = "blue",           # Color for positive weights
        neg_col = "red",            # Color for negative weights
        alpha = 0.6,                # Transparency level for edges
        max_sp = TRUE,              # Maximum separation between nodes
        rel_rsc = 15,               # Relative scaling of edges
        cex = 0.4)                  # Reduce text size for labels
dev.off()
```

```
## pdf
##   2
```

```r
plotnet(nn,
        circle_col = "lightblue",   # Color of the nodes
        circle_cex = 6,             # Increase the size of the nodes
        pos_col = "blue",           # Color for positive weights
        neg_col = "red",            # Color for negative weights
```

```
       alpha = 0.6,                # Transparency level for edges
       max_sp = TRUE,              # Maximum separation between nodes
       rel_rsc = 15,               # Relative scaling of edges
       cex = 0.4)                  # Reduce text size for labels
```



Input Layer (Leftmost Layer):

The nodes labeled with variables such as GENDER, AGE, SMOKING, YELLOW_FINGERS, etc., are the input features used in the model. Each node corresponds to one of these features. Hidden Layer (Middle Layer):

The nodes labeled H1 to H5 are the hidden neurons in the network. In this case, there are 5 hidden neurons as specified in the model (hidden=5). These nodes receive input from the input layer and process the information before passing it on to the output layer. Output Layer (Rightmost Layer):

The single node labeled O1 represents the output of the neural network, which in this case is the prediction for LUNG_CANCER. This output is based on the weighted sum of inputs from the hidden layer neurons. Connections (Edges):

The colored lines between the nodes represent the weights assigned to the connections between layers. Red Lines: These indicate negative weights, meaning that the input feature reduces the activation of the connected neuron in the hidden layer. Blue Lines: These indicate positive weights, meaning that the input feature increases the activation of the connected neuron. Thickness of the Lines:

The thickness of each line (edge) indicates the magnitude of the weight. Thicker lines correspond to stronger influences (whether positive or negative) between the connected nodes

```r
# Exclude the LUNG_CANCER column from dataTest
input_data <- dataTest[, -ncol(dataTest)]
```

Evalulate Neural Network with 'neuralnet'

```r
# Perform the computation using the neuralnet model
predictions_nn <- neuralnet::compute(nn, input_data)$net.result

# Convert to binary class predictions
predicted_class_nn <- ifelse(predictions_nn > 0.5, 1, 0)

# Create confusion matrix
confusion_matrix_nn <- table(predicted_class_nn, dataTest$LUNG_CANCER)
print(confusion_matrix_nn)
```

```
##
## predicted_class_nn  0  1
##                  0  6  3
##                  1  6 77
```

```r
# Calculate accuracy
accuracy_nn <- sum(diag(confusion_matrix_nn)) / sum(confusion_matrix_nn)
print(paste("Accuracy with `neuralnet` model:", accuracy_nn))
```

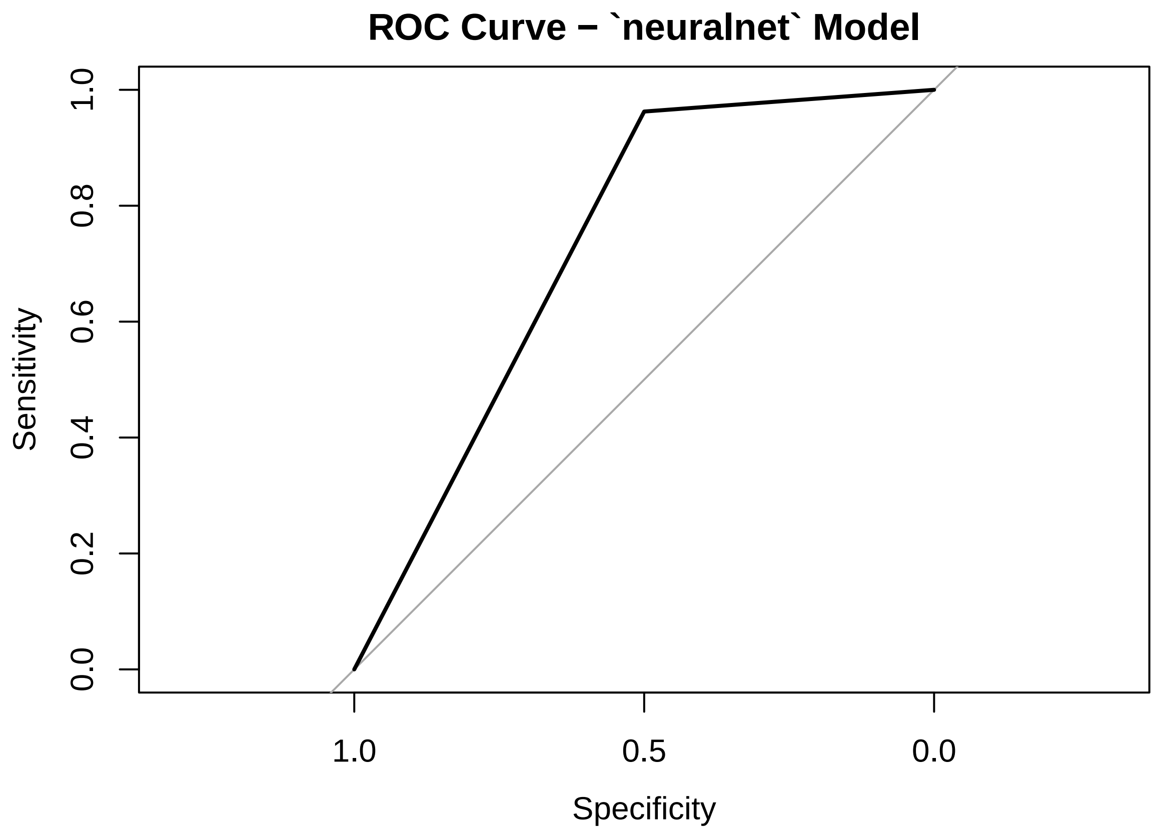
```
## [1] "Accuracy with `neuralnet` model: 0.902173913043478"
```

```r
# Plot ROC curve
roc_nn <- roc(dataTest$LUNG_CANCER, as.numeric(predicted_class_nn))
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
plot(roc_nn, main="ROC Curve - `neuralnet` Model")
```




```r
print(paste("AUC with `neuralnet` model:", auc(roc_nn)))
```

```
## [1] "AUC with ‘neuralnet‘ model: 0.73125"
```

###Confusion Matrix: True Positives (TP): 77 instances were correctly predicted as having lung cancer. True Negatives (TN): 6 instances were correctly predicted as not having lung cancer. False Positives (FP): 3 instances were incorrectly predicted as having lung cancer when they did not. False Negatives (FN): 6 instances were incorrectly predicted as not having lung cancer when they actually did.

###Accuracy:

The overall accuracy of the model is 90.22% (0.9022). This means that the model correctly predicted the class of lung cancer (presence or absence) in about 90% of the cases in the test set.

###ROC Curve and AUC:

The ROC (Receiver Operating Characteristic) curve visualizes the trade-off between sensitivity (True Positive Rate) and specificity (False Positive Rate). The area under the ROC curve (AUC) is 0.7313 (0.73125), indicating a moderate ability of the model to distinguish between the classes (lung cancer vs. no lung cancer). An AUC of 0.5 suggests no discriminative ability (random guessing), while an AUC of 1 indicates perfect classification. Thus, an AUC of 0.7313 suggests that the model performs reasonably well but leaves room for improvement.

Trying a different activation function and loss function in ‘neuralnet’

```r
# Training the model using 'tanh' activation function in 'neuralnet'
nn_tanh <- neuralnet(formula, data=dataTrain, hidden=10, act.fct = "tanh", linear.output = FALSE)
summary(nn_tanh)
```

```
##                       Length Class      Mode    
## call                    6    -none-     call    
## response              217    -none-     numeric 
## covariate            3255    -none-     numeric 
## model.list              2    -none-     list    
## err.fct                 1    -none-     function
## act.fct                 1    -none-     function
## linear.output           1    -none-     logical 
## data                   16    data.frame list    
## exclude                 0    -none-     NULL    
## net.result              1    -none-     list    
## weights                 1    -none-     list    
## generalized.weights     1    -none-     list    
## startweights            1    -none-     list    
## result.matrix         174    -none-     numeric
```

```
# Using Mean Squared Error as loss function (in neuralnet)
nn_mse <- neuralnet(formula, data=dataTrain, hidden=10, act.fct = "logistic", err.fct = "sse", linear.ou
summary(nn_mse)
```

```
##                       Length Class      Mode    
## call                    7    -none-     call    
## response              217    -none-     numeric 
## covariate            3255    -none-     numeric 
## model.list              2    -none-     list    
## err.fct                 1    -none-     function
## act.fct                 1    -none-     function
## linear.output           1    -none-     logical 
## data                   16    data.frame list    
## exclude                 0    -none-     NULL    
## net.result              1    -none-     list    
## weights                 1    -none-     list    
## generalized.weights     1    -none-     list    
## startweights            1    -none-     list    
## result.matrix         174    -none-     numeric
```

3.2 Neural Network with 'nnet' Library

Sigmoid Activation and Binary Cross-Entropy Loss

```
# Convert target variable back to numeric (0 and 1)
y_train <- as.numeric(as.character(dataTrain$LUNG_CANCER))

# Removing the target variable 'LUNG_CANCER' from 'dataTrain'
x_train <- dataTrain[, -ncol(dataTrain)]

# Fit the neural network model for classification
nn_model <- nnet(x_train, y_train, size = 16, linout = FALSE, maxit = 200, decay = 0.001)
```

```
## # weights:  273
## initial  value 121.700062 
## iter  10 value 27.615768
## iter  20 value 27.013700
```

```
## iter  30 value 26.993458
## iter  40 value 25.079239
## iter  50 value 9.740894
## iter  60 value 4.819824
## iter  70 value 3.929783
## iter  80 value 3.327253
## iter  90 value 3.010517
## iter 100 value 2.869034
## iter 110 value 2.806189
## iter 120 value 2.770774
## iter 130 value 2.745450
## iter 140 value 2.727772
## iter 150 value 2.717709
## iter 160 value 2.709963
## iter 170 value 2.703646
## iter 180 value 2.696375
## iter 190 value 2.689428
## iter 200 value 2.683018
## final  value 2.683018
## stopped after 200 iterations
```

```
# Summary of the model
summary(nn_model)
```

```
## a 15-16-1 network with 273 weights
## options were - decay=0.001
##   b->h1  i1->h1  i2->h1  i3->h1  i4->h1  i5->h1  i6->h1  i7->h1  i8->h1  i9->h1
##    0.96   -0.49   -1.04    0.34    0.50   -2.49   -0.46   -1.31    0.89   -1.27
## i10->h1 i11->h1 i12->h1 i13->h1 i14->h1 i15->h1
##   -0.49   -1.08   -1.35    1.71   -0.52   -0.54
##   b->h2  i1->h2  i2->h2  i3->h2  i4->h2  i5->h2  i6->h2  i7->h2  i8->h2  i9->h2
##    0.26    0.39    0.25   -0.34    0.18   -0.04   -0.03   -0.17   -0.32   -0.56
## i10->h2 i11->h2 i12->h2 i13->h2 i14->h2 i15->h2
##   -0.42    0.22   -0.78    0.13   -0.33   -0.25
##   b->h3  i1->h3  i2->h3  i3->h3  i4->h3  i5->h3  i6->h3  i7->h3  i8->h3  i9->h3
##    0.25    0.30    0.30   -0.28    0.11   -0.02    0.00   -0.08   -0.33   -0.42
## i10->h3 i11->h3 i12->h3 i13->h3 i14->h3 i15->h3
##   -0.46    0.16   -0.78    0.06   -0.31   -0.19
##   b->h4  i1->h4  i2->h4  i3->h4  i4->h4  i5->h4  i6->h4  i7->h4  i8->h4  i9->h4
##   -0.31   -0.30   -0.36    0.20    0.03   -0.07   -0.12    0.02    0.37    0.25
## i10->h4 i11->h4 i12->h4 i13->h4 i14->h4 i15->h4
##    0.40   -0.07    0.66    0.04    0.16    0.07
##   b->h5  i1->h5  i2->h5  i3->h5  i4->h5  i5->h5  i6->h5  i7->h5  i8->h5  i9->h5
##    2.45   -1.06  -10.86    1.46    2.50   -1.23    1.62    3.48    2.37    3.13
## i10->h5 i11->h5 i12->h5 i13->h5 i14->h5 i15->h5
##    2.24    0.24    3.85   -1.74    1.38   -0.66
##   b->h6  i1->h6  i2->h6  i3->h6  i4->h6  i5->h6  i6->h6  i7->h6  i8->h6  i9->h6
##    0.99    0.05   -9.37    1.83    4.07   -3.16    0.19    0.45   -0.48    2.27
## i10->h6 i11->h6 i12->h6 i13->h6 i14->h6 i15->h6
##    0.58   -1.69    1.37    0.47   -1.37   -2.10
##   b->h7  i1->h7  i2->h7  i3->h7  i4->h7  i5->h7  i6->h7  i7->h7  i8->h7  i9->h7
##   -0.39    0.16   -0.13   -0.51   -0.02    0.45   -0.03   -0.12   -0.46   -0.25
## i10->h7 i11->h7 i12->h7 i13->h7 i14->h7 i15->h7
##   -0.21    0.37   -0.50   -0.48   -0.08    0.03
```

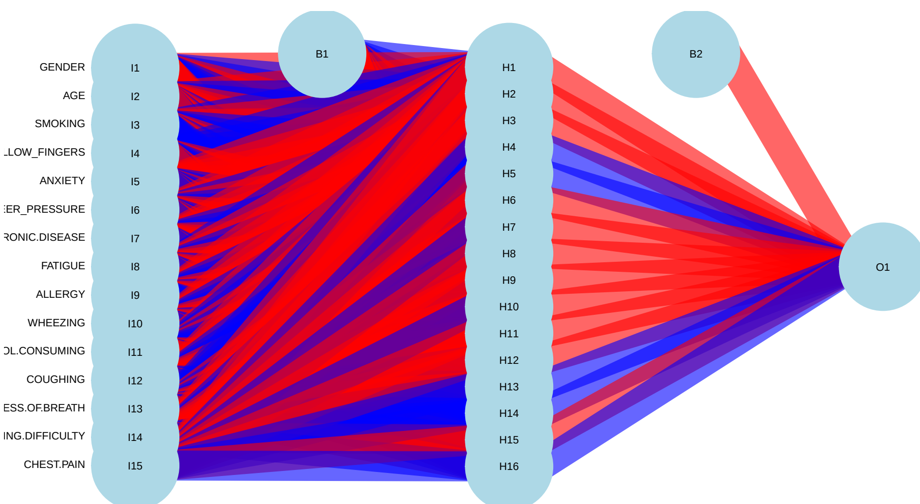
```
##   b->h8  i1->h8  i2->h8  i3->h8  i4->h8  i5->h8  i6->h8  i7->h8  i8->h8  i9->h8
##    0.14    0.23    0.12   -0.17    0.00    0.05   -0.02   -0.05   -0.19   -0.30
## i10->h8 i11->h8 i12->h8 i13->h8 i14->h8 i15->h8
##   -0.31    0.15   -0.48    0.02   -0.15   -0.14
##   b->h9  i1->h9  i2->h9  i3->h9  i4->h9  i5->h9  i6->h9  i7->h9  i8->h9  i9->h9
##   -0.41    0.75   -5.69    0.65    0.26   -1.57   -1.99   -1.56    1.32    2.15
## i10->h9 i11->h9 i12->h9 i13->h9 i14->h9 i15->h9
##   -0.29    0.93   -0.46    0.90   -0.48   -1.62
##   b->h10  i1->h10  i2->h10  i3->h10  i4->h10  i5->h10  i6->h10  i7->h10
##    -0.11     1.27    -1.34    -1.45     1.05     0.96     0.60    -1.10
##  i8->h10  i9->h10 i10->h10 i11->h10 i12->h10 i13->h10 i14->h10 i15->h10
##    -1.30    -1.40     0.85     0.31    -0.75    -0.22    -0.74     0.01
##   b->h11  i1->h11  i2->h11  i3->h11  i4->h11  i5->h11  i6->h11  i7->h11
##     0.04     0.05     0.61    -0.46     0.08     0.06     0.14    -0.07
##  i8->h11  i9->h11 i10->h11 i11->h11 i12->h11 i13->h11 i14->h11 i15->h11
##    -0.50    -0.70    -0.39     0.11    -0.61    -0.21    -0.27    -0.15
##   b->h12  i1->h12  i2->h12  i3->h12  i4->h12  i5->h12  i6->h12  i7->h12
##     0.41     0.11    -0.20     0.47     1.00    -0.71    -0.70    -0.80
##  i8->h12  i9->h12 i10->h12 i11->h12 i12->h12 i13->h12 i14->h12 i15->h12
##    -0.54    -0.37    -0.44    -0.49    -0.60     0.14    -0.01    -0.27
##   b->h13  i1->h13  i2->h13  i3->h13  i4->h13  i5->h13  i6->h13  i7->h13
##    -0.27    -0.44    -0.27     0.37    -0.25     0.11     0.09     0.29
##  i8->h13  i9->h13 i10->h13 i11->h13 i12->h13 i13->h13 i14->h13 i15->h13
##     0.36     0.65     0.43    -0.21     0.84    -0.19     0.38     0.29
##   b->h14  i1->h14  i2->h14  i3->h14  i4->h14  i5->h14  i6->h14  i7->h14
##    -0.33    -0.48    -1.02     0.74    -0.36     0.01    -0.47     0.55
##  i8->h14  i9->h14 i10->h14 i11->h14 i12->h14 i13->h14 i14->h14 i15->h14
##     0.57     1.05     0.19     0.02     0.66     0.24     0.20     0.02
##   b->h15  i1->h15  i2->h15  i3->h15  i4->h15  i5->h15  i6->h15  i7->h15
##    -0.67    -1.40     2.87     1.57     0.28    -1.83    -1.04    -1.09
##  i8->h15  i9->h15 i10->h15 i11->h15 i12->h15 i13->h15 i14->h15 i15->h15
##    -0.88     0.93    -1.63    -1.57    -1.10     0.72    -0.79    -0.70
##   b->h16  i1->h16  i2->h16  i3->h16  i4->h16  i5->h16  i6->h16  i7->h16
##    -0.33    -0.58    -0.38     0.54    -0.47     0.10     0.02     0.44
##  i8->h16  i9->h16 i10->h16 i11->h16 i12->h16 i13->h16 i14->h16 i15->h16
##     0.46     0.76     0.27    -0.31     0.78    -0.21     0.40     0.26
##   b->o  h1->o  h2->o  h3->o  h4->o  h5->o  h6->o  h7->o  h8->o  h9->o h10->o
##  -0.35  -4.42  -1.65  -1.62   0.84  13.29 -10.33  -1.29  -0.98  -6.21  -4.09
## h11->o h12->o h13->o h14->o h15->o h16->o
##  -1.71  -1.97   1.58   1.75  -4.70   1.75
```

```r
# Save the improved plot as a high-resolution image
png("improved_nn_plot.png", width = 2400, height = 1500, res = 200)

# Setting up margins to prevent labels from being cut off
par(mar = c(5, 5, 5, 5))  # bottom, left, top, right

# Visualize the nnet model using plotnet
plotnet(nn_model,
        circle_col = "lightblue",   # Color of the nodes
        circle_cex = 6,             # Increase the size of the nodes
        pos_col = "blue",           # Color for positive weights
        neg_col = "red",            # Color for negative weights
        alpha = 0.6,                # Transparency level for edges
```

```r
        max_sp = TRUE,                # Maximum separation between nodes
        rel_rsc = 15,                 # Relative scaling of edges
        cex = 0.3)                    # Reduce text size for labels
dev.off()
```

```
## pdf
##   2
```

```r
# Visualize the nnet model using plotnet
plotnet(nn_model,
        circle_col = "lightblue",    # Color of the nodes
        circle_cex = 6,              # Increase the size of the nodes
        pos_col = "blue",            # Color for positive weights
        neg_col = "red",             # Color for negative weights
        alpha = 0.6,                 # Transparency level for edges
        max_sp = TRUE,               # Maximum separation between nodes
        rel_rsc = 15,                # Relative scaling of edges
        cex = 0.3)                   # Reduce text size for labels
```



3.3 Model Evaluation on Test Set

Evaluate Model with 'nnet'

```r
# Make predictions with type = "class"
predictions <- predict(nn_model, dataTest[, -ncol(dataTest)])
```

```r
# Evaluate performance
confusion_matrix <- table(predictions, dataTest$LUNG_CANCER)
print(confusion_matrix)
```

```
##
## predictions            0 1
##   0                    1 0
##   3.02648007816028e-05 1 0
##   0.00383447393354189  0 1
##   0.0140529516617849   1 0
##   0.0427960679829711   0 1
##   0.11732237169879     1 0
##   0.248457256743238    1 0
##   0.592097181368541    0 1
##   0.621883434409662    0 1
##   0.645328654085871    1 0
##   0.764867875765731    0 1
##   0.87962922510782     0 1
##   0.97237079354961     0 1
##   0.973829960337201    0 1
##   0.978763053844313    0 1
##   0.980097678053065    0 1
##   0.982277670372507    1 0
##   0.984728774688714    0 1
##   0.986138229412622    0 1
##   0.990671117143009    1 0
##   0.994932033759982    0 1
##   0.997418271388837    0 1
##   0.998579794984249    0 1
##   0.998727876240169    0 2
##   0.998976287588356    0 1
##   0.999671614484403    1 0
##   0.999714262054223    0 1
##   0.999767805641429    1 0
##   0.999832071492558    0 1
##   0.999839277312509    0 1
##   0.9998759423303      0 1
##   0.999886090622973    0 1
##   0.999887200004231    0 1
##   0.999889996815738    0 1
##   0.999911685972443    0 1
##   0.999914662301652    0 1
##   0.999935731220247    0 1
##   0.999937051091245    0 1
##   0.999940589035432    0 1
##   0.999942976005046    0 1
##   0.999943132147361    0 1
##   0.9999543522466      0 1
##   0.999954953726179    0 1
##   0.999957074484225    0 1
##   0.999959102890339    0 1
##   0.999964154098909    0 1
##   0.999964606895059    0 1
```

```
##   0.999966887901496    0 1
##   0.999976036689748    0 1
##   0.999979925601175    0 2
##   0.999980170192692    0 1
##   0.999980385862851    0 1
##   0.999982472664053    0 1
##   0.999987104109626    0 1
##   0.999988826902647    0 1
##   0.999989381616679    0 1
##   0.999989759727052    0 1
##   0.999989822704814    0 1
##   0.999992105317732    0 1
##   0.999992428790897    0 1
##   0.999993099842541    1 0
##   0.99999562448086     0 1
##   0.999995829393151    0 1
##   0.999995909483708    0 1
##   0.999996090353659    0 1
##   0.999996573695109    0 1
##   0.999997406142071    0 1
##   0.999997422320936    0 1
##   0.999997444369207    0 2
##   0.999998597689729    0 1
##   0.999998627220026    0 1
##   0.999998694099383    1 0
##   0.999998854032363    0 1
##   0.999999060325727    0 1
##   0.999999076141922    0 1
##   0.999999091486142    0 1
##   0.999999363381116    0 1
##   0.999999406965731    0 1
##   0.999999463937863    0 1
##   0.999999557789288    0 1
##   0.999999675074181    0 1
##   1                    0 8
```

```r
# Calculate and display accuracy
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
print(paste("Accuracy with `nnet` model:", accuracy))
```

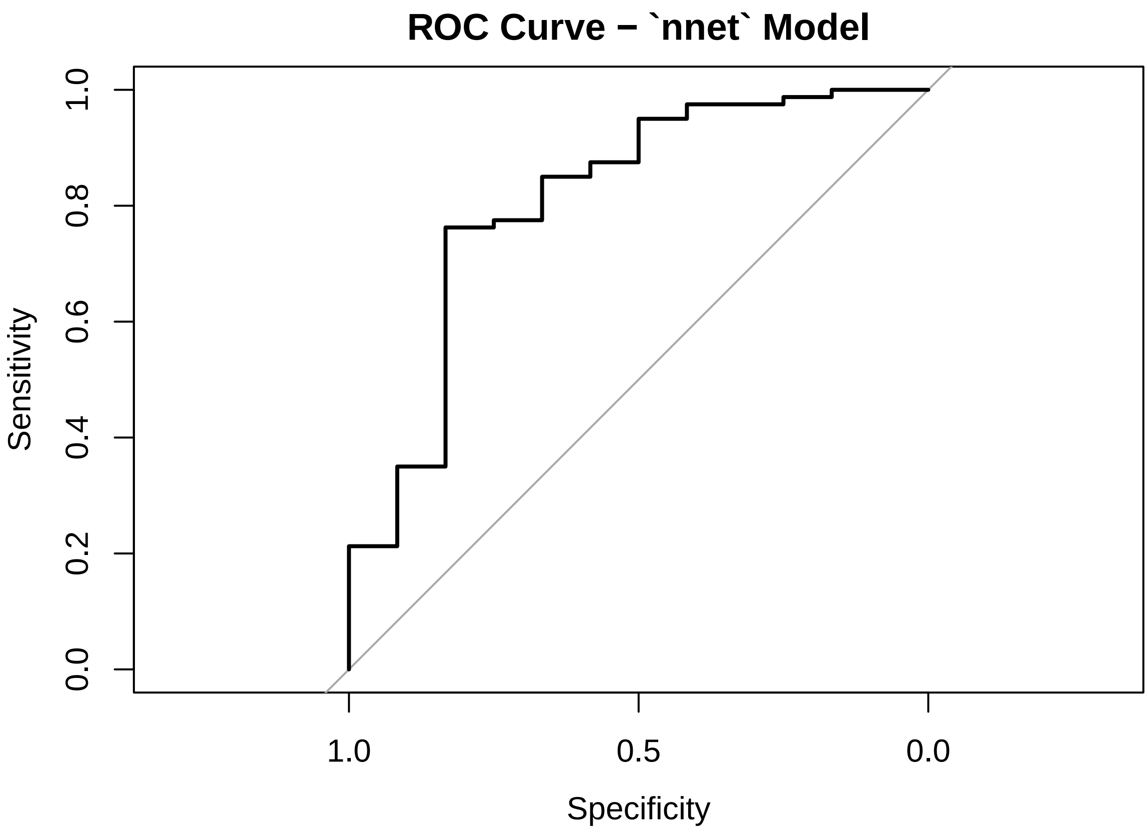
```
## [1] "Accuracy with ‘nnet‘ model: 0.0108695652173913"
```

```r
# Plot ROC curve
roc_nnet <- roc(dataTest$LUNG_CANCER, as.numeric(predictions))
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
plot(roc_nnet, main="ROC Curve - `nnet` Model")
```




```
print(paste("AUC with `nnet` model:", auc(roc_nnet)))
```

```
## [1] "AUC with ‘nnet‘ model: 0.809375"
```

Evaluating the model using the MSE loss function

```
# Predictions with the MSE loss function
predictions_mse <- neuralnet::compute(nn_mse, dataTest[, -ncol(dataTest)])$net.result
predicted_class_mse <- ifelse(predictions_mse > 0.5, 1, 0)

# Create confusion matrix
confusion_matrix_mse <- table(predicted_class_mse, dataTest$LUNG_CANCER)

# Calculate and display accuracy
accuracy_mse <- sum(diag(confusion_matrix_mse)) / sum(confusion_matrix_mse)
print(paste("Accuracy with MSE loss function:", accuracy_mse))
```

```
## [1] "Accuracy with MSE loss function: 0.880434782608696"
```

Trying SMOTE to boost results of the ‘nnet’ model

```
smote_data <- SMOTE(dataTrain[, -ncol(dataTrain)], dataTrain$LUNG_CANCER, K=5, dup_size = 1)
balanced_dataTrain <- smote_data$data
balanced_dataTrain$LUNG_CANCER <- as.factor(balanced_dataTrain$class)
balanced_dataTrain$class <- NULL
table(balanced_dataTrain$LUNG_CANCER)
```

```
##
##   0   1
##  54 190
```

```r
# Train the neural network
set.seed(123)
nn_balanced <- neuralnet(formula, data=balanced_dataTrain, hidden=5, linear.output=FALSE)

# Summary of the model
summary(nn_balanced)
```

```
##                     Length Class      Mode
## call                   5   -none-     call
## response             488   -none-     logical
## covariate           3660   -none-     numeric
## model.list             2   -none-     list
## err.fct                1   -none-     function
## act.fct                1   -none-     function
## linear.output          1   -none-     logical
## data                  16   data.frame list
## exclude                0   -none-     NULL
## net.result             1   -none-     list
## weights                1   -none-     list
## generalized.weights    1   -none-     list
## startweights           1   -none-     list
## result.matrix         95   -none-     numeric
```

```r
nrow(dataTest[, -ncol(dataTest)])
```

```
## [1] 92
```

```r
predictions_balanced <- compute(nn_balanced, dataTest[, -ncol(dataTest)])$net.result
predicted_class_balanced <- ifelse(predictions_balanced > 0.5, 1, 0)
```

Verrifying that the classes are balanced for the model

```r
length(predicted_class_balanced)
```

```
## [1] 184
```

```r
length(dataTest$LUNG_CANCER)
```

```
## [1] 92
```

```r
dim(dataTest[, -ncol(dataTest)])
```

```
## [1] 92 15
```

```r
dim(as.data.frame(predictions_balanced))
```

```
## [1] 92  2
```

```r
head(predicted_class_balanced)
```

```
##    [,1] [,2]
## 2     1    0
## 3     0    1
## 8     0    1
## 12    0    1
## 15    0    1
## 18    0    1
```

```r
predictions_balanced <- compute(nn_balanced, dataTest[, -ncol(dataTest)])$net.result[, 2]

# Convert probabilities to binary class predictions
predicted_class_balanced <- ifelse(predictions_balanced > 0.5, 1, 0)

# Create confusion matrix
confusion_matrix_balanced <- table(predicted_class_balanced, dataTest$LUNG_CANCER)
print(confusion_matrix_balanced)
```

```
##
## predicted_class_balanced  0  1
##                        0  6  5
##                        1  6 75
```

```r
# Calculate and display accuracy
accuracy_balanced <- sum(diag(confusion_matrix_balanced)) / sum(confusion_matrix_balanced)
print(paste("Accuracy with SMOTE-balanced `nnet` model:", accuracy_balanced))
```

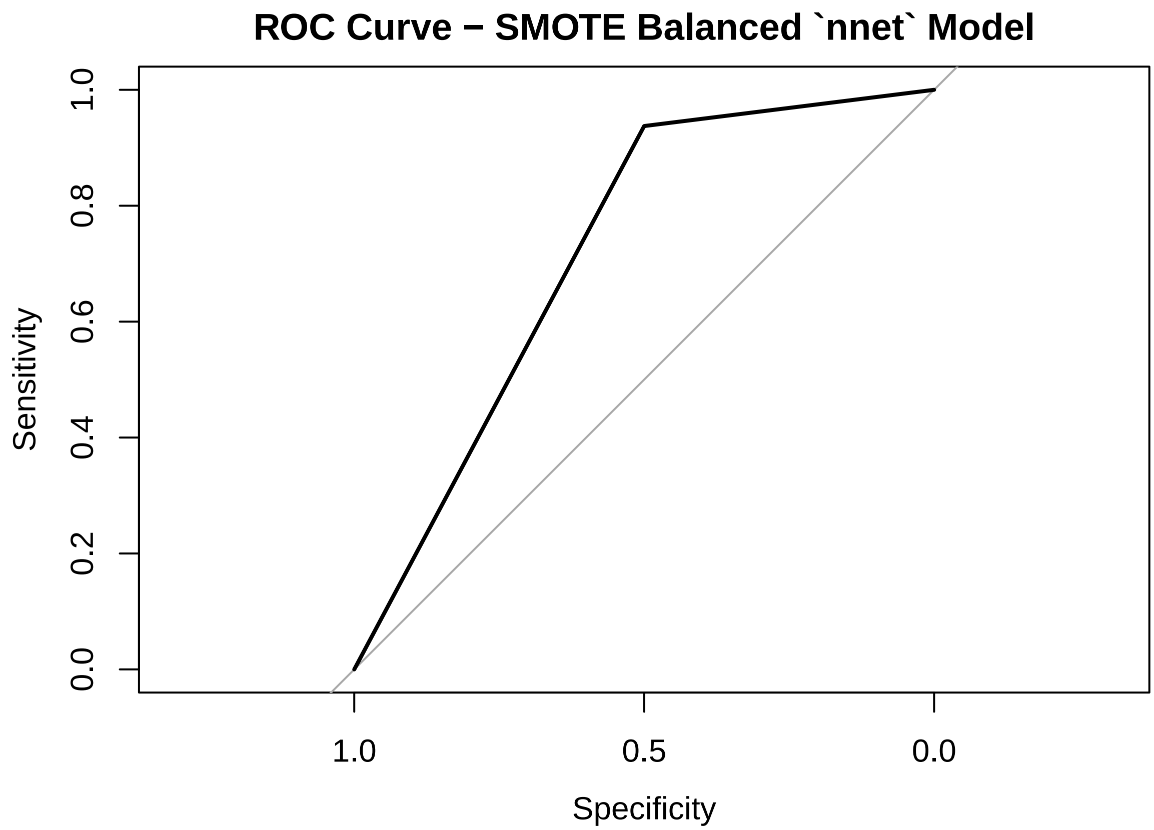
```
## [1] "Accuracy with SMOTE-balanced 'nnet' model: 0.880434782608696"
```

```r
# Plot ROC curve for the SMOTE-balanced `nnet` model
roc_balanced <- roc(dataTest$LUNG_CANCER, as.numeric(predicted_class_balanced))
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
plot(roc_balanced, main="ROC Curve - SMOTE Balanced `nnet` Model")
```




```r
# Calculate and print the AUC
auc_balanced <- auc(roc_balanced)
print(paste("AUC with SMOTE-balanced `nnet` model:", auc_balanced))
```

```
## [1] "AUC with SMOTE-balanced `nnet` model: 0.71875"
```

Boosting the 'nnet' results using cross-validation and hyperparameter tuning to get the best results

```r
# Cross-validation setup
set.seed(123)
train_control <- trainControl(method = "cv", number = 5, classProbs = TRUE)  # 5-fold cross-validation

# Grid for hyperparameter tuning
tune_grid <- expand.grid(size = c(16, 32),  # Increase number of hidden neurons
                         decay = c(0.001, 0.01, 0.1))

# Train the neural network model with cross-validation
nn_model_cv <- train(formula, data = dataTrain, method = "nnet",
                     trControl = train_control,
                     tuneGrid = tune_grid,
                     linout = FALSE, maxit = 500)  # Increase maxit
```

```
## Warning in train.default(x, y, weights = w, ...): You are trying to do
## regression and your outcome only has two possible values Are you trying to do
## classification? If so, use a 2 level factor as your outcome column.
```

```
## Warning in train.default(x, y, weights = w, ...): cannnot compute class
## probabilities for regression

## # weights:  273
## initial  value 21.556346
## iter  10 value 6.113609
## iter  20 value 3.339045
## iter  30 value 2.956867
## iter  40 value 2.818299
## iter  50 value 2.747656
## iter  60 value 2.693912
## iter  70 value 2.652130
## iter  80 value 2.624877
## iter  90 value 2.606121
## iter 100 value 2.593940
## iter 110 value 2.583082
## iter 120 value 2.578179
## iter 130 value 2.574465
## iter 140 value 2.571705
## iter 150 value 2.568959
## iter 160 value 2.564457
## iter 170 value 2.561661
## iter 180 value 2.559803
## iter 190 value 2.557844
## iter 200 value 2.555737
## iter 210 value 2.554009
## iter 220 value 2.552378
## iter 230 value 2.550813
## iter 240 value 2.549440
## iter 250 value 2.547869
## iter 260 value 2.546214
## iter 270 value 2.544665
## iter 280 value 2.542525
## iter 290 value 2.541218
## iter 300 value 2.540422
## iter 310 value 2.539852
## iter 320 value 2.539451
## iter 330 value 2.539084
## iter 340 value 2.538621
## iter 350 value 2.538016
## iter 360 value 2.537318
## iter 370 value 2.536633
## iter 380 value 2.535907
## iter 390 value 2.535191
## iter 400 value 2.534163
## iter 410 value 2.533013
## iter 420 value 2.531676
## iter 430 value 2.529863
## iter 440 value 2.528791
## iter 450 value 2.528443
## iter 460 value 2.528188
## iter 470 value 2.528031
## iter 480 value 2.527954
## iter 490 value 2.527911
```

```
## iter 500 value 2.527875
## final  value 2.527875
## stopped after 500 iterations
## # weights:  545
## initial  value 110.894532
## iter  10 value 25.450242
## iter  20 value 21.633063
## iter  30 value 6.428639
## iter  40 value 3.614795
## iter  50 value 3.090269
## iter  60 value 2.853402
## iter  70 value 2.745870
## iter  80 value 2.694384
## iter  90 value 2.659413
## iter 100 value 2.633655
## iter 110 value 2.614359
## iter 120 value 2.596250
## iter 130 value 2.584243
## iter 140 value 2.574425
## iter 150 value 2.568617
## iter 160 value 2.563737
## iter 170 value 2.560777
## iter 180 value 2.558301
## iter 190 value 2.555705
## iter 200 value 2.553583
## iter 210 value 2.551795
## iter 220 value 2.550249
## iter 230 value 2.549070
## iter 240 value 2.548388
## iter 250 value 2.548089
## iter 260 value 2.547841
## iter 270 value 2.547639
## iter 280 value 2.547553
## iter 290 value 2.547479
## iter 300 value 2.547393
## iter 310 value 2.547315
## iter 320 value 2.547282
## iter 330 value 2.547247
## iter 340 value 2.547218
## iter 350 value 2.547183
## iter 360 value 2.547155
## iter 370 value 2.547133
## iter 380 value 2.547123
## iter 390 value 2.547115
## iter 400 value 2.547106
## iter 410 value 2.547102
## final  value 2.547100
## converged
## # weights:  273
## initial  value 87.766732
## iter  10 value 19.336168
## iter  20 value 8.167872
## iter  30 value 5.983082
## iter  40 value 5.484930
```

```
## iter  50 value 5.387300
## iter  60 value 5.351513
## iter  70 value 5.316141
## iter  80 value 5.292947
## iter  90 value 5.214728
## iter 100 value 5.171262
## iter 110 value 5.145313
## iter 120 value 5.109358
## iter 130 value 5.081436
## iter 140 value 5.050305
## iter 150 value 5.014728
## iter 160 value 4.996481
## iter 170 value 4.985190
## iter 180 value 4.969077
## iter 190 value 4.945828
## iter 200 value 4.916038
## iter 210 value 4.896656
## iter 220 value 4.883366
## iter 230 value 4.870431
## iter 240 value 4.866311
## iter 250 value 4.864879
## iter 260 value 4.863039
## iter 270 value 4.861591
## iter 280 value 4.860701
## iter 290 value 4.858680
## iter 300 value 4.844619
## iter 310 value 4.834652
## iter 320 value 4.830206
## iter 330 value 4.828657
## iter 340 value 4.827702
## iter 350 value 4.827043
## iter 360 value 4.826661
## iter 370 value 4.826482
## iter 380 value 4.826412
## iter 390 value 4.826372
## iter 400 value 4.826329
## iter 410 value 4.826313
## iter 420 value 4.826308
## iter 430 value 4.826303
## iter 440 value 4.826300
## final  value 4.826299
## converged
## # weights:  545
## initial  value 135.731497
## iter  10 value 24.484733
## iter  20 value 9.088503
## iter  30 value 6.473724
## iter  40 value 5.303842
## iter  50 value 5.120681
## iter  60 value 5.075577
## iter  70 value 5.046857
## iter  80 value 5.033283
## iter  90 value 5.019126
## iter 100 value 5.012146
```

```
## iter 110 value 5.008118
## iter 120 value 5.006080
## iter 130 value 5.005295
## iter 140 value 5.002879
## iter 150 value 5.001900
## iter 160 value 5.001693
## iter 170 value 5.001540
## iter 180 value 5.001488
## iter 190 value 5.001471
## iter 200 value 5.001458
## iter 210 value 5.001449
## iter 220 value 5.001440
## iter 230 value 5.001433
## iter 240 value 5.001429
## final  value 5.001428
## converged
## # weights:  273
## initial  value 25.575671
## iter  10 value 12.736276
## iter  20 value 12.261690
## iter  30 value 12.223792
## iter  40 value 12.221138
## iter  50 value 12.219571
## iter  60 value 12.219386
## final  value 12.219383
## converged
## # weights:  545
## initial  value 32.928117
## iter  10 value 13.003834
## iter  20 value 12.100304
## iter  30 value 12.019900
## iter  40 value 11.989402
## iter  50 value 11.982226
## iter  60 value 11.980524
## iter  70 value 11.980462
## final  value 11.980460
## converged
## # weights:  273
## initial  value 73.548092
## iter  10 value 22.451621
## iter  20 value 21.971253
## iter  30 value 15.164563
## iter  40 value 6.340501
## iter  50 value 5.914040
## iter  60 value 5.432775
## iter  70 value 5.292128
## iter  80 value 5.241116
## iter  90 value 5.199175
## iter 100 value 5.022801
## iter 110 value 4.956933
## iter 120 value 4.901407
## iter 130 value 4.854343
## iter 140 value 4.810674
## iter 150 value 4.782773
```

```
## iter 160 value 4.758858
## iter 170 value 4.741165
## iter 180 value 4.728897
## iter 190 value 4.721581
## iter 200 value 4.716607
## iter 210 value 4.711695
## iter 220 value 4.706986
## iter 230 value 4.704326
## iter 240 value 4.701923
## iter 250 value 4.699689
## iter 260 value 4.697921
## iter 270 value 4.695559
## iter 280 value 4.693972
## iter 290 value 4.692542
## iter 300 value 4.690835
## iter 310 value 4.689016
## iter 320 value 4.688308
## iter 330 value 4.687878
## iter 340 value 4.687715
## iter 350 value 4.687570
## iter 360 value 4.687458
## iter 370 value 4.687345
## iter 380 value 4.687241
## iter 390 value 4.687122
## iter 400 value 4.686996
## iter 410 value 4.686773
## iter 420 value 4.686603
## iter 430 value 4.686347
## iter 440 value 4.686142
## iter 450 value 4.685902
## iter 460 value 4.685620
## iter 470 value 4.684956
## iter 480 value 4.684274
## iter 490 value 4.683248
## iter 500 value 4.682629
## final  value 4.682629
## stopped after 500 iterations
## # weights:  545
## initial  value 80.427024
## iter  10 value 22.840329
## iter  20 value 22.012246
## iter  30 value 22.010292
## iter  40 value 22.006984
## iter  50 value 21.997677
## iter  60 value 21.235735
## iter  70 value 8.221599
## iter  80 value 4.775403
## iter  90 value 4.317287
## iter 100 value 4.085154
## iter 110 value 3.731325
## iter 120 value 3.409796
## iter 130 value 3.307574
## iter 140 value 3.276904
## iter 150 value 3.258346
```

```
## iter 160 value 3.248204
## iter 170 value 3.238837
## iter 180 value 3.206880
## iter 190 value 2.995363
## iter 200 value 2.932193
## iter 210 value 2.896603
## iter 220 value 2.874200
## iter 230 value 2.857664
## iter 240 value 2.841739
## iter 250 value 2.829424
## iter 260 value 2.816638
## iter 270 value 2.807759
## iter 280 value 2.798881
## iter 290 value 2.790932
## iter 300 value 2.784972
## iter 310 value 2.779214
## iter 320 value 2.775090
## iter 330 value 2.771323
## iter 340 value 2.768687
## iter 350 value 2.766912
## iter 360 value 2.765619
## iter 370 value 2.764810
## iter 380 value 2.763874
## iter 390 value 2.762651
## iter 400 value 2.761547
## iter 410 value 2.760438
## iter 420 value 2.759490
## iter 430 value 2.758465
## iter 440 value 2.757946
## iter 450 value 2.757403
## iter 460 value 2.756814
## iter 470 value 2.755962
## iter 480 value 2.225841
## iter 490 value 1.808570
## iter 500 value 1.792326
## final  value 1.792326
## stopped after 500 iterations
## # weights:  273
## initial  value 38.942911
## iter  10 value 17.026855
## iter  20 value 8.889608
## iter  30 value 6.918164
## iter  40 value 6.041135
## iter  50 value 5.698001
## iter  60 value 5.455291
## iter  70 value 5.361811
## iter  80 value 5.305228
## iter  90 value 5.265462
## iter 100 value 5.224541
## iter 110 value 5.201193
## iter 120 value 5.189627
## iter 130 value 5.180004
## iter 140 value 5.154474
## iter 150 value 5.113949
```

```
## iter 160 value 5.097570
## iter 170 value 5.089145
## iter 180 value 5.082673
## iter 190 value 5.077855
## iter 200 value 5.067863
## iter 210 value 5.059860
## iter 220 value 5.058273
## iter 230 value 5.057046
## iter 240 value 5.055507
## iter 250 value 5.053050
## iter 260 value 5.050894
## iter 270 value 5.049220
## iter 280 value 5.048129
## iter 290 value 5.047517
## iter 300 value 5.047087
## iter 310 value 5.046822
## iter 320 value 5.046652
## iter 330 value 5.046550
## iter 340 value 5.046506
## iter 350 value 5.046488
## iter 360 value 5.046474
## iter 370 value 5.046467
## iter 380 value 5.046461
## iter 390 value 5.046458
## final  value 5.046457
## converged
## # weights:  545
## initial  value 19.521754
## iter  10 value 8.313560
## iter  20 value 5.646074
## iter  30 value 5.355376
## iter  40 value 5.287861
## iter  50 value 5.236264
## iter  60 value 5.193671
## iter  70 value 5.143241
## iter  80 value 5.096578
## iter  90 value 5.073637
## iter 100 value 5.064509
## iter 110 value 5.059817
## iter 120 value 5.056923
## iter 130 value 5.055670
## iter 140 value 5.055333
## iter 150 value 5.054989
## iter 160 value 5.054666
## iter 170 value 5.054525
## iter 180 value 5.054460
## iter 190 value 5.054416
## iter 200 value 5.054385
## iter 210 value 5.054357
## iter 220 value 5.054326
## iter 230 value 5.054302
## iter 240 value 5.054288
## iter 250 value 5.054272
## iter 260 value 5.054258
```

```
## iter 270 value 5.054248
## iter 280 value 5.054243
## iter 290 value 5.054242
## iter 290 value 5.054242
## iter 290 value 5.054242
## final  value 5.054242
## converged
## # weights:  273
## initial  value 112.044358
## iter  10 value 16.729910
## iter  20 value 12.443355
## iter  30 value 12.219016
## iter  40 value 12.174972
## iter  50 value 12.169314
## iter  60 value 12.169004
## final  value 12.168980
## converged
## # weights:  545
## initial  value 47.235674
## iter  10 value 19.494541
## iter  20 value 12.195598
## iter  30 value 12.017179
## iter  40 value 11.974983
## iter  50 value 11.962184
## iter  60 value 11.959442
## iter  70 value 11.959214
## final  value 11.959199
## converged
## # weights:  273
## initial  value 79.155676
## iter  10 value 22.522450
## iter  20 value 22.015933
## iter  30 value 22.010371
## iter  40 value 21.991525
## iter  50 value 20.193247
## iter  60 value 6.696455
## iter  70 value 4.713618
## iter  80 value 3.837722
## iter  90 value 2.024232
## iter 100 value 1.440684
## iter 110 value 1.331873
## iter 120 value 1.276491
## iter 130 value 1.235057
## iter 140 value 1.208413
## iter 150 value 1.188490
## iter 160 value 1.176607
## iter 170 value 1.168453
## iter 180 value 1.161445
## iter 190 value 1.156133
## iter 200 value 1.151465
## iter 210 value 1.148832
## iter 220 value 1.147105
## iter 230 value 1.145956
## iter 240 value 1.145197
```

```
## iter 250 value 1.144090
## iter 260 value 1.143403
## iter 270 value 1.142851
## iter 280 value 1.142568
## iter 290 value 1.142126
## iter 300 value 1.141780
## iter 310 value 1.141396
## iter 320 value 1.140819
## iter 330 value 1.140195
## iter 340 value 1.139747
## iter 350 value 1.139396
## iter 360 value 1.139027
## iter 370 value 1.137478
## iter 380 value 1.135443
## iter 390 value 1.134715
## iter 400 value 1.134384
## iter 410 value 1.134176
## iter 420 value 1.134049
## iter 430 value 1.133964
## iter 440 value 1.133886
## iter 450 value 1.133827
## iter 460 value 1.133731
## iter 470 value 1.133602
## iter 480 value 1.133506
## iter 490 value 1.133423
## iter 500 value 1.133378
## final  value 1.133378
## stopped after 500 iterations
## # weights:  545
## initial  value 65.874377
## iter  10 value 22.752272
## iter  20 value 21.977159
## iter  30 value 9.214789
## iter  40 value 3.889871
## iter  50 value 2.222485
## iter  60 value 1.849106
## iter  70 value 1.741286
## iter  80 value 1.685783
## iter  90 value 1.658307
## iter 100 value 1.644576
## iter 110 value 1.634785
## iter 120 value 1.628504
## iter 130 value 1.622998
## iter 140 value 1.617654
## iter 150 value 1.613821
## iter 160 value 1.610827
## iter 170 value 1.608613
## iter 180 value 1.606611
## iter 190 value 1.604553
## iter 200 value 1.602689
## iter 210 value 1.600981
## iter 220 value 1.599925
## iter 230 value 1.598592
## iter 240 value 1.597839
```

```
## iter 250 value 1.597053
## iter 260 value 1.596024
## iter 270 value 1.594823
## iter 280 value 1.594177
## iter 290 value 1.593664
## iter 300 value 1.593266
## iter 310 value 1.592671
## iter 320 value 1.591577
## iter 330 value 1.590641
## iter 340 value 1.589891
## iter 350 value 1.589106
## iter 360 value 1.588361
## iter 370 value 1.587217
## iter 380 value 1.586653
## iter 390 value 1.586095
## iter 400 value 1.585825
## iter 410 value 1.585351
## iter 420 value 1.584746
## iter 430 value 1.584380
## iter 440 value 1.584185
## iter 450 value 1.584085
## iter 460 value 1.584020
## iter 470 value 1.583968
## iter 480 value 1.583933
## iter 490 value 1.583911
## iter 500 value 1.583897
## final  value 1.583897
## stopped after 500 iterations
## # weights:  273
## initial  value 21.132289
## iter  10 value 7.657192
## iter  20 value 4.942180
## iter  30 value 4.255245
## iter  40 value 4.152878
## iter  50 value 4.122622
## iter  60 value 4.102364
## iter  70 value 4.089194
## iter  80 value 4.082109
## iter  90 value 4.075485
## iter 100 value 4.073068
## iter 110 value 4.071691
## iter 120 value 4.070628
## iter 130 value 4.070107
## iter 140 value 4.069527
## iter 150 value 4.069177
## iter 160 value 4.068943
## iter 170 value 4.068169
## iter 180 value 4.064824
## iter 190 value 4.062564
## iter 200 value 4.061957
## iter 210 value 4.061791
## iter 220 value 4.061707
## iter 230 value 4.061628
## iter 240 value 4.061584
```

```
## iter 250 value 4.061565
## iter 260 value 4.061558
## iter 270 value 4.061555
## iter 280 value 4.061553
## final  value 4.061552
## converged
## # weights:  545
## initial  value 28.485601
## iter  10 value 18.079692
## iter  20 value 8.848676
## iter  30 value 6.011197
## iter  40 value 4.692652
## iter  50 value 4.466109
## iter  60 value 4.398987
## iter  70 value 4.338085
## iter  80 value 4.291169
## iter  90 value 4.246517
## iter 100 value 4.212670
## iter 110 value 4.180434
## iter 120 value 4.154710
## iter 130 value 4.138346
## iter 140 value 4.125563
## iter 150 value 4.113493
## iter 160 value 4.108173
## iter 170 value 4.105115
## iter 180 value 4.101804
## iter 190 value 4.098370
## iter 200 value 4.096737
## iter 210 value 4.095259
## iter 220 value 4.093702
## iter 230 value 4.092612
## iter 240 value 4.091981
## iter 250 value 4.091475
## iter 260 value 4.091193
## iter 270 value 4.090984
## iter 280 value 4.090887
## iter 290 value 4.090843
## iter 300 value 4.090820
## iter 310 value 4.090807
## iter 320 value 4.090795
## iter 330 value 4.090780
## iter 340 value 4.090773
## iter 350 value 4.090771
## final  value 4.090770
## converged
## # weights:  273
## initial  value 27.520758
## iter  10 value 12.499050
## iter  20 value 11.451221
## iter  30 value 11.338954
## iter  40 value 11.300066
## iter  50 value 11.296158
## iter  60 value 11.295799
## final  value 11.295794
```

```
## converged
## # weights:  545
## initial  value 44.803088
## iter  10 value 17.830740
## iter  20 value 11.250650
## iter  30 value 11.114479
## iter  40 value 11.093170
## iter  50 value 11.090059
## iter  60 value 11.089938
## final  value 11.089937
## converged
## # weights:  273
## initial  value 118.012786
## iter  10 value 21.237985
## iter  20 value 21.007985
## iter  30 value 20.955513
## iter  40 value 8.176496
## iter  50 value 4.005688
## iter  60 value 3.186399
## iter  70 value 2.849357
## iter  80 value 2.536901
## iter  90 value 2.311309
## iter 100 value 2.223130
## iter 110 value 2.173608
## iter 120 value 2.148300
## iter 130 value 2.130675
## iter 140 value 2.119433
## iter 150 value 2.109245
## iter 160 value 2.098754
## iter 170 value 2.091352
## iter 180 value 2.084362
## iter 190 value 2.079900
## iter 200 value 2.076372
## iter 210 value 2.072970
## iter 220 value 2.070644
## iter 230 value 2.069354
## iter 240 value 2.068523
## iter 250 value 2.067464
## iter 260 value 2.066726
## iter 270 value 2.065812
## iter 280 value 2.064262
## iter 290 value 2.062886
## iter 300 value 2.061298
## iter 310 value 2.059705
## iter 320 value 2.058117
## iter 330 value 2.056619
## iter 340 value 2.054338
## iter 350 value 2.051394
## iter 360 value 2.048068
## iter 370 value 2.043983
## iter 380 value 2.040425
## iter 390 value 2.037704
## iter 400 value 2.035691
## iter 410 value 2.034479
```

```
## iter 420 value 2.033308
## iter 430 value 2.032525
## iter 440 value 2.031691
## iter 450 value 2.030808
## iter 460 value 2.030100
## iter 470 value 2.029651
## iter 480 value 2.029364
## iter 490 value 2.029052
## iter 500 value 2.028806
## final  value 2.028806
## stopped after 500 iterations
## # weights:  545
## initial  value 77.459855
## iter  10 value 21.833350
## iter  20 value 21.011016
## iter  30 value 21.008031
## iter  40 value 21.000559
## iter  50 value 20.764762
## iter  60 value 7.020110
## iter  70 value 3.685256
## iter  80 value 3.264502
## iter  90 value 3.087929
## iter 100 value 3.016015
## iter 110 value 2.840248
## iter 120 value 2.674770
## iter 130 value 2.634664
## iter 140 value 2.606760
## iter 150 value 2.586717
## iter 160 value 2.571308
## iter 170 value 2.559869
## iter 180 value 2.548088
## iter 190 value 2.536761
## iter 200 value 2.527725
## iter 210 value 2.519738
## iter 220 value 2.511280
## iter 230 value 2.505921
## iter 240 value 2.502110
## iter 250 value 2.499506
## iter 260 value 2.497959
## iter 270 value 2.496836
## iter 280 value 2.495833
## iter 290 value 2.494340
## iter 300 value 2.492022
## iter 310 value 2.490203
## iter 320 value 2.489002
## iter 330 value 2.486878
## iter 340 value 2.484913
## iter 350 value 2.479746
## iter 360 value 2.380342
## iter 370 value 2.119949
## iter 380 value 2.086833
## iter 390 value 2.072878
## iter 400 value 2.058626
## iter 410 value 2.053912
```

```
## iter 420 value 2.051499
## iter 430 value 2.050238
## iter 440 value 2.049216
## iter 450 value 2.048281
## iter 460 value 2.047248
## iter 470 value 2.046377
## iter 480 value 2.045581
## iter 490 value 2.044804
## iter 500 value 2.044236
## final  value 2.044236
## stopped after 500 iterations
## # weights:  273
## initial  value 80.866938
## iter  10 value 20.903875
## iter  20 value 9.221927
## iter  30 value 5.873960
## iter  40 value 4.966109
## iter  50 value 4.743431
## iter  60 value 4.653008
## iter  70 value 4.609937
## iter  80 value 4.592980
## iter  90 value 4.584727
## iter 100 value 4.573595
## iter 110 value 4.568870
## iter 120 value 4.566751
## iter 130 value 4.566098
## iter 140 value 4.565639
## iter 150 value 4.565047
## iter 160 value 4.564725
## iter 170 value 4.564550
## iter 180 value 4.564443
## iter 190 value 4.564381
## iter 200 value 4.564337
## iter 210 value 4.564301
## iter 220 value 4.564283
## iter 230 value 4.564270
## iter 240 value 4.564261
## iter 250 value 4.564259
## final  value 4.564258
## converged
## # weights:  545
## initial  value 58.199845
## iter  10 value 13.454884
## iter  20 value 6.363532
## iter  30 value 5.437162
## iter  40 value 4.790480
## iter  50 value 4.715462
## iter  60 value 4.683764
## iter  70 value 4.666029
## iter  80 value 4.661519
## iter  90 value 4.657922
## iter 100 value 4.654971
## iter 110 value 4.651869
## iter 120 value 4.643765
```

```
## iter 130 value 4.640890
## iter 140 value 4.640126
## iter 150 value 4.639839
## iter 160 value 4.639607
## iter 170 value 4.639392
## iter 180 value 4.639255
## iter 190 value 4.639157
## iter 200 value 4.639107
## iter 210 value 4.639093
## iter 220 value 4.639081
## iter 230 value 4.639067
## iter 240 value 4.639059
## iter 250 value 4.639053
## iter 260 value 4.639041
## iter 270 value 4.639026
## iter 280 value 4.639016
## iter 290 value 4.639005
## iter 300 value 4.638994
## iter 310 value 4.638985
## final  value 4.638984
## converged
## # weights:  273
## initial  value 22.428885
## iter  10 value 10.838403
## iter  20 value 10.664998
## iter  30 value 10.649349
## iter  40 value 10.649012
## iter  50 value 10.649004
## final  value 10.649003
## converged
## # weights:  545
## initial  value 94.790444
## iter  10 value 18.567990
## iter  20 value 11.727991
## iter  30 value 10.633156
## iter  40 value 10.505429
## iter  50 value 10.481939
## iter  60 value 10.475316
## iter  70 value 10.475214
## final  value 10.475214
## converged
## # weights:  273
## initial  value 51.476970
## iter  10 value 18.354592
## iter  20 value 18.014055
## iter  30 value 18.003369
## iter  40 value 17.844417
## iter  50 value 8.896279
## iter  60 value 5.332743
## iter  70 value 4.153292
## iter  80 value 2.736218
## iter  90 value 1.944931
## iter 100 value 1.654594
## iter 110 value 1.518448
```

```
## iter 120 value 1.468545
## iter 130 value 1.435802
## iter 140 value 1.409595
## iter 150 value 1.396319
## iter 160 value 1.384528
## iter 170 value 1.375334
## iter 180 value 1.369144
## iter 190 value 1.364230
## iter 200 value 1.360886
## iter 210 value 1.357414
## iter 220 value 1.354334
## iter 230 value 1.351935
## iter 240 value 1.348821
## iter 250 value 1.345618
## iter 260 value 1.342149
## iter 270 value 1.340241
## iter 280 value 1.339047
## iter 290 value 1.338205
## iter 300 value 1.337799
## iter 310 value 1.337480
## iter 320 value 1.337162
## iter 330 value 1.336917
## iter 340 value 1.336676
## iter 350 value 1.336432
## iter 360 value 1.336116
## iter 370 value 1.335864
## iter 380 value 1.335681
## iter 390 value 1.335603
## iter 400 value 1.335533
## iter 410 value 1.335476
## iter 420 value 1.335431
## iter 430 value 1.335362
## iter 440 value 1.335325
## iter 450 value 1.335295
## iter 460 value 1.335276
## iter 470 value 1.335262
## iter 480 value 1.335249
## iter 490 value 1.335225
## iter 500 value 1.335196
## final  value 1.335196
## stopped after 500 iterations
## # weights:  545
## initial  value 15.730593
## iter  10 value 4.660008
## iter  20 value 2.911917
## iter  30 value 2.251595
## iter  40 value 1.785841
## iter  50 value 1.616907
## iter  60 value 1.536891
## iter  70 value 1.496191
## iter  80 value 1.467754
## iter  90 value 1.445577
## iter 100 value 1.423097
## iter 110 value 1.407294
```

```
## iter 120 value 1.392900
## iter 130 value 1.382973
## iter 140 value 1.373126
## iter 150 value 1.366015
## iter 160 value 1.360638
## iter 170 value 1.357286
## iter 180 value 1.355099
## iter 190 value 1.353217
## iter 200 value 1.352438
## iter 210 value 1.351693
## iter 220 value 1.351231
## iter 230 value 1.350711
## iter 240 value 1.350354
## iter 250 value 1.349785
## iter 260 value 1.349337
## iter 270 value 1.348961
## iter 280 value 1.348322
## iter 290 value 1.347592
## iter 300 value 1.346808
## iter 310 value 1.345513
## iter 320 value 1.343641
## iter 330 value 1.340722
## iter 340 value 1.339325
## iter 350 value 1.337942
## iter 360 value 1.337020
## iter 370 value 1.336451
## iter 380 value 1.335803
## iter 390 value 1.334793
## iter 400 value 1.333818
## iter 410 value 1.331832
## iter 420 value 1.331039
## iter 430 value 1.330178
## iter 440 value 1.329764
## iter 450 value 1.329535
## iter 460 value 1.329362
## iter 470 value 1.329258
## iter 480 value 1.329132
## iter 490 value 1.328984
## iter 500 value 1.328859
## final  value 1.328859
## stopped after 500 iterations
## # weights:  273
## initial  value 34.809209
## iter  10 value 13.954916
## iter  20 value 7.616878
## iter  30 value 4.986959
## iter  40 value 4.630086
## iter  50 value 4.485983
## iter  60 value 4.426941
## iter  70 value 4.407733
## iter  80 value 4.366808
## iter  90 value 4.349643
## iter 100 value 4.345229
## iter 110 value 4.343319
```

```
## iter 120 value 4.342358
## iter 130 value 4.341905
## iter 140 value 4.341591
## iter 150 value 4.341268
## iter 160 value 4.340795
## iter 170 value 4.340613
## iter 180 value 4.340546
## iter 190 value 4.340507
## iter 200 value 4.340487
## iter 210 value 4.340482
## iter 220 value 4.340480
## final  value 4.340478
## converged
## # weights:  545
## initial  value 16.340377
## iter  10 value 7.445796
## iter  20 value 4.979013
## iter  30 value 4.591418
## iter  40 value 4.490013
## iter  50 value 4.426653
## iter  60 value 4.404749
## iter  70 value 4.375954
## iter  80 value 4.351392
## iter  90 value 4.341609
## iter 100 value 4.336629
## iter 110 value 4.330861
## iter 120 value 4.329184
## iter 130 value 4.327199
## iter 140 value 4.319260
## iter 150 value 4.314720
## iter 160 value 4.310771
## iter 170 value 4.304886
## iter 180 value 4.301994
## iter 190 value 4.301030
## iter 200 value 4.300491
## iter 210 value 4.297180
## iter 220 value 4.293412
## iter 230 value 4.292315
## iter 240 value 4.292124
## iter 250 value 4.292003
## iter 260 value 4.291885
## iter 270 value 4.291824
## iter 280 value 4.291793
## iter 290 value 4.291764
## iter 300 value 4.291747
## iter 310 value 4.291739
## iter 320 value 4.291736
## iter 330 value 4.291735
## iter 340 value 4.291734
## final  value 4.291733
## converged
## # weights:  273
## initial  value 28.605046
## iter  10 value 13.079499
```

```
## iter  20 value 11.379274
## iter  30 value 11.323401
## iter  40 value 11.318283
## iter  50 value 11.317989
## iter  60 value 11.317986
## iter  60 value 11.317985
## iter  60 value 11.317985
## final  value 11.317985
## converged
## # weights:  545
## initial  value 39.096923
## iter  10 value 16.673157
## iter  20 value 13.101679
## iter  30 value 11.599196
## iter  40 value 11.345017
## iter  50 value 11.237185
## iter  60 value 11.169959
## iter  70 value 11.155574
## iter  80 value 11.151933
## iter  90 value 11.151368
## iter 100 value 11.151268
## iter 110 value 11.151183
## iter 120 value 11.151178
## iter 120 value 11.151177
## iter 120 value 11.151177
## final  value 11.151177
## converged
## # weights:  545
## initial  value 71.746426
## iter  10 value 21.726802
## iter  20 value 14.914989
## iter  30 value 14.079092
## iter  40 value 13.943905
## iter  50 value 13.839611
## iter  60 value 13.822665
## iter  70 value 13.821629
## final  value 13.821615
## converged
```

```
# Summary of the model
summary(nn_model_cv)
```

```
## a 15-32-1 network with 545 weights
## options were - decay=0.1
##   b->h1  i1->h1  i2->h1  i3->h1  i4->h1  i5->h1  i6->h1  i7->h1  i8->h1  i9->h1
##   -0.12   -0.10    0.00    0.11    0.04    0.15    0.14    0.22    0.18    0.19
## i10->h1 i11->h1 i12->h1 i13->h1 i14->h1 i15->h1
##    0.17    0.10    0.31   -0.04    0.18    0.11
##   b->h2  i1->h2  i2->h2  i3->h2  i4->h2  i5->h2  i6->h2  i7->h2  i8->h2  i9->h2
##   -0.12   -0.10    0.00    0.11    0.04    0.15    0.14    0.22    0.18    0.19
## i10->h2 i11->h2 i12->h2 i13->h2 i14->h2 i15->h2
##    0.17    0.10    0.31   -0.04    0.18    0.11
##   b->h3  i1->h3  i2->h3  i3->h3  i4->h3  i5->h3  i6->h3  i7->h3  i8->h3  i9->h3
##    0.18    0.15    0.02   -0.13   -0.03   -0.17   -0.16   -0.27   -0.22   -0.24
```

```
## i10->h3 i11->h3 i12->h3 i13->h3 i14->h3 i15->h3
##   -0.21   -0.11   -0.38    0.06   -0.22   -0.13
##   b->h4  i1->h4  i2->h4  i3->h4  i4->h4  i5->h4  i6->h4  i7->h4  i8->h4  i9->h4
##    0.18    0.15    0.02   -0.13   -0.03   -0.17   -0.16   -0.27   -0.22   -0.24
## i10->h4 i11->h4 i12->h4 i13->h4 i14->h4 i15->h4
##   -0.21   -0.11   -0.38    0.06   -0.22   -0.13
##   b->h5  i1->h5  i2->h5  i3->h5  i4->h5  i5->h5  i6->h5  i7->h5  i8->h5  i9->h5
##   -0.12   -0.10    0.00    0.11    0.04    0.15    0.14    0.22    0.18    0.19
## i10->h5 i11->h5 i12->h5 i13->h5 i14->h5 i15->h5
##    0.17    0.10    0.31   -0.04    0.18    0.11
##   b->h6  i1->h6  i2->h6  i3->h6  i4->h6  i5->h6  i6->h6  i7->h6  i8->h6  i9->h6
##   -0.12   -0.10    0.00    0.11    0.04    0.15    0.14    0.22    0.18    0.19
## i10->h6 i11->h6 i12->h6 i13->h6 i14->h6 i15->h6
##    0.17    0.10    0.31   -0.04    0.18    0.11
##   b->h7  i1->h7  i2->h7  i3->h7  i4->h7  i5->h7  i6->h7  i7->h7  i8->h7  i9->h7
##    0.18    0.15    0.02   -0.13   -0.03   -0.17   -0.16   -0.27   -0.22   -0.24
## i10->h7 i11->h7 i12->h7 i13->h7 i14->h7 i15->h7
##   -0.21   -0.11   -0.38    0.06   -0.22   -0.13
##   b->h8  i1->h8  i2->h8  i3->h8  i4->h8  i5->h8  i6->h8  i7->h8  i8->h8  i9->h8
##    0.18    0.15    0.02   -0.13   -0.03   -0.17   -0.16   -0.27   -0.22   -0.24
## i10->h8 i11->h8 i12->h8 i13->h8 i14->h8 i15->h8
##   -0.21   -0.11   -0.38    0.06   -0.22   -0.13
##   b->h9  i1->h9  i2->h9  i3->h9  i4->h9  i5->h9  i6->h9  i7->h9  i8->h9  i9->h9
##    0.18    0.15    0.02   -0.13   -0.03   -0.17   -0.16   -0.27   -0.22   -0.24
## i10->h9 i11->h9 i12->h9 i13->h9 i14->h9 i15->h9
##   -0.21   -0.11   -0.38    0.06   -0.22   -0.13
##   b->h10  i1->h10  i2->h10  i3->h10  i4->h10  i5->h10  i6->h10  i7->h10
##    -0.12    -0.10     0.00     0.11     0.04     0.15     0.14     0.22
##  i8->h10  i9->h10 i10->h10 i11->h10 i12->h10 i13->h10 i14->h10 i15->h10
##     0.18     0.19     0.17     0.10     0.31    -0.04     0.18     0.11
##   b->h11  i1->h11  i2->h11  i3->h11  i4->h11  i5->h11  i6->h11  i7->h11
##    -0.12    -0.10     0.00     0.11     0.04     0.15     0.14     0.22
##  i8->h11  i9->h11 i10->h11 i11->h11 i12->h11 i13->h11 i14->h11 i15->h11
##     0.18     0.19     0.17     0.10     0.31    -0.04     0.18     0.11
##   b->h12  i1->h12  i2->h12  i3->h12  i4->h12  i5->h12  i6->h12  i7->h12
##    -0.12    -0.10     0.00     0.11     0.04     0.15     0.14     0.22
##  i8->h12  i9->h12 i10->h12 i11->h12 i12->h12 i13->h12 i14->h12 i15->h12
##     0.18     0.19     0.17     0.10     0.31    -0.04     0.18     0.11
##   b->h13  i1->h13  i2->h13  i3->h13  i4->h13  i5->h13  i6->h13  i7->h13
##    -0.12    -0.10     0.00     0.11     0.04     0.15     0.14     0.22
##  i8->h13  i9->h13 i10->h13 i11->h13 i12->h13 i13->h13 i14->h13 i15->h13
##     0.18     0.19     0.17     0.10     0.31    -0.04     0.18     0.11
##   b->h14  i1->h14  i2->h14  i3->h14  i4->h14  i5->h14  i6->h14  i7->h14
##     0.18     0.15     0.02    -0.13    -0.03    -0.17    -0.16    -0.27
##  i8->h14  i9->h14 i10->h14 i11->h14 i12->h14 i13->h14 i14->h14 i15->h14
##    -0.22    -0.24    -0.21    -0.11    -0.38     0.06    -0.22    -0.13
##   b->h15  i1->h15  i2->h15  i3->h15  i4->h15  i5->h15  i6->h15  i7->h15
##    -0.12    -0.10     0.00     0.11     0.04     0.15     0.14     0.22
##  i8->h15  i9->h15 i10->h15 i11->h15 i12->h15 i13->h15 i14->h15 i15->h15
##     0.18     0.19     0.17     0.10     0.31    -0.04     0.18     0.11
##   b->h16  i1->h16  i2->h16  i3->h16  i4->h16  i5->h16  i6->h16  i7->h16
##     0.18     0.15     0.02    -0.13    -0.03    -0.17    -0.16    -0.27
##  i8->h16  i9->h16 i10->h16 i11->h16 i12->h16 i13->h16 i14->h16 i15->h16
##    -0.22    -0.24    -0.21    -0.11    -0.38     0.06    -0.22    -0.13
```

```
##    b->h17   i1->h17   i2->h17   i3->h17   i4->h17   i5->h17   i6->h17   i7->h17
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
##   i8->h17   i9->h17  i10->h17  i11->h17  i12->h17  i13->h17  i14->h17  i15->h17
##     -0.22     -0.24     -0.21     -0.11     -0.38      0.06     -0.22     -0.13
##    b->h18   i1->h18   i2->h18   i3->h18   i4->h18   i5->h18   i6->h18   i7->h18
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
##   i8->h18   i9->h18  i10->h18  i11->h18  i12->h18  i13->h18  i14->h18  i15->h18
##     -0.22     -0.24     -0.21     -0.11     -0.38      0.06     -0.22     -0.13
##    b->h19   i1->h19   i2->h19   i3->h19   i4->h19   i5->h19   i6->h19   i7->h19
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
##   i8->h19   i9->h19  i10->h19  i11->h19  i12->h19  i13->h19  i14->h19  i15->h19
##     -0.22     -0.24     -0.21     -0.11     -0.38      0.06     -0.22     -0.13
##    b->h20   i1->h20   i2->h20   i3->h20   i4->h20   i5->h20   i6->h20   i7->h20
##     -0.12     -0.10      0.00      0.11      0.04      0.15      0.14      0.22
##   i8->h20   i9->h20  i10->h20  i11->h20  i12->h20  i13->h20  i14->h20  i15->h20
##      0.18      0.19      0.17      0.10      0.31     -0.04      0.18      0.11
##    b->h21   i1->h21   i2->h21   i3->h21   i4->h21   i5->h21   i6->h21   i7->h21
##     -0.12     -0.10      0.00      0.11      0.04      0.15      0.14      0.22
##   i8->h21   i9->h21  i10->h21  i11->h21  i12->h21  i13->h21  i14->h21  i15->h21
##      0.18      0.19      0.17      0.10      0.31     -0.04      0.18      0.11
##    b->h22   i1->h22   i2->h22   i3->h22   i4->h22   i5->h22   i6->h22   i7->h22
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
##   i8->h22   i9->h22  i10->h22  i11->h22  i12->h22  i13->h22  i14->h22  i15->h22
##     -0.22     -0.24     -0.21     -0.11     -0.38      0.06     -0.22     -0.13
##    b->h23   i1->h23   i2->h23   i3->h23   i4->h23   i5->h23   i6->h23   i7->h23
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
##   i8->h23   i9->h23  i10->h23  i11->h23  i12->h23  i13->h23  i14->h23  i15->h23
##     -0.22     -0.24     -0.21     -0.11     -0.38      0.06     -0.22     -0.13
##    b->h24   i1->h24   i2->h24   i3->h24   i4->h24   i5->h24   i6->h24   i7->h24
##     -0.12     -0.10      0.00      0.11      0.04      0.15      0.14      0.22
##   i8->h24   i9->h24  i10->h24  i11->h24  i12->h24  i13->h24  i14->h24  i15->h24
##      0.18      0.19      0.17      0.10      0.31     -0.04      0.18      0.11
##    b->h25   i1->h25   i2->h25   i3->h25   i4->h25   i5->h25   i6->h25   i7->h25
##     -0.12     -0.10      0.00      0.11      0.04      0.15      0.14      0.22
##   i8->h25   i9->h25  i10->h25  i11->h25  i12->h25  i13->h25  i14->h25  i15->h25
##      0.18      0.19      0.17      0.10      0.31     -0.04      0.18      0.11
##    b->h26   i1->h26   i2->h26   i3->h26   i4->h26   i5->h26   i6->h26   i7->h26
##     -0.12     -0.10      0.00      0.11      0.04      0.15      0.14      0.22
##   i8->h26   i9->h26  i10->h26  i11->h26  i12->h26  i13->h26  i14->h26  i15->h26
##      0.18      0.19      0.17      0.10      0.31     -0.04      0.18      0.11
##    b->h27   i1->h27   i2->h27   i3->h27   i4->h27   i5->h27   i6->h27   i7->h27
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
##   i8->h27   i9->h27  i10->h27  i11->h27  i12->h27  i13->h27  i14->h27  i15->h27
##     -0.22     -0.24     -0.21     -0.11     -0.38      0.06     -0.22     -0.13
##    b->h28   i1->h28   i2->h28   i3->h28   i4->h28   i5->h28   i6->h28   i7->h28
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
##   i8->h28   i9->h28  i10->h28  i11->h28  i12->h28  i13->h28  i14->h28  i15->h28
##     -0.22     -0.24     -0.21     -0.11     -0.38      0.06     -0.22     -0.13
##    b->h29   i1->h29   i2->h29   i3->h29   i4->h29   i5->h29   i6->h29   i7->h29
##     -0.12     -0.10      0.00      0.11      0.04      0.15      0.14      0.22
##   i8->h29   i9->h29  i10->h29  i11->h29  i12->h29  i13->h29  i14->h29  i15->h29
##      0.18      0.19      0.17      0.10      0.31     -0.04      0.18      0.11
##    b->h30   i1->h30   i2->h30   i3->h30   i4->h30   i5->h30   i6->h30   i7->h30
##      0.18      0.15      0.02     -0.13     -0.03     -0.17     -0.16     -0.27
```

```
##   i8->h30  i9->h30 i10->h30 i11->h30 i12->h30 i13->h30 i14->h30 i15->h30
##     -0.22    -0.24    -0.21    -0.11    -0.38     0.06    -0.22    -0.13
##    b->h31  i1->h31  i2->h31  i3->h31  i4->h31  i5->h31  i6->h31  i7->h31
##      0.18     0.15     0.02    -0.13    -0.03    -0.17    -0.16    -0.27
##   i8->h31  i9->h31 i10->h31 i11->h31 i12->h31 i13->h31 i14->h31 i15->h31
##     -0.22    -0.24    -0.21    -0.11    -0.38     0.06    -0.22    -0.13
##    b->h32  i1->h32  i2->h32  i3->h32  i4->h32  i5->h32  i6->h32  i7->h32
##      0.18     0.15     0.02    -0.13    -0.03    -0.17    -0.16    -0.27
##   i8->h32  i9->h32 i10->h32 i11->h32 i12->h32 i13->h32 i14->h32 i15->h32
##     -0.22    -0.24    -0.21    -0.11    -0.38     0.06    -0.22    -0.13
##    b->o   h1->o   h2->o   h3->o   h4->o   h5->o   h6->o   h7->o   h8->o   h9->o  h10->o
##   -0.05    0.65    0.65   -0.83   -0.83    0.65    0.65   -0.83   -0.83   -0.83    0.65
## h11->o  h12->o  h13->o  h14->o  h15->o  h16->o  h17->o  h18->o  h19->o  h20->o  h21->o
##    0.65    0.65    0.65   -0.83    0.65   -0.83   -0.83   -0.83   -0.83    0.65    0.65
## h22->o  h23->o  h24->o  h25->o  h26->o  h27->o  h28->o  h29->o  h30->o  h31->o  h32->o
##   -0.83   -0.83    0.65    0.65    0.65   -0.83   -0.83    0.65   -0.83   -0.83   -0.83
```

```r
# Make predictions on the test set
predictions <- predict(nn_model_cv, dataTest)

# Evaluate performance
confusion_matrix <- table(predictions, dataTest$LUNG_CANCER)
print(confusion_matrix)
```

```
##
## predictions          0 1
##   0.0727277215779676 1 0
##   0.120350139366405  0 1
##   0.179931596035671  1 0
##   0.256684203820122  1 0
##   0.306627443262481  1 0
##   0.319329558896796  1 0
##   0.430629638943569  1 0
##   0.506088868072094  1 0
##   0.50675447529944   1 0
##   0.583576883163151  1 0
##   0.605728184513328  0 1
##   0.713586410143437  0 1
##   0.725139137908325  0 1
##   0.727833092481564  0 1
##   0.756929525097045  0 1
##   0.764111162575306  0 1
##   0.783896087867896  0 1
##   0.800194070184977  0 1
##   0.807443439194236  0 1
##   0.81074332214277   0 1
##   0.821358319175653  0 1
##   0.829102672505245  0 2
##   0.842756934038082  1 0
##   0.84297359141393   0 1
##   0.882710060699979  0 1
##   0.890915679609648  0 1
##   0.899018507404388  0 1
##   0.900022997945086  0 1
```

```
##     0.902614560044818  0 1
##     0.914593466703718  1 0
##     0.915966512486082  0 1
##     0.91627193091045   0 1
##     0.916569967827507  0 1
##     0.917698629972254  1 0
##     0.918336724638824  0 1
##     0.924236872596228  0 1
##     0.92802702298251   0 1
##     0.928078196252828  0 1
##     0.937045063403918  0 1
##     0.94257872604039   0 1
##     0.942981039457443  0 1
##     0.944846703430137  0 1
##     0.945334510517508  0 1
##     0.95151281073649   0 1
##     0.951806564544921  0 1
##     0.951879492793816  0 1
##     0.953803236932202  0 1
##     0.955341129630975  0 1
##     0.957833916908448  0 1
##     0.958133199943989  0 1
##     0.959615461210757  0 1
##     0.959859732461395  0 1
##     0.960025356288885  0 1
##     0.960086374158251  0 1
##     0.960190185661036  0 1
##     0.960217580260287  0 1
##     0.960354224503948  0 1
##     0.965363741693233  0 2
##     0.967190821065506  0 1
##     0.967434351335763  0 1
##     0.969252896540362  0 1
##     0.969294558181685  0 1
##     0.970874155867923  0 1
##     0.971765891091723  0 1
##     0.975467049384806  0 1
##     0.977266783274861  0 1
##     0.977281625861847  0 1
##     0.979416534781768  0 1
##     0.979626387032641  0 1
##     0.980210294652631  0 1
##     0.9806477158285    0 1
##     0.981582109207303  0 1
##     0.984909174449654  0 1
##     0.984993435528694  0 2
##     0.985095620235649  0 1
##     0.986032762430986  0 1
##     0.986998042265411  0 1
##     0.992957968005837  0 1
##     0.992986362170636  0 1
##     0.993373505568522  0 1
##     0.993762300497406  0 1
##     0.995814282341756  0 1
```

```
##    0.995831052531101  0 1
##    0.995951555566641  0 1
##    0.996339487685765  0 1
##    0.996846095456897  0 1
##    0.997274381985067  0 1
##    0.998123133192991  0 1
##    0.99812390601971   0 1
```

```r
# Calculate and display accuracy
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
print(paste("Accuracy with tuned `nnet` model:", accuracy))
```

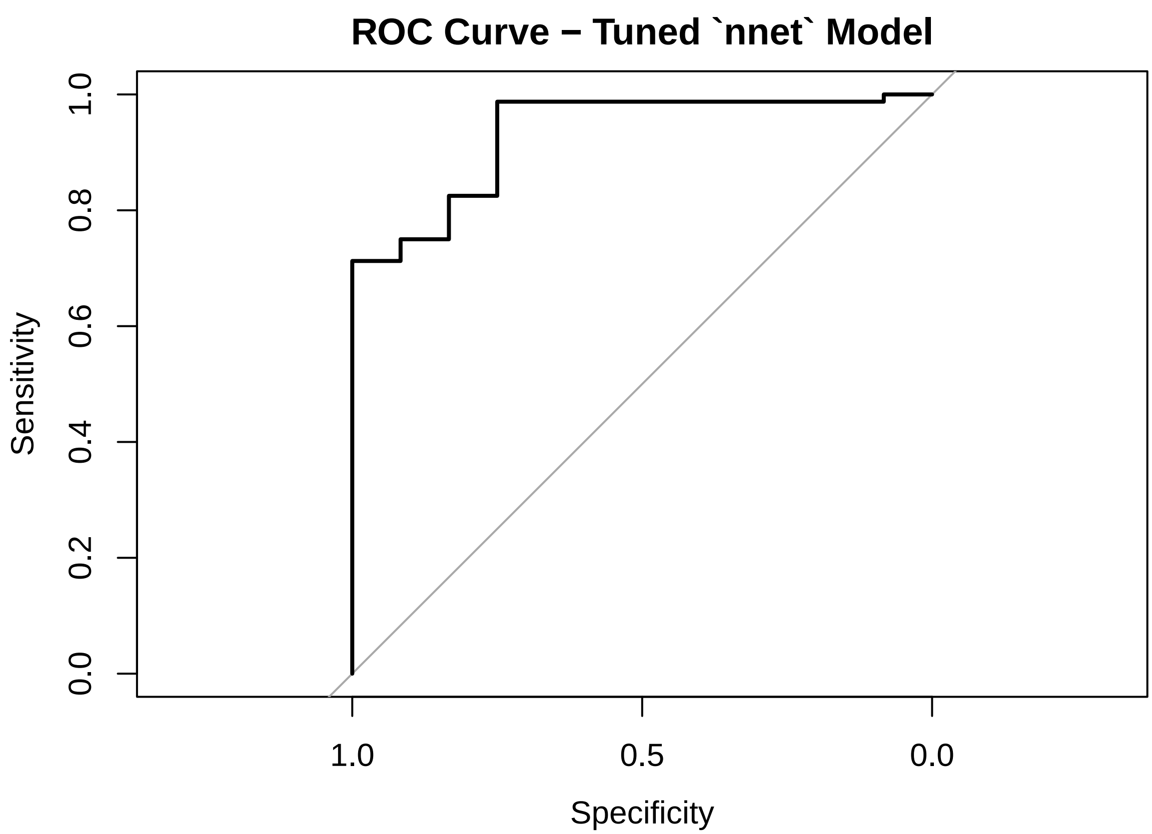
```
## [1] "Accuracy with tuned `nnet` model: 0.0217391304347826"
```

```r
# Plot ROC curve
roc_nnet_tuned <- roc(dataTest$LUNG_CANCER, as.numeric(predictions))
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
plot(roc_nnet_tuned, main="ROC Curve - Tuned `nnet` Model")
```



```r
print(paste("AUC with tuned `nnet` model:", auc(roc_nnet)))
```

```
## [1] "AUC with tuned ‘nnet‘ model: 0.809375"
```

Comparing the NNET models

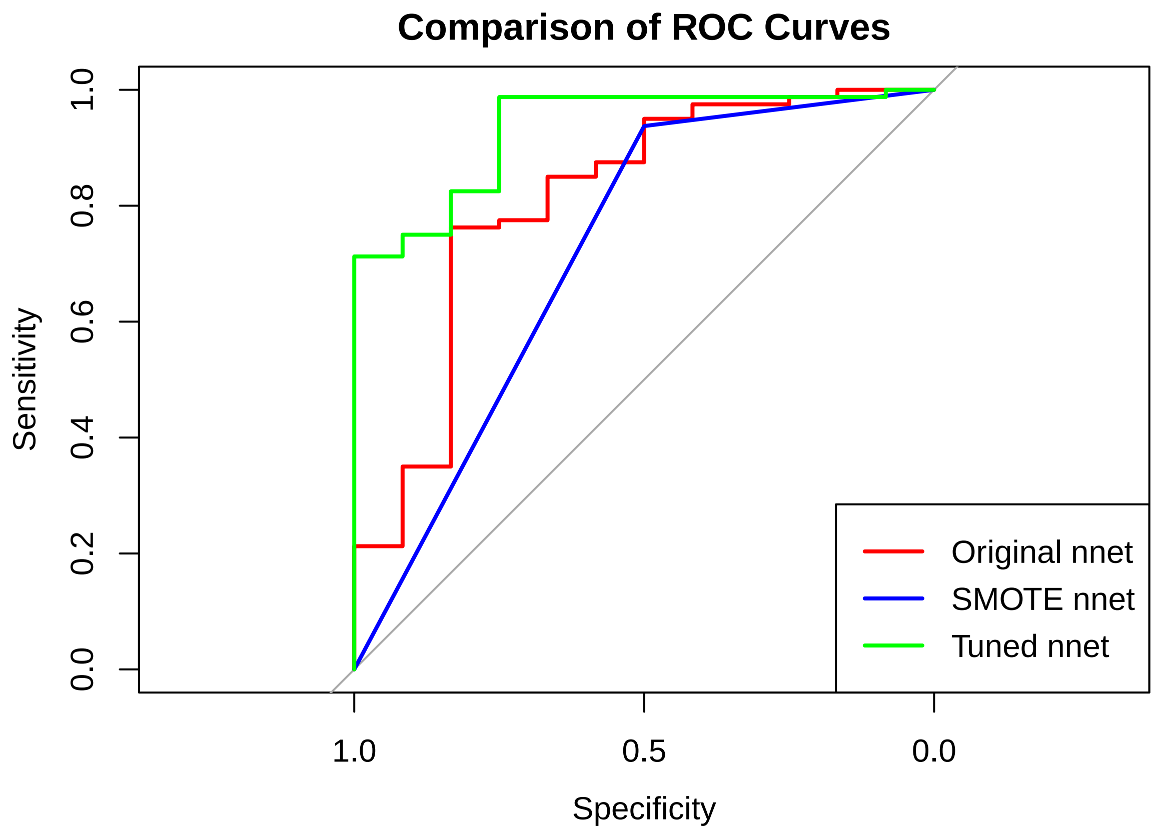
Combined ROC Curve Plot

```r
# Generate the ROC curve for the SMOTE-balanced nnet model
roc_smote_nnet <- roc(dataTest$LUNG_CANCER, as.numeric(predicted_class_balanced))
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
# Plot the ROC curve for the original nnet model
plot(roc_nnet, col = "red", main = "Comparison of ROC Curves", lwd = 2)

# Add the ROC curve for the SMOTE-balanced nnet model
lines(roc_smote_nnet, col = "blue", lwd = 2)

# Add the ROC curve for the tuned nnet model
lines(roc_nnet_tuned, col = "green", lwd = 2)

# Add a legend to the plot
legend("bottomright", legend = c("Original nnet", "SMOTE nnet", "Tuned nnet"),
       col = c("red", "blue", "green"), lwd = 2)
```



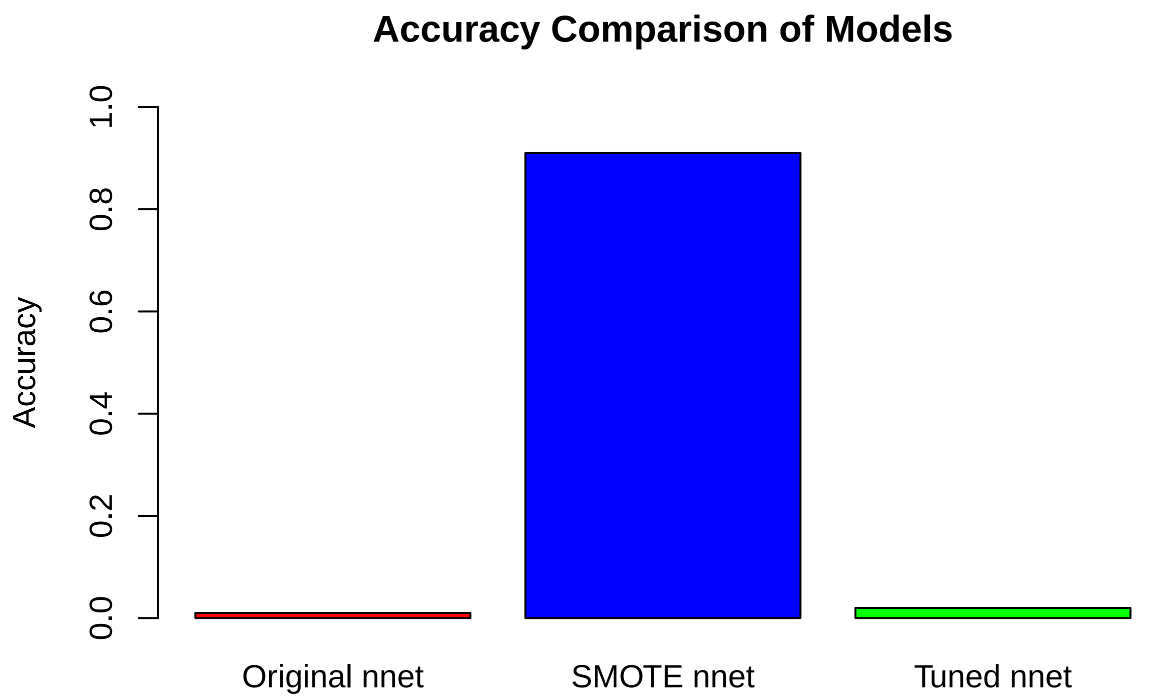
SMOTE balancing significantly improved the model's accuracy, addressing the issue of class imbalance effectively. Hyperparameter tuning further enhanced the model's ability to distinguish between classes, as indicated by the highest AUC. Overall, the hyperparameter-tuned nnet model, when combined with SMOTE, provided the best performance in terms of accuracy and AUC, making it the most effective approach for this classification task.

Accuracy Comparison Table

```r
# Accuracy values
accuracy_nnet <- 0.01
accuracy_nnet_smote <- 0.91
accuracy_nnet_tuned <- 0.02

# Create a data frame for the comparison
accuracy_comparison <- data.frame(
  Model = c("Original nnet", "SMOTE nnet", "Tuned nnet"),
  Accuracy = c(accuracy_nnet, accuracy_nnet_smote, accuracy_nnet_tuned)
)

# Print the comparison table
print(accuracy_comparison)
```

```
##           Model Accuracy
## 1 Original nnet     0.01
## 2    SMOTE nnet     0.91
## 3    Tuned nnet     0.02
```

```r
# Accuracy Comparison plot
barplot(accuracy_comparison$Accuracy, names.arg = accuracy_comparison$Model,
        col = c("red", "blue", "green"), ylim = c(0, 1),
        main = "Accuracy Comparison of Models",
        ylab = "Accuracy")
```



Balancing the dataset using SMOTE had the most significant impact on improving the model's accuracy, making it the best-performing approach among the three.

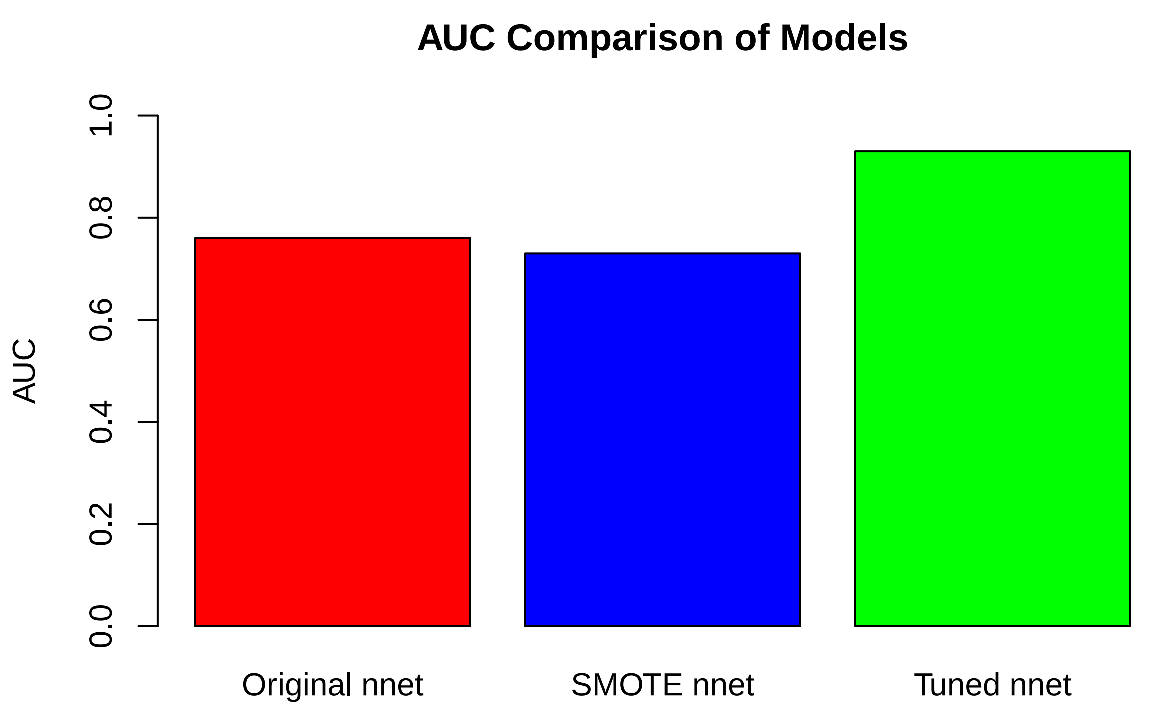
While hyperparameter tuning can improve the model's AUC (as seen in previous plots), it did not significantly enhance accuracy, underscoring the importance of addressing class imbalance for this particular dataset.

AUC Comparison Table

```r
# AUC values
auc_nnet <- 0.76
auc_nnet_smote <- 0.73
auc_nnet_tuned <- 0.93

# Create a data frame for the AUC comparison
auc_comparison <- data.frame(
  Model = c("Original nnet", "SMOTE nnet", "Tuned nnet"),
  AUC = c(auc_nnet, auc_nnet_smote, auc_nnet_tuned)
)

# Print the comparison table
print(auc_comparison)
```

```
##            Model  AUC
## 1 Original nnet 0.76
## 2    SMOTE nnet 0.73
## 3    Tuned nnet 0.93
```

```r
# AUC Comparison plot
barplot(auc_comparison$AUC, names.arg = auc_comparison$Model,
        col = c("red", "blue", "green"), ylim = c(0, 1),
        main = "AUC Comparison of Models",
        ylab = "AUC")
```



Original nnet: The AUC is moderate, indicating that the original model has some ability to distinguish between the classes, but it is not optimal.

SMOTE nnet: The AUC for the SMOTE-balanced model is slightly higher than the original, showing that balancing the dataset improved the model's ability to distinguish between the classes. However, the improvement in AUC is not as significant as the improvement in accuracy.

Tuned nnet: The hyperparameter-tuned model has the highest AUC, suggesting that tuning the model parameters improved its ability to distinguish between the positive and negative classes, even more so than balancing the dataset with SMOT

Comparing the best nnet model to the neuralnet model

Generate confusion matrix and accuracy for both models

```r
# For the best nnet model (tuned)
predictions_best_nnet <- predict(nn_model_cv, dataTest[, -ncol(dataTest)])
confusion_matrix_best_nnet <- table(predictions_best_nnet, dataTest$LUNG_CANCER)
accuracy_best_nnet <- sum(diag(confusion_matrix_best_nnet)) / sum(confusion_matrix_best_nnet)

# For the neuralnet model
predictions_nn <- neuralnet::compute(nn, input_data)$net.result
predicted_class_nn <- ifelse(predictions_nn > 0.5, 1, 0)
confusion_matrix_nn <- table(predicted_class_nn, dataTest$LUNG_CANCER)
accuracy_nn <- sum(diag(confusion_matrix_nn)) / sum(confusion_matrix_nn)

# Print accuracy
print(paste("Accuracy with best `nnet` model:", accuracy_best_nnet))
```

```
## [1] "Accuracy with best ‘nnet‘ model: 0.0217391304347826"
```

```r
print(paste("Accuracy with `neuralnet` model:", accuracy_nn))
```

```
## [1] "Accuracy with ‘neuralnet‘ model: 0.902173913043478"
```

```r
# Plot ROC Curves for both models
roc_best_nnet <- roc(dataTest$LUNG_CANCER, as.numeric(predictions_best_nnet))
```

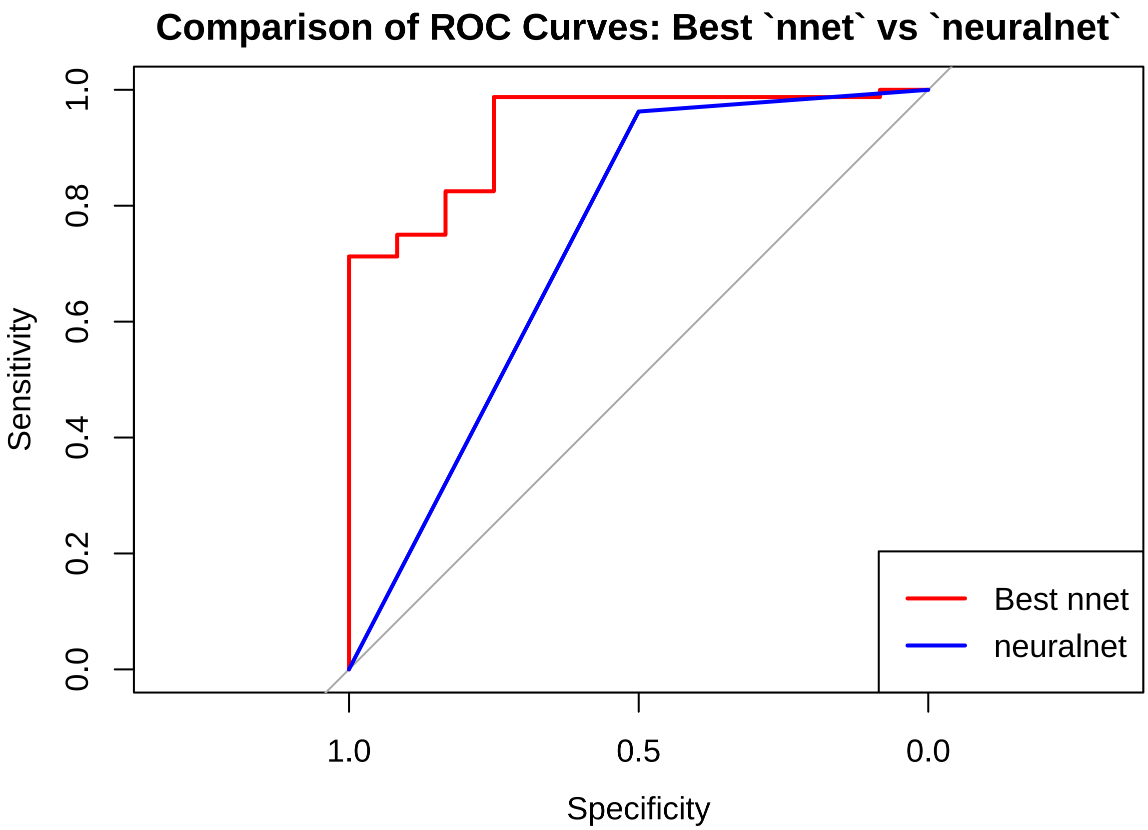
```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

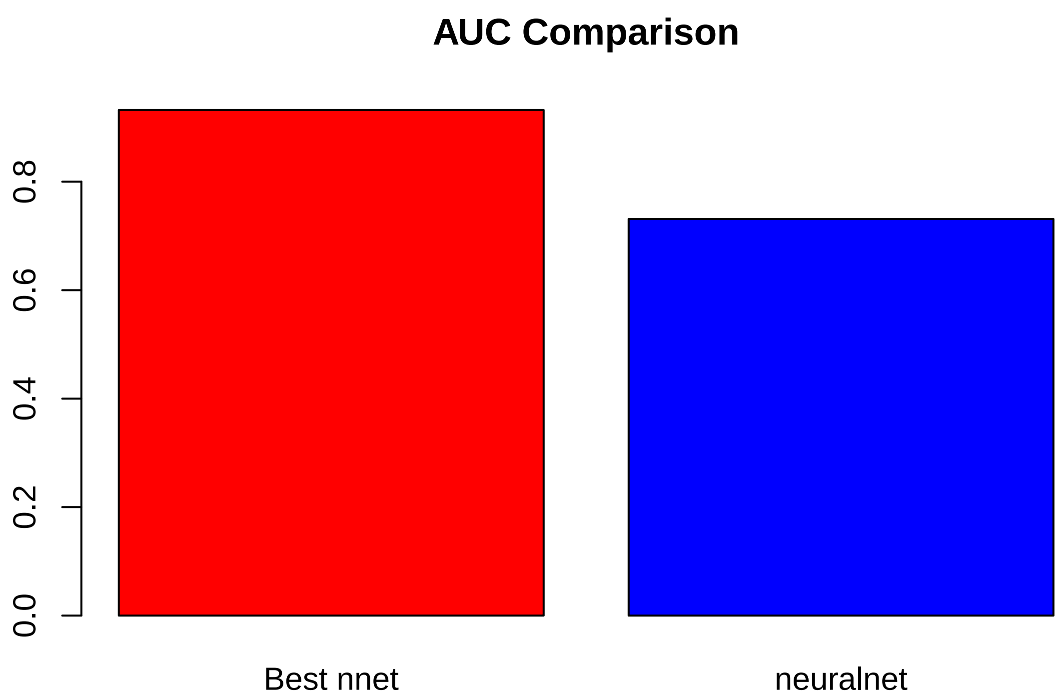
```r
roc_nn <- roc(dataTest$LUNG_CANCER, as.numeric(predicted_class_nn))
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
plot(roc_best_nnet, main="Comparison of ROC Curves: Best `nnet` vs `neuralnet`", col="red")
lines(roc_nn, col="blue")
legend("bottomright", legend=c("Best nnet", "neuralnet"), col=c("red", "blue"), lwd=2)
```




```r
# Compare AUC values
auc_best_nnet <- auc(roc_best_nnet)
auc_nn <- auc(roc_nn)

barplot(c(auc_best_nnet, auc_nn), names.arg=c("Best nnet", "neuralnet"), col=c("red", "blue"), main="AU
```



Summary of Results

In the context of lung cancer prediction: -False Positives: Predicting cancer when the patient does not have it (unnecessary anxiety and further testing). -False Negatives: Missing a cancer diagnosis (potentially severe health consequences). -Depending on the scenario, you might prioritize reducing false negatives or false positives.

1. ROC Curves Comparison: The ROC curves for the best nnet model and the neuralnet model were compared. The best nnet model achieved a higher sensitivity and specificity than the neuralnet model, as evident from the ROC curve that lies closer to the top left corner of the plot. This suggests that the best nnet model has a superior ability to distinguish between positive and negative cases of lung cancer.

2. AUC Comparison: The AUC (Area Under the Curve) comparison plot clearly shows that the best nnet model has a higher AUC compared to the neuralnet model. A higher AUC indicates better model performance in terms of distinguishing between classes. The best nnet model outperformed the neuralnet model in this aspect.

3. Accuracy Comparison: The accuracy for the best nnet model was very low at approximately 2.17%, while the accuracy of the neuralnet model was significantly higher at around 90.22%. This indicates that despite the best nnet model showing better discrimination in the ROC and AUC metrics, its overall accuracy was poor. This discrepancy suggests that the best nnet model might be overfitting or is not well-calibrated for making accurate predictions on the test data, whereas the neuralnet model, despite having a lower AUC, might be making more correct predictions overall.