# Final Project_Team 7_Gabi

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## Sensor-Fusion Smoke Detection Classification

The goal is to devise a Machine Learning model that that will detect smoke through the use of loT data to trigger a fire alarm.

**Information about the Features:**

*Air Temperature*
*Air Humidity*
*TVOC:* Total Volatile Organic Compounds; measured in parts per billion (Source)
*eCO2:* co2 equivalent concentration; calculated from different values like TVCO
*Raw H2:* raw molecular hydrogen; not compensated (Bias, temperature, etc.)
*Raw Ethanol:* raw ethanol gas (Source)
*Air Pressure*
*PM 1.0 and PM 2.5:* particulate matter size $<$ 1.0 µm (PM1.0). 1.0 µm $<$ 2.5 µm (PM2.5)
*Fire Alarm:* ground truth is "1" if a fire is there
*CNT:* Sample counter
*UTC:* Timestamp UTC seconds
*NC0.5/NC1.0 and NC2.5:* Number concentration of particulate matter. This differs from PM because NC gives the actual number of particles in the air. The raw NC is also classified by the particle size: $<$ 0.5 µm (NC0.5); 0.5 µm $<$ 1.0 µm (NC1.0); 1.0 µm $<$ 2.5 µm (NC2.5);

### Pre-Processing:

```
# List of libraries
library(caret)
library(tidyverse)
library(naniar)
library(gt)
library(ggplot2)
```

```
library(dplyr)
library(tidyr)
library(GGally)
library(corrplot)
library(e1071)
library(tibble)
library(MASS)
library(mice)
library(reshape2)
library(ROSE)
library(pROC)
library(lubridate)
```

Note:

- Train dataset has 5000 observations, 14 predictors, and an outcome variable.
- Test dataset has 12437 observations and 14 predictors.

```
# Upload datasets
train <- read.csv("train_dataset.csv")
test <- read.csv("test_dataset.csv")

# Use train_dataset moving forward
smokedf <- train
str(smokedf)
```

```
'data.frame':   5000 obs. of  15 variables:
 $ UTC           : int  1655127646 1654734418 1654714047 1654715196 1655125243 1654712431 165
 $ Temperature.C.: num  15.1 27.1 26.4 26 -1.2 ...
 $ Humidity...   : num  43 54.8 45.8 48.4 41.4 ...
 $ TVOC.ppb.     : int  199 0 144 180 76 58 60000 81 656 223 ...
 $ eCO2.ppm.     : int  426 400 409 431 400 420 9147 447 400 467 ...
 $ Raw.H2        : int  12775 13058 12784 12771 12791 12834 11410 12785 13732 12747 ...
 $ Raw.Ethanol   : int  20524 19961 20580 20537 20673 20724 16840 20690 20533 20502 ...
 $ Pressure.hPa. : num  937 940 937 937 938 ...
 $ PM1.0         : num  1.55 0.21 1.97 1.93 1.9 ...
 $ PM2.5         : num  1.61 0.22 2.05 2.01 1.97 ...
 $ NC0.5         : num  10.66 1.46 13.59 13.31 13.08 ...
 $ NC1.0         : num  1.663 0.228 2.118 2.075 2.04 ...
 $ NC2.5         : num  0.038 0.005 0.048 0.047 0.046 ...
 $ CNT           : int  3338 1087 1860 3009 935 244 5222 677 5693 3353 ...
 $ Fire.Alarm    : int  0 0 0 0 0 0 0 0 0 0 ...
```

```r
class(smokedf)
```

```
[1] "data.frame"
```

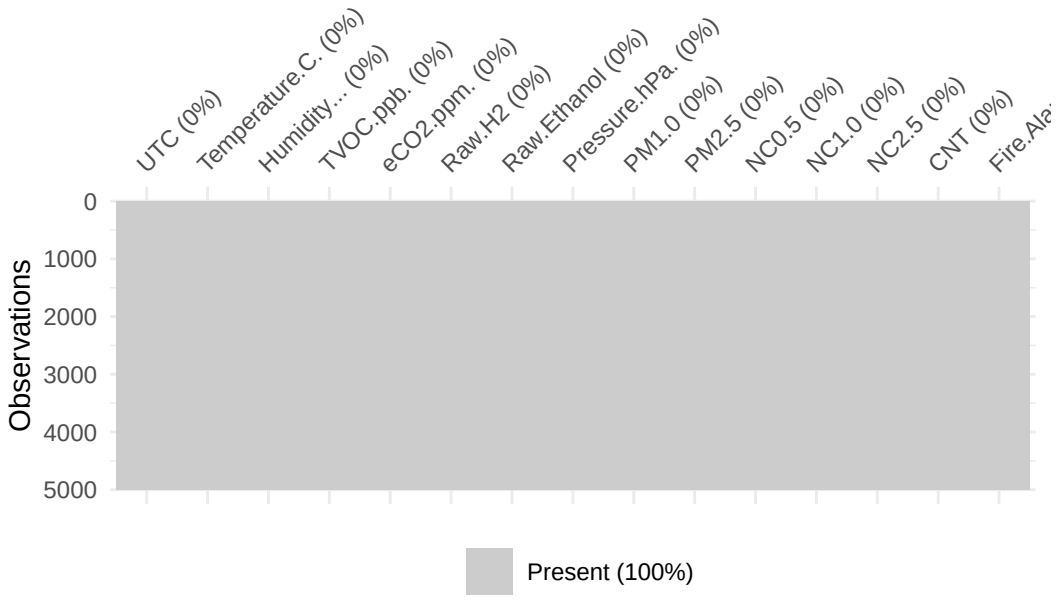
```r
#summary(smokedf)
```

```r
# Missing Values
smokedf[smokedf == ""] <- NA
na_value <- sapply(smokedf, function(x) sum(is.na(x)))
predictors_with_missing <- names(na_value[na_value > 0])

missing_values_table <- data.frame(Predictor = predictors_with_missing,
Missing_Values = na_value[predictors_with_missing])
missing_values_table |> head() |> gt() |>
  tab_header(title = "Predictors with Missing Values")
```

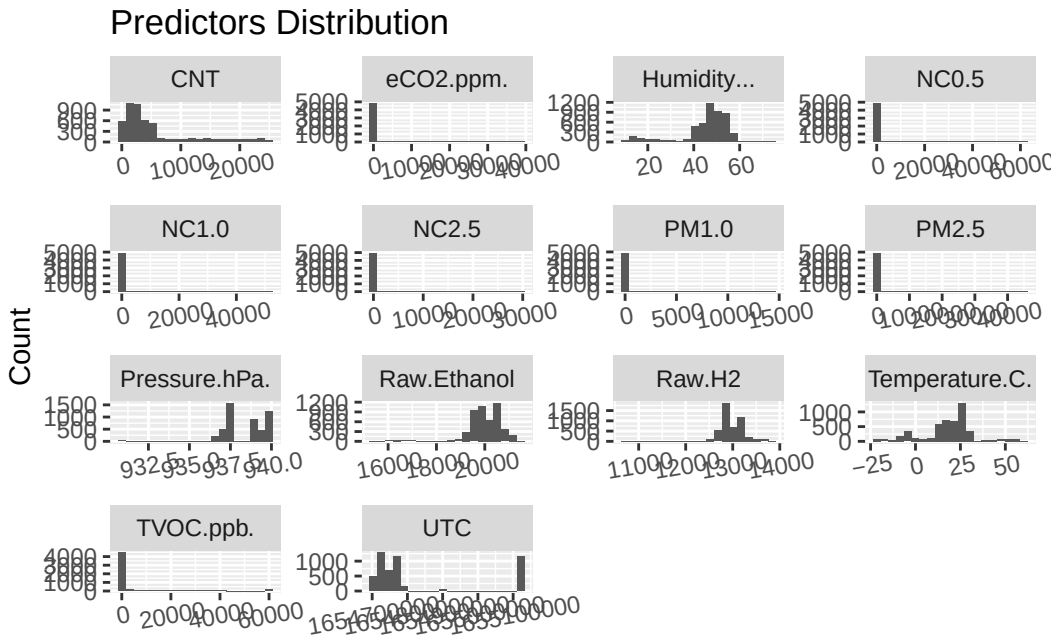
Predictors with Missing Values

| Predictor | Missing_Values |
|---|---|

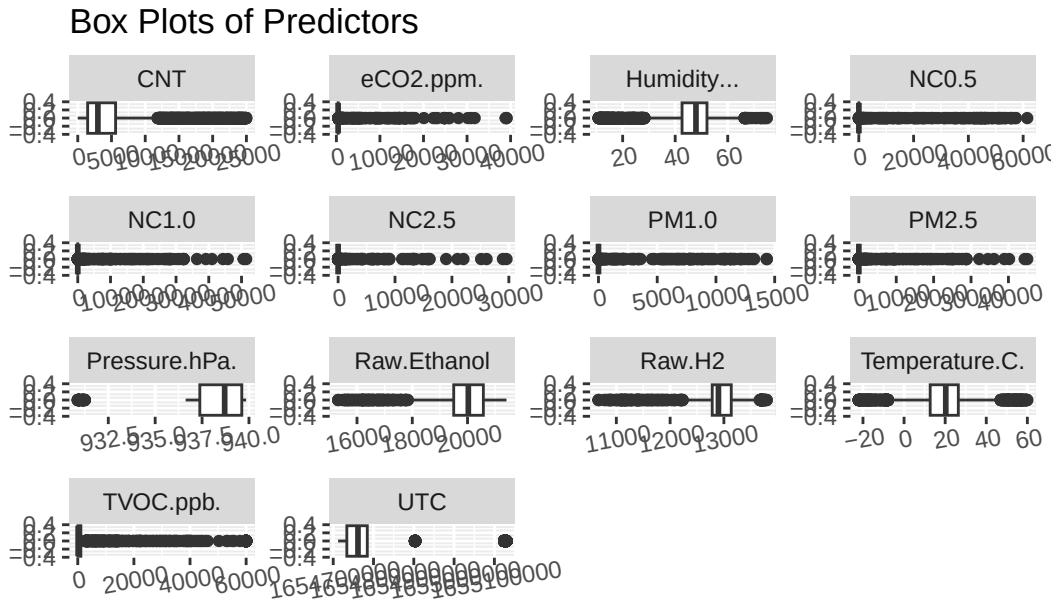
```r
vis_miss(smokedf)
```



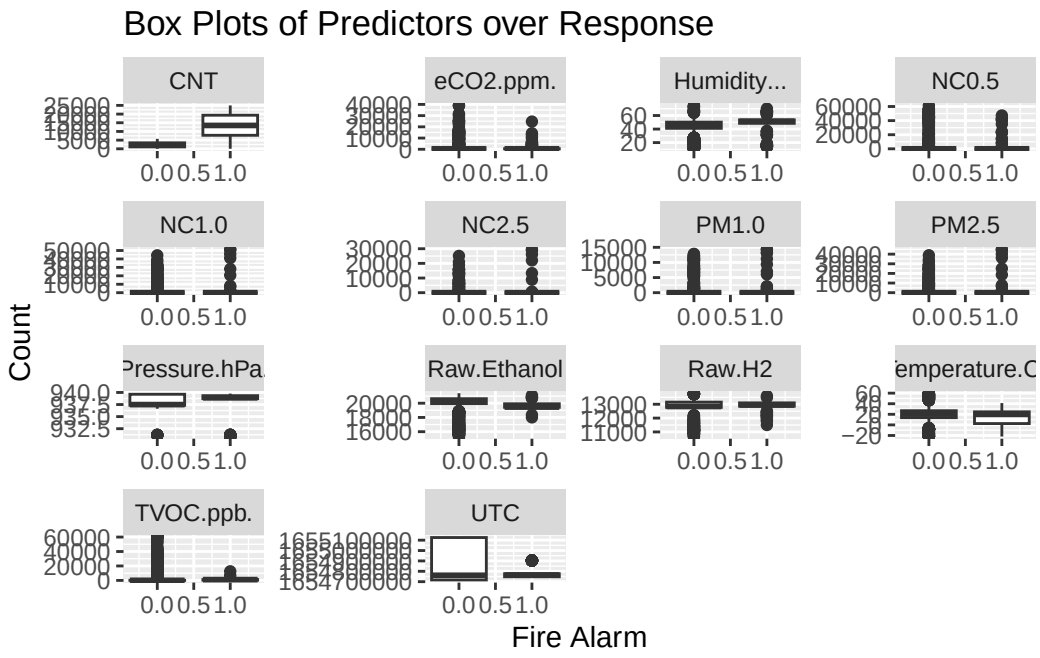
```
# Histogram of each predictors
smokedf |>
  pivot_longer(-Fire.Alarm, names_to = 'Element', values_to = 'value') |>
  ggplot(aes(x = value)) +
  geom_histogram(bins = 20) +
  facet_wrap(~Element, scales = 'free', ncol = 4) +
  theme(axis.text.x = element_text(angle = 10)) +
  labs(title = 'Predictors Distribution', x = NULL, y = "Count")
```




```
# Create box plots for each predictors:
smokedf |>
  pivot_longer(-Fire.Alarm, names_to = 'Element', values_to = 'value') |>
  ggplot(aes(value)) +
  geom_boxplot() +
  facet_wrap(~Element, scales = "free", ncol = 4) +
  theme(axis.text.x = element_text(angle = 10)) +
  labs(title = 'Box Plots of Predictors', x = "Count")
```



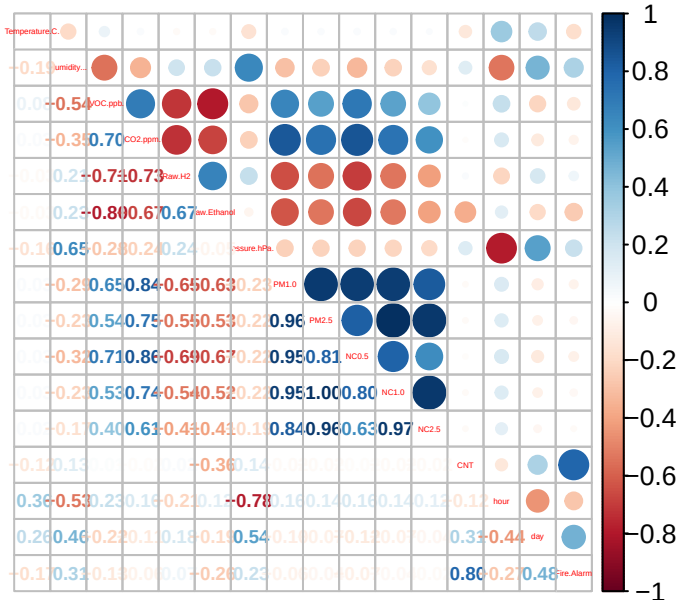

```
# Create box plots of response for each predictors:
smokedf |>
  pivot_longer(-Fire.Alarm, names_to = 'Element', values_to = 'value') |>
  ggplot(aes(Fire.Alarm, value, group = Fire.Alarm)) +
  geom_boxplot() +
  facet_wrap(~Element, scales = "free", ncol = 4) +
  theme(axis.text.x = element_text(angle = 0)) +
  labs(title = 'Box Plots of Predictors over Response', x = "Fire Alarm", y = "Count")
```



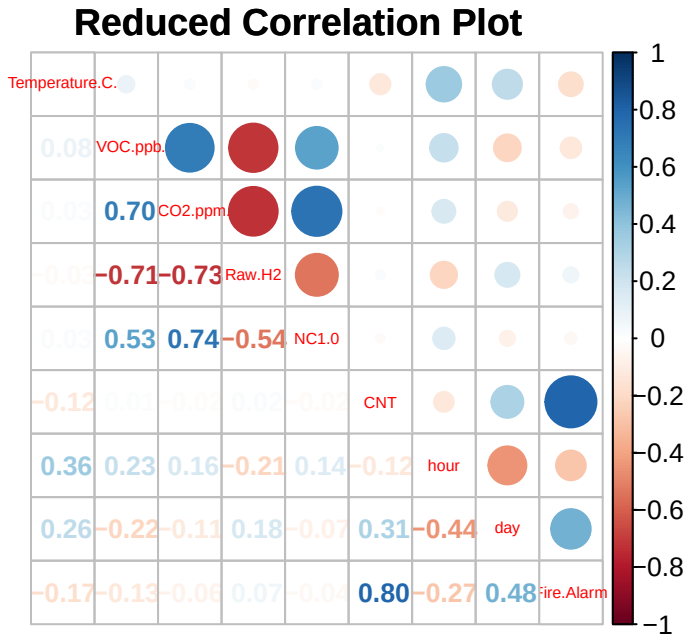

```
# Convert UTC format into hours of day and day of week
smokedf$UTC_datetime <- as.POSIXct(smokedf$UTC, origin = "1970-01-01", tz = "UTC")
# all from 2022 and June

smokedf$hour <- hour(smokedf$UTC_datetime)
smokedf$day <- wday(smokedf$UTC_datetime, week_start = 1)

# Reorder variables and remove UTC_datetime
other_columns <- setdiff(names(smokedf), "Fire.Alarm")
smokedf <- smokedf[, c(other_columns, "Fire.Alarm")]
smokedf <- subset(smokedf, select = c(-UTC_datetime, -UTC))
```

```
# Correlation plot including outcome variable
smokedf |>
mutate(Fire.Alarm = as.numeric(Fire.Alarm)) |>
cor() |>
corrplot.mixed(title = "Correlation Plot Between Outcome and Predictors",
tl.cex = .25, number.cex = 0.6, mar = c(1, 1, 1, 1))
```

## Correlation Plot Between Outcome and Predictors




```r
# Remove highly correlated predictors
correlation_matrix <- cor(smokedf[, -1])
highly_correlated <- findCorrelation(correlation_matrix, cutoff = 0.75)
highly_correlated_names <- colnames(smokedf[, -1])[highly_correlated]
smokedf_reduced <- smokedf[, -highly_correlated]

# Correlation plot including outcome variable
smokedf_reduced |>
  mutate(Fire.Alarm = as.numeric(Fire.Alarm)) |>
  cor() |>
  corrplot.mixed(title = "Reduced Correlation Plot",
                 tl.cex = .5, number.cex = 0.8, mar = c(1, 1, 1, 1))
```




```
# Calculate skewness of each predictors
# Skew values less than ±0.5 should be considered 'normal enough'
skew_fa <- smokedf_reduced |>
  dplyr::select(-Fire.Alarm) |>
  map_dbl(skewness) |> round(3)

skew_fa_tibble <- tibble(Variable = names(skew_fa), Skewness = skew_fa)
skew_fa_tibble |> gt()
```

| Variable | Skewness |
|---|---|
| Temperature.C. | -0.303 |
| TVOC.ppb. | 4.248 |
| eCO2.ppm. | 8.395 |
| Raw.H2 | -2.335 |
| NC1.0 | 10.232 |
| CNT | 1.669 |
| hour | -0.237 |
| day | -0.904 |

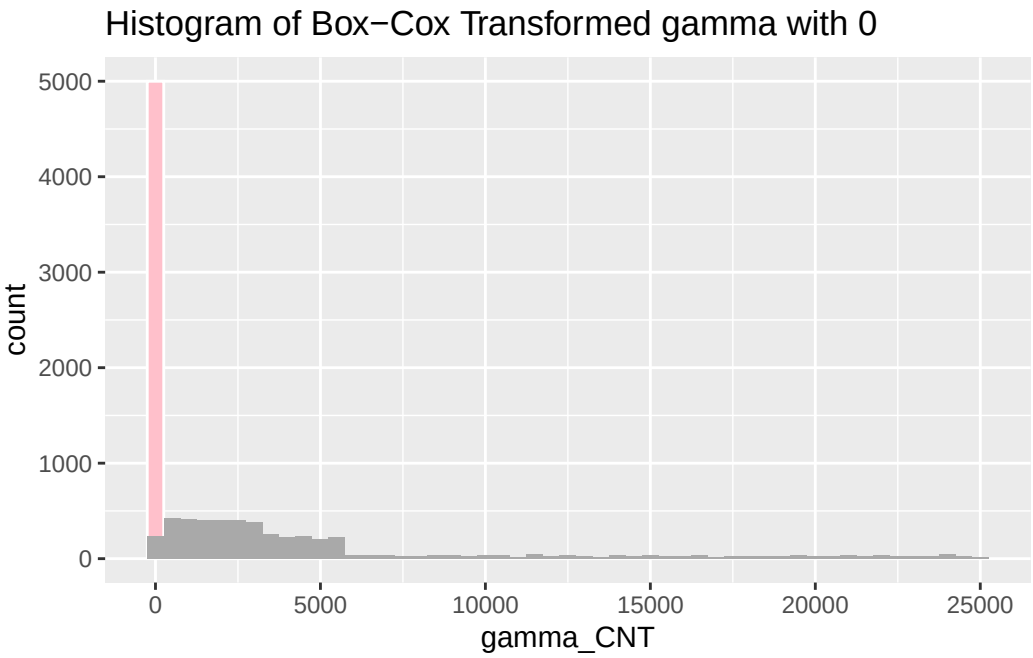
```
# Determine zero values in the dataframe
zero_counts <- sapply(smokedf, function(x) sum(x == 0, na.rm = TRUE))
```

```
# Perform Box Cox Tranformation Analysis and determine predictors with >50% improvement
bct_test <- function(x, property = 'skew') {
  stopifnot(property %in% c('skew', 'lambda'))

  x <- x[which(! is.na(x))]
  x2 <- x + ifelse(any(x == 0), 0.0001, 0)

  bct <- BoxCoxTrans(x2)
  x_trans <- predict(bct, x2 )
if (property == 'skew') return(e1071::skewness(x_trans))
return(bct$lambda)}

skew_smfa_bct <- smokedf_reduced |>
  dplyr::select(-Fire.Alarm) |>
  map_dbl(bct_test)

bct_analysis <- tibble(
  Property = names(skew_fa),
  `Original Skew` = skew_fa,
  `Skew after BoxCox`= round(skew_smfa_bct,4),
  Lambda = smokedf_reduced |> dplyr::select(-Fire.Alarm) |>
    map_dbl( ~ bct_test(.x, 'lambda')))

bct_keep <- bct_analysis |>
  filter(abs(`Original Skew`) > 0.5,
         abs(`Skew after BoxCox`) < 0.5)

bct_keep |>
gt::gt()
```

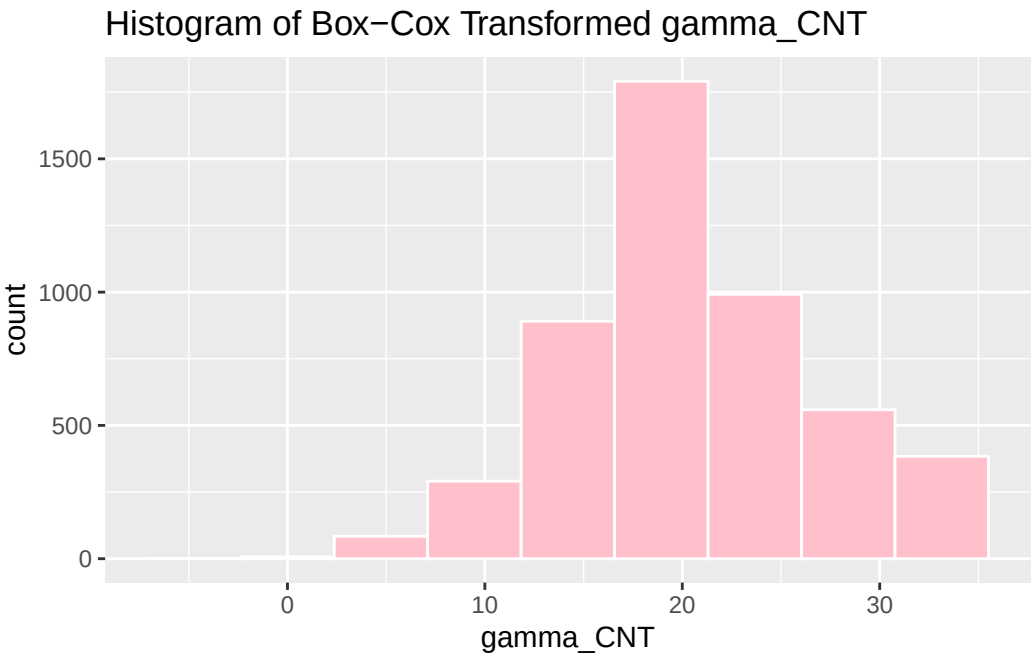
| Property | Original Skew | Skew after BoxCox | Lambda |
|---|---|---|---|
| CNT | 1.669 | 0.0728 | 0.2 |

```
# Apply BCT Analysis result in reduced dataframe
bct <- BoxCoxTrans(smokedf_reduced$CNT +
                     ifelse(any(smokedf_reduced$CNT == 0), 0.0001, 0))
smokedf_reduced$gamma_CNT <- predict(bct, smokedf_reduced$CNT)

# Plot Changes
smokedf_reduced |> ggplot(aes(x = gamma_CNT)) +
```

```
    geom_histogram(binwidth = 500, fill = "pink", color = "white") +
    geom_histogram(aes(x = CNT), binwidth = 500, fill = "darkgray", alpha = 10) +
    labs(title = "Histogram of Box-Cox Transformed gamma with 0")
```



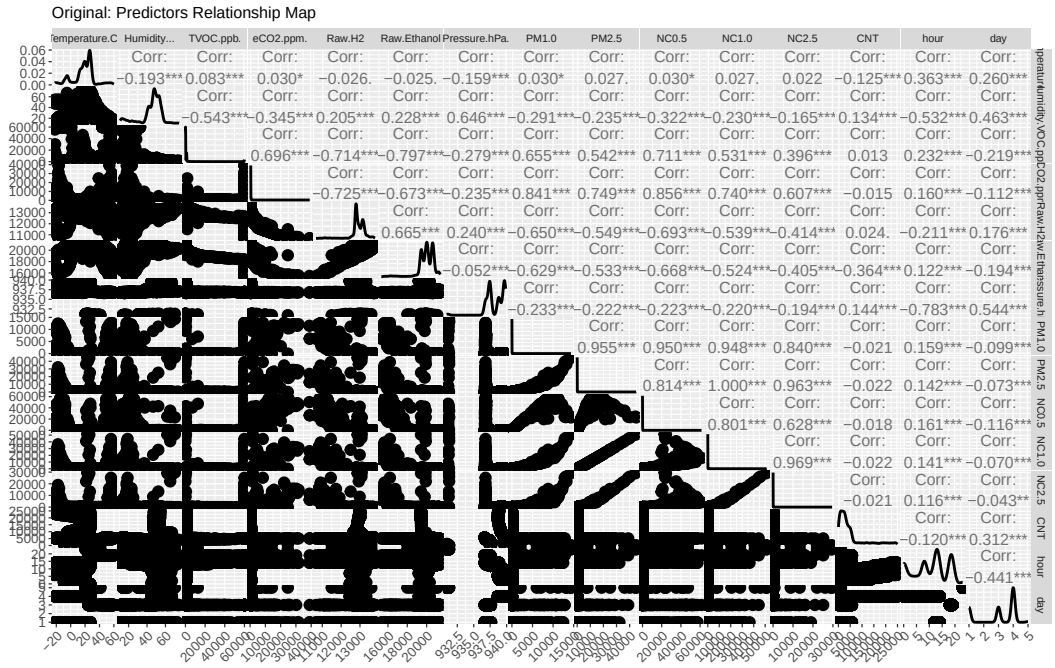

```
smokedf_reduced |>
ggplot(aes(x = gamma_CNT)) +
geom_histogram(bins= 9, color = "white", fill = "pink") +
labs(title ="Histogram of Box-Cox Transformed gamma_CNT")
```




```
# Remove Original CNT in reduced dataframe
smokedf_reduced <- smokedf_reduced |> dplyr::select(-CNT) |>
  relocate("Fire.Alarm", .after = last_col())
```

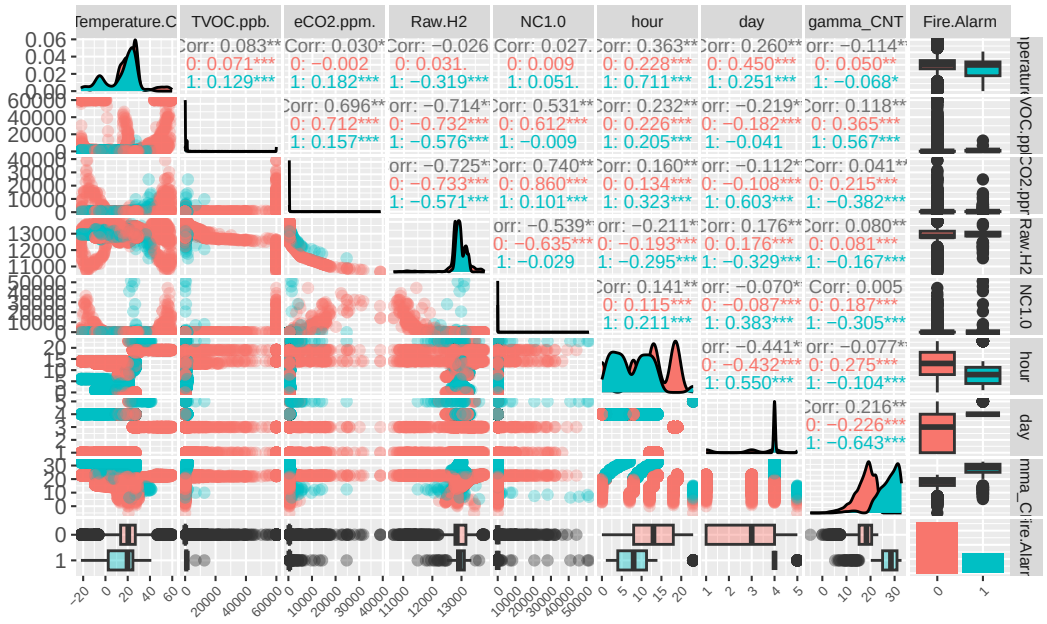
### Exploratory Data Analysis

```
# General relationship plot: Multivariate Analysis (Original Data)
smokedf |>
  dplyr::select(-Fire.Alarm) |>
  ggpairs(title = 'Original: Predictors Relationship Map', progress = TRUE,
          upper = list(continuous = wrap("cor", size = 2))) +
  theme_grey(base_size = 5) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 5),
        axis.text.y = element_text(size = 5),
        panel.spacing = unit(0.01, "lines"))
```

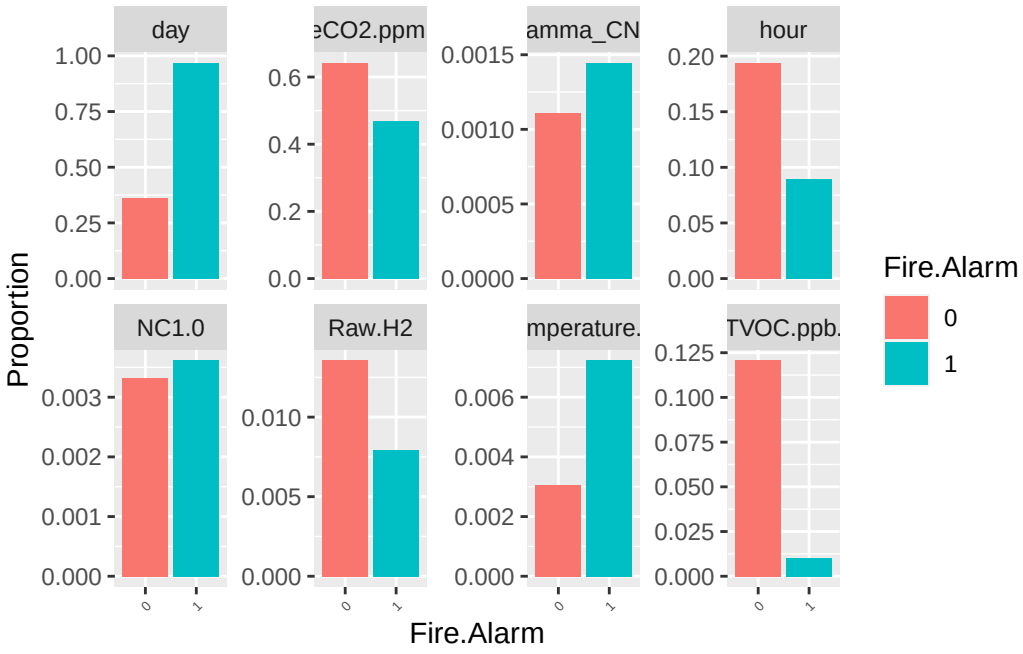



```
# General relationship plot: Multivariate Analysis (Reduced Data)
smokedf_reduced$Fire.Alarm <- as.factor(smokedf_reduced$Fire.Alarm)

smokedf_reduced |>
  ggpairs(title = 'Reduced: Predictors Relationship Map', progress = TRUE,
          upper = list(continuous = wrap("cor", size = 2.5)),
          lower = list(continuous = wrap("points", alpha = 0.3),
                       combo = wrap("box_no_facet", alpha = 0.4)),
          columns = 1:9, ggplot2::aes(colour = Fire.Alarm)) +
  theme_grey(base_size = 8) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 5),
        axis.text.y = element_text(size = 8),
        panel.spacing = unit(0.1, "lines"))
```

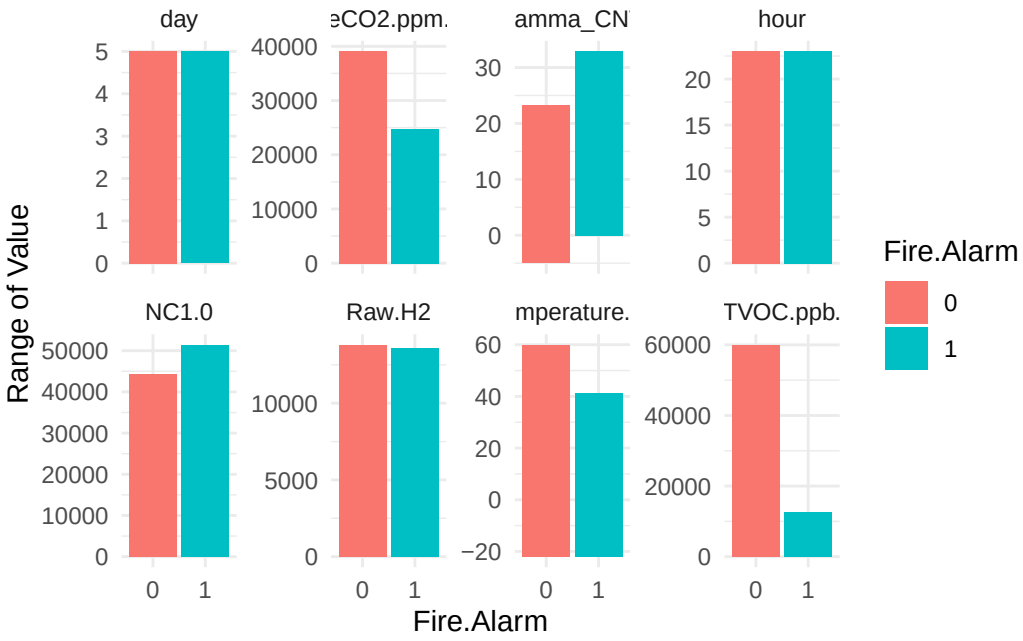
Reduced: Predictors Relationship Map



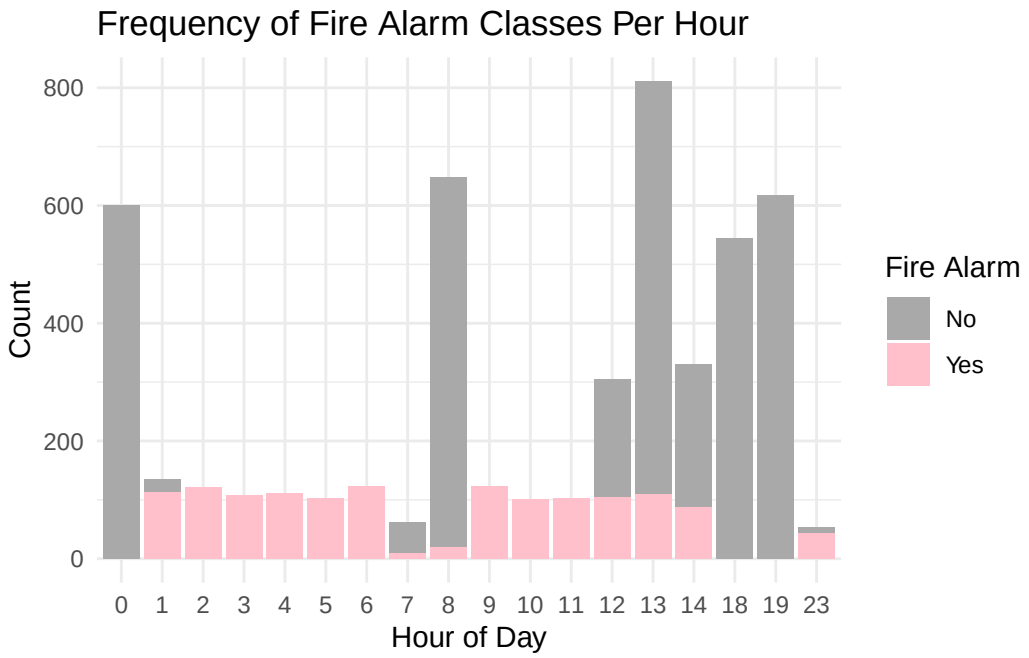

```
# Explore proportion of Fire.Alarm classes against each predictors
proportions <- smokedf_reduced |>
  pivot_longer(-Fire.Alarm, names_to = 'variable', values_to = 'value') |>
  group_by(Fire.Alarm, variable, value) |>
  summarize(Count = n(), .groups = 'drop') |>
  group_by(variable, Fire.Alarm) |>
  mutate(Proportion = Count / sum(Count))

# Create the bar plot
proportions |>
  ggplot(aes(x = Fire.Alarm, y = Proportion, fill = Fire.Alarm)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~ variable, scales = "free_y", ncol = 4) +
  labs(x = "Fire.Alarm", y = "Proportion") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 5))
```



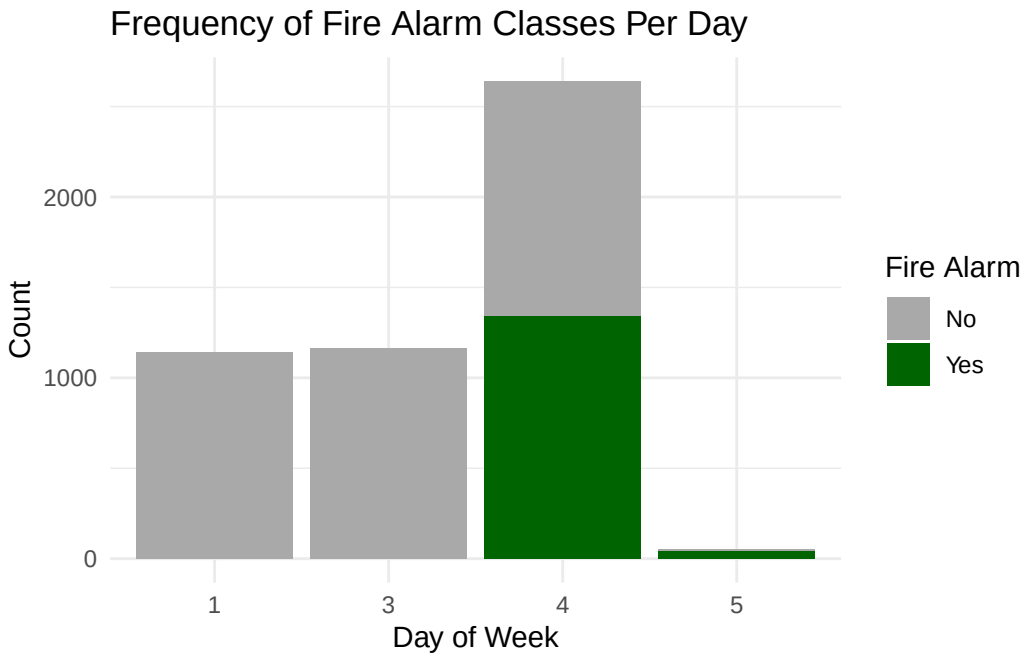

```
# Explore the the value range of Fire.Alarm classes against each predictors
smokedf_reduced |>
  pivot_longer(-Fire.Alarm, names_to = 'variable', values_to = 'value') |>
  ggplot(aes(x = Fire.Alarm, y = value, fill = Fire.Alarm)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~ variable, scales = "free_y", ncol = 4) +
  labs(x = "Fire.Alarm", y = "Range of Value") +
  theme_minimal()
```




```
# Prevelent hour of the day
smokedf$Fire.Alarm1 <- factor(smokedf$Fire.Alarm, levels = c(0, 1), labels = c("No", "Yes"))

smokedf|>
  ggplot(aes(x = factor(hour), fill = Fire.Alarm1)) +
  geom_bar(position = "stack") +
  labs(title = 'Frequency of Fire Alarm Classes Per Hour', x = "Hour of Day",
       y = "Count", fill = "Fire Alarm") +
  scale_x_discrete(labels = function(x) as.numeric(x)) +
  scale_fill_manual(values = c("Yes" = "pink", "No" = "darkgray")) +
  theme_minimal()
```




```
# Prevelent day of the week
smokedf |>
  ggplot(aes(x = factor(day), fill = Fire.Alarm1)) +
  geom_bar(position = "stack") +
  labs(title = 'Frequency of Fire Alarm Classes Per Day', x = "Day of Week",
       y = "Count", fill = "Fire Alarm") +
  scale_x_discrete(labels = function(x) as.numeric(x)) +
  scale_fill_manual(values = c("Yes" = "darkgreen", "No" = "darkgray")) +
  theme_minimal()
```




### Training and Test Sets

```
set.seed(503)
smokedf_reduced$Fire.Alarm <- ifelse(smokedf_reduced$Fire.Alarm == 0, "No", "Yes")
smokedf_predictors <- smokedf_reduced[ ,-1]
smokedf_yield <- smokedf_reduced[ ,1]

# Split the data into training and test sets
smokedf_index <- createDataPartition(smokedf_yield, p = 0.8, list = FALSE)
smokedf_train <- smokedf_predictors[smokedf_index, ]
smokedf_test <- smokedf_predictors[-smokedf_index, ]
```

```
# Center and scaling using preProcess
smokedf_prep <- preProcess(smokedf_train, method = c("center", "scale"))

# Apply the transformation to the training data
smokedf_train_transformed <- predict(smokedf_prep, smokedf_train)
smokedf_test_transformed <- predict(smokedf_prep, smokedf_test)

# Rebalance train dataset
cat("Number of non-triggered fire alarm (No) = ",
    sum(smokedf_train_transformed$Fire.Alarm == "No"), "\n")
```

```
Number of non-triggered fire alarm (No) =  2900
```

```
cat("Number of triggered fire alarm (Yes) =",
    sum(smokedf_train_transformed$Fire.Alarm == "Yes"))
```

```
Number of triggered fire alarm (Yes) = 1101
```

```
train_balanced <- ROSE(Fire.Alarm ~ ., data = smokedf_train_transformed)$data

rebalanced <- as.data.frame(table(train_balanced$Fire.Alarm))
rebalanced |> gt() |>
  tab_header(title = "Rebalanced Fire Alarm Counts")
```

Rebalanced Fire Alarm Counts

| Var1 | Freq |
|---|---|
| No | 2010 |
| Yes | 1991 |

### Model Strategies

```
set.seed(503)
ctrl <- trainControl(method = "cv", summaryFunction = twoClassSummary,
                     classProbs = TRUE, savePredictions = TRUE)

# Create Logistic Regression
lrFit <- train(Fire.Alarm ~ .,
               data = train_balanced,
               method = "glm",
               metric = "ROC",
               trControl = ctrl)
# Logistic regression final model using train data set
lrFit$finalModel
```

```
Call:  NULL

Coefficients:
```

```
(Intercept)    TVOC.ppb.    eCO2.ppm.       Raw.H2        NC1.0          hour
   -2.87487     -1.11846      0.23798     -0.19185      0.37800       0.09592
        day    gamma_CNT
    3.44715      3.39890

Degrees of Freedom: 4000 Total (i.e. Null);  3993 Residual
Null Deviance:      5546
Residual Deviance: 1387     AIC: 1403
```

```
lrFit
```

```
Generalized Linear Model

4001 samples
   7 predictor
   2 classes: 'No', 'Yes'

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 3601, 3601, 3601, 3601, 3600, 3601, ...
Resampling results:

  ROC        Sens       Spec
  0.9813664  0.9268657  0.9216432
```

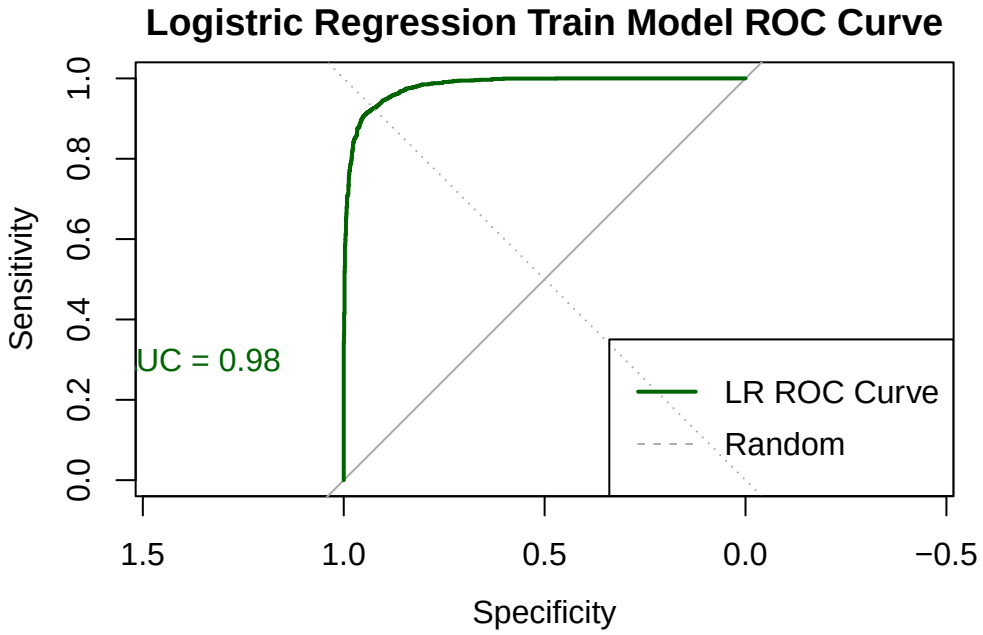
```
# Confusion matrix
lrCM <- confusionMatrix(lrFit, norm = "none")
lrCM
```

```
Cross-Validated (10 fold) Confusion Matrix

(entries are un-normalized aggregated counts)

          Reference
Prediction   No  Yes
       No  1863  156
       Yes  147 1835

 Accuracy (average) : 0.9243
```

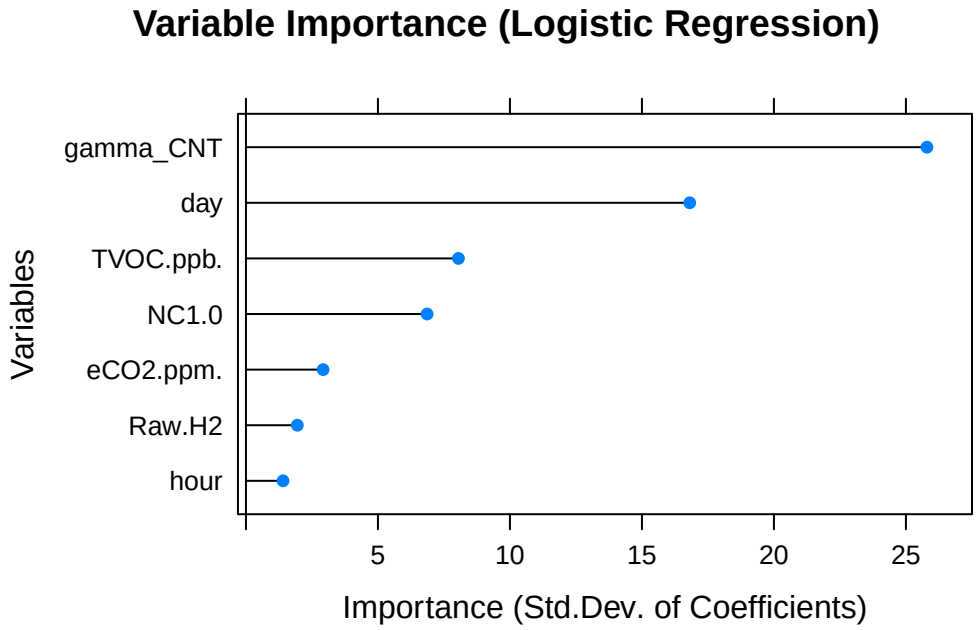
```
# Logistic Regression ROC curve and AUC score
lrRoc <- roc(response = lrFit$pred$obs,
             predictor = lrFit$pred$Yes,
             levels = rev(levels(lrFit$pred$obs)))
```

```
Setting direction: controls > cases
```

```
auc_score_lr <- auc(lrRoc )

plot(lrRoc, main = "Logistic Regression Train Model ROC Curve",
     col = "darkgreen", lwd = 2)
abline(a = 0, b = 1, lty = 3, col = "darkgray")
text(0.5, 0.3, paste0("AUC = ", round(auc_score_lr, 2)), adj = 2.6, col = "darkgreen")
legend("bottomright", legend = c("LR ROC Curve", "Random"),
       col = c("darkgreen", "darkgray"), lty = c(1, 2), lwd = c(2, 1))
```




```
# Variable importance
lrImp <- varImp(lrFit, scale = FALSE)
plot(lrImp, main = "Variable Importance (Logistic Regression)",
     xlab = "Importance (Std.Dev. of Coefficients)", ylab = "Variables")
```

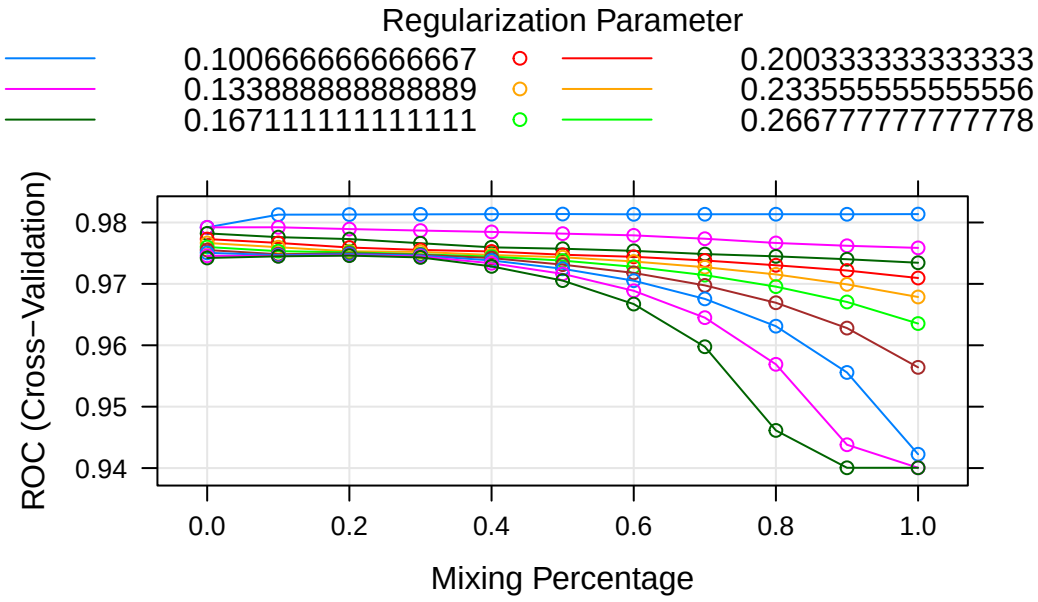



```
# Create Penalized Logistic Regression
glmnGrid <- expand.grid(alpha = seq(0, 1, by = 0.1),
lambda = seq(.001, .3, length = 10))
glmnFit <- train(Fire.Alarm ~ .,
                 data = train_balanced,
                 method = "glmnet",
                 tuneGrid = glmnGrid,
                 preProc = c("center", "scale"),
                 metric = "ROC",
                 trControl = ctrl)
optimal_a <- glmnFit$bestTune$alpha
optimal_l <- glmnFit$bestTune$lambda
glmnmodel <- train(Fire.Alarm ~ .,
                   data = train_balanced,
                   method = "glmnet",
                   preProc = c("center", "scale"),
                   metric = "ROC",
                   trControl = ctrl,
                   tuneGrid = expand.grid(alpha = optimal_a,
                                          lambda = optimal_l))

glmnmodel
```

```
glmnet
```

```
4001 samples
   7 predictor
   2 classes: 'No', 'Yes'

Pre-processing: centered (7), scaled (7)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 3601, 3601, 3601, 3601, 3601, 3600, ...
Resampling results:

  ROC        Sens       Spec
  0.9813901  0.9273632  0.9251734

Tuning parameter 'alpha' was held constant at a value of 0.5
Tuning
 parameter 'lambda' was held constant at a value of 0.001
```

```r
plot(glmnFit)
```




```r
# Confusion matrix
glmnCM <- confusionMatrix(glmnmodel, norm = "none")
glmnCM
```

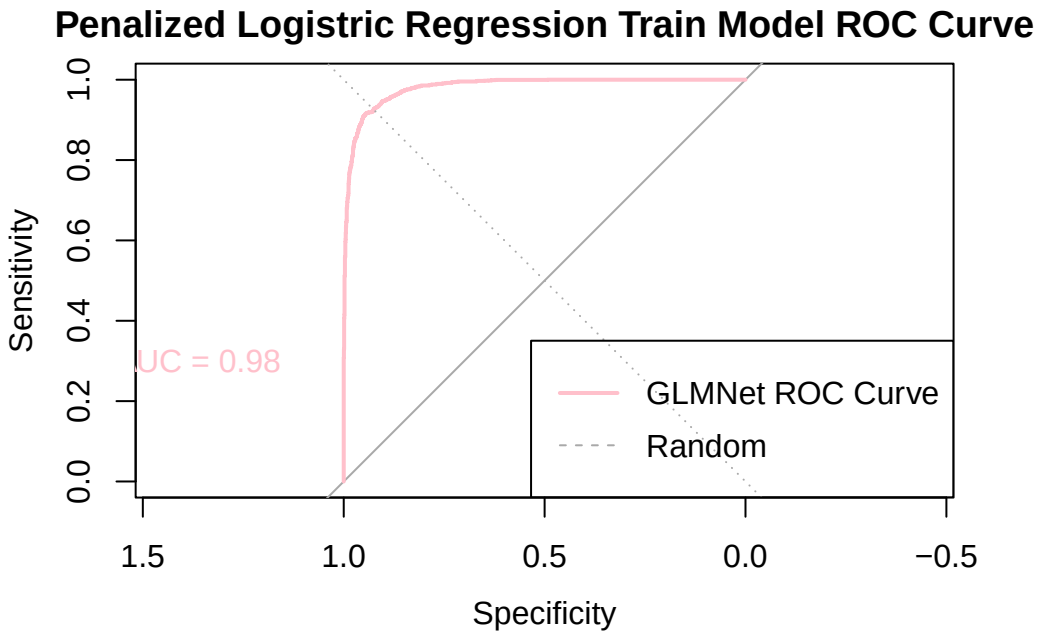
```
Cross-Validated (10 fold) Confusion Matrix
```

```
(entries are un-normalized aggregated counts)

          Reference
Prediction   No  Yes
       No  1864  149
       Yes  146 1842

 Accuracy (average) : 0.9263
```

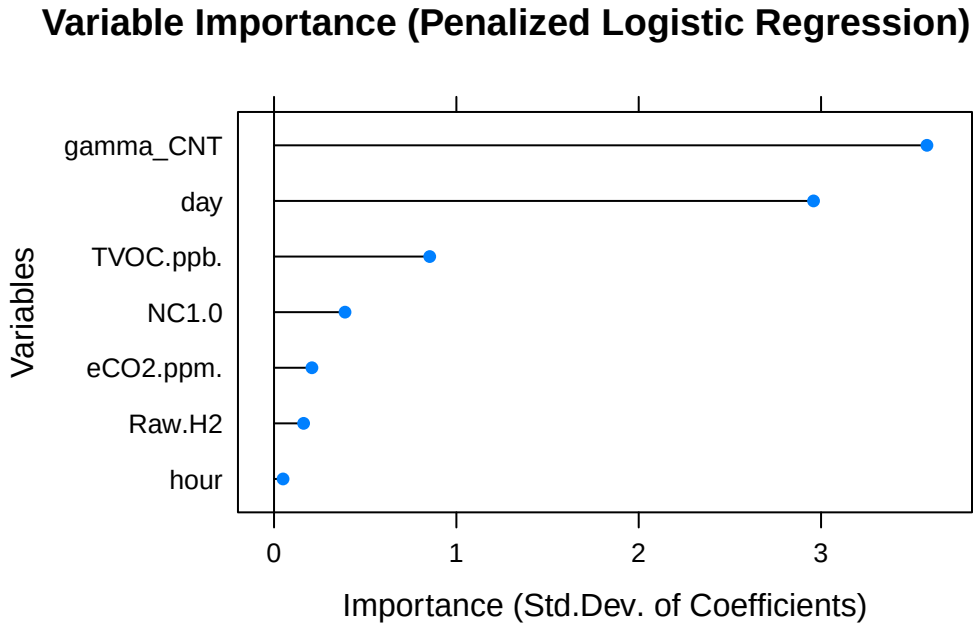
```r
# Penalized Logistic Regression ROC curve and AUC score
glmnRoc <- roc(response = glmnmodel$pred$obs,
             predictor = glmnmodel$pred$Yes,
             levels = rev(levels(glmnmodel$pred$obs)))
```

```
Setting direction: controls > cases
```

```r
auc_score_glmn <- auc(glmnRoc )

plot(glmnRoc, main = "Penalized Logistic Regression Train Model ROC Curve",
     col = "pink", lwd = 2)
abline(a = 0, b = 1, lty = 3, col = "darkgray")
text(0.5, 0.3, paste0("AUC = ", round(auc_score_glmn, 2)), adj = 2.6, col = "pink")
legend("bottomright", legend = c("GLMNet ROC Curve", "Random"),
       col = c("pink", "darkgray"), lty = c(1, 2), lwd = c(2, 1))
```




```r
# Variable importance
glmnImp <- varImp(glmnmodel, scale = FALSE)
plot(glmnImp, main = "Variable Importance (Penalized Logistic Regression)",
     xlab = "Importance (Std.Dev. of Coefficients)", ylab = "Variables")
```



```r
# Create Nearest Shrunken Centroids
nscGrid <- expand.grid(threshold = seq(0, 25, length = 30))
nscFit <- train(Fire.Alarm ~ .,
                data = train_balanced,
                method = "pam",
                tuneGrid = nscGrid,
                metric = "ROC",
                trControl = ctrl)
```

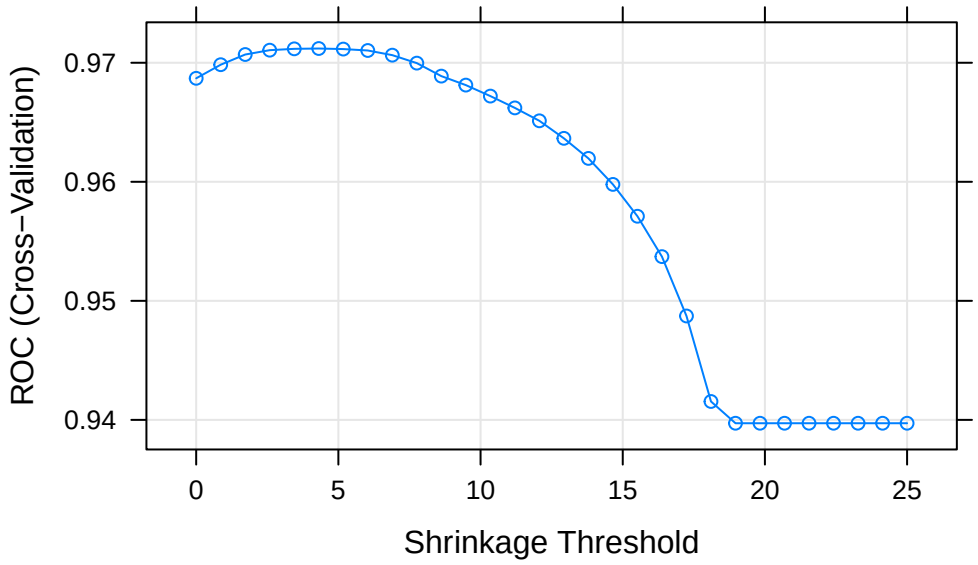
```
11111111111
```

```r
nscFit
```

```
Nearest Shrunken Centroids

4001 samples
   7 predictor
   2 classes: 'No', 'Yes'

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 3601, 3601, 3600, 3601, 3601, 3601, ...
Resampling results across tuning parameters:

  threshold  ROC        Sens       Spec
   0.000000  0.9686959  0.8890547  0.9507789
   0.862069  0.9698367  0.9049751  0.9467613
   1.724138  0.9706940  0.9104478  0.9432462
   2.586207  0.9710589  0.9218905  0.9372161
   3.448276  0.9711713  0.9273632  0.9331960
   4.310345  0.9711962  0.9303483  0.9291784
   5.172414  0.9711510  0.9343284  0.9291784
   6.034483  0.9710311  0.9388060  0.9236533
   6.896552  0.9706385  0.9427861  0.9186281
   7.758621  0.9699685  0.9398010  0.9126005
   8.620690  0.9688788  0.9398010  0.9060678
   9.482759  0.9681242  0.9437811  0.9025528
  10.344828  0.9671996  0.9457711  0.8985327
  11.206897  0.9662076  0.9497512  0.8970251
  12.068966  0.9651229  0.9482587  0.8955176
  12.931034  0.9636511  0.9502488  0.8920025
```

```
  13.793103  0.9619642  0.9507463  0.8884874
  14.655172  0.9597800  0.9482587  0.8839698
  15.517241  0.9571061  0.9442786  0.8789497
  16.379310  0.9537149  0.9412935  0.8704171
  17.241379  0.9487269  0.9338308  0.8663995
  18.103448  0.9415450  0.9213930  0.8563492
  18.965517  0.9397175  0.9194030  0.8533367
  19.827586  0.9397175  0.9203980  0.8528367
  20.689655  0.9397175  0.9208955  0.8518317
  21.551724  0.9397175  0.9223881  0.8503241
  22.413793  0.9397175  0.9238806  0.8488191
  23.275862  0.9397175  0.9253731  0.8478141
  24.137931  0.9397175  0.9273632  0.8432940
  25.000000  0.9397175  0.9318408  0.8387739

ROC was used to select the optimal model using the largest value.
The final value used for the model was threshold = 4.310345.
```

```r
plot(nscFit)
```




```r
# Confusion matrix
nscCM <- confusionMatrix(nscFit, norm = "none")
nscCM
```

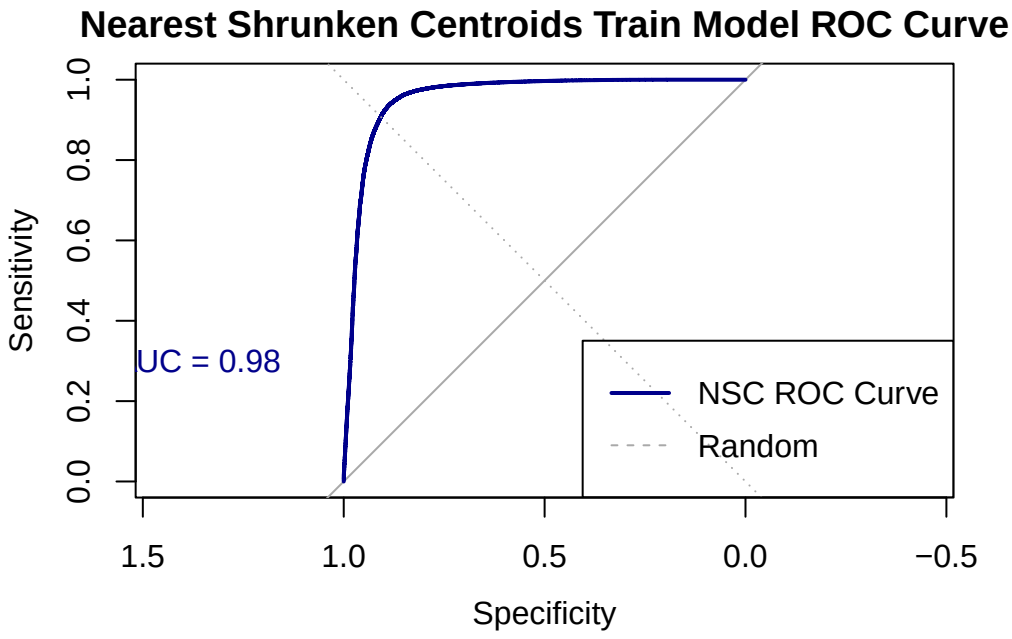
```
Cross-Validated (10 fold) Confusion Matrix
```

```
(entries are un-normalized aggregated counts)

          Reference
Prediction   No  Yes
       No  1870  141
       Yes  140 1850

 Accuracy (average) : 0.9298
```

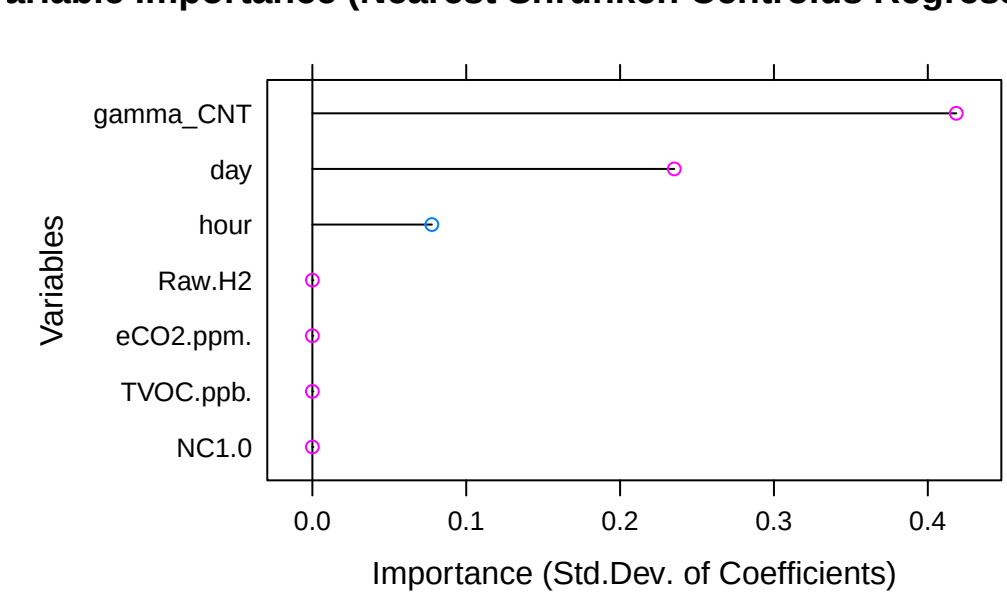
```r
# Nearest Shrunken Centroids ROC curve and AUC score
nscRoc <- roc(response = nscFit$pred$obs,
              predictor = nscFit$pred$Yes,
              levels = rev(levels(nscFit$pred$obs)))
```

```
Setting direction: controls > cases
```

```r
auc_score_nsc <- auc(nscRoc)

plot(nscRoc, main = "Nearest Shrunken Centroids Train Model ROC Curve",
     col = "darkblue", lwd = 2)
abline(a = 0, b = 1, lty = 3, col = "darkgray")
text(0.5, 0.3, paste0("AUC = ", round(auc_score_glmn, 2)), adj = 2.6, col = "darkblue")
legend("bottomright", legend = c("NSC ROC Curve", "Random"),
       col = c("darkblue", "darkgray"), lty = c(1, 2), lwd = c(2, 1))
```




```
# Variable importance
nscImp <- varImp(nscFit, scale = FALSE)
plot(nscImp, main = "Variable Importance (Nearest Shrunken Centroids Regression)",
     xlab = "Importance (Std.Dev. of Coefficients)", ylab = "Variables")
```



### Validation and Testing

```
# Predict test data using logistic regression
test_predictors <- smokedf_test_transformed[, -8]
test_org <- data.frame(Fire.Alarm = smokedf_test_transformed$Fire.Alarm)
test_org$Fire.Alarm <- factor(test_org$Fire.Alarm)

lr_predictions <- predict(lrFit, newdata = test_predictors, type = "raw")
lr_predictions <- data.frame(Fire.Alarm = lr_predictions)

# Confusion Matrix
lrCM_test <- confusionMatrix(data = as.factor(lr_predictions$Fire.Alarm),
                             reference = test_org$Fire.Alarm, positive = "Yes")
lrCM_test
```

```
Confusion Matrix and Statistics

          Reference
Prediction  No Yes
       No  716  10
       Yes   0 273

               Accuracy : 0.99
                 95% CI : (0.9817, 0.9952)
    No Information Rate : 0.7167
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9751

 Mcnemar's Test P-Value : 0.004427

            Sensitivity : 0.9647
            Specificity : 1.0000
         Pos Pred Value : 1.0000
         Neg Pred Value : 0.9862
             Prevalence : 0.2833
         Detection Rate : 0.2733
   Detection Prevalence : 0.2733
      Balanced Accuracy : 0.9823

       'Positive' Class : Yes
```

```r
# Predict test data using penalized logistic regression
glmn_predictions <- predict(glmnmodel, newdata = test_predictors, type = "raw")
glmn_predictions <- data.frame(Fire.Alarm = glmn_predictions)

# Confusion Matrix
glmnCM_test <- confusionMatrix(data = as.factor(glmn_predictions$Fire.Alarm),
                               reference = test_org$Fire.Alarm, positive = "Yes")
glmnCM_test
```

```
Confusion Matrix and Statistics

          Reference
Prediction  No Yes
       No  716  12
       Yes   0 271

               Accuracy : 0.988
                 95% CI : (0.9791, 0.9938)
    No Information Rate : 0.7167
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.97

 Mcnemar's Test P-Value : 0.001496

            Sensitivity : 0.9576
            Specificity : 1.0000
         Pos Pred Value : 1.0000
         Neg Pred Value : 0.9835
             Prevalence : 0.2833
         Detection Rate : 0.2713
   Detection Prevalence : 0.2713
      Balanced Accuracy : 0.9788

       'Positive' Class : Yes
```

```r
# Predict test data using nearest shrunken centroid
nsc_predictions <- predict(nscFit, newdata = test_predictors, type = "raw")
nsc_predictions <- data.frame(Fire.Alarm = nsc_predictions)
```

```r
# Confusion Matrix
nscCM_test <- confusionMatrix(data = as.factor(nsc_predictions$Fire.Alarm),
                              reference = test_org$Fire.Alarm, positive = "Yes")
nscCM_test
```

```
Confusion Matrix and Statistics

          Reference
Prediction  No Yes
       No  702   8
       Yes  14 275

               Accuracy : 0.978
                 95% CI : (0.9668, 0.9861)
    No Information Rate : 0.7167
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.9461

 Mcnemar's Test P-Value : 0.2864

            Sensitivity : 0.9717
            Specificity : 0.9804
         Pos Pred Value : 0.9516
         Neg Pred Value : 0.9887
             Prevalence : 0.2833
         Detection Rate : 0.2753
   Detection Prevalence : 0.2893
      Balanced Accuracy : 0.9761

       'Positive' Class : Yes
```

### Performance Evaluation

```r
roc_test_lr <- roc(response = as.factor(test_org$Fire.Alarm),
                   predictor = as.numeric(lr_predictions$Fire.Alarm))
```

```
Setting levels: control = No, case = Yes
```

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

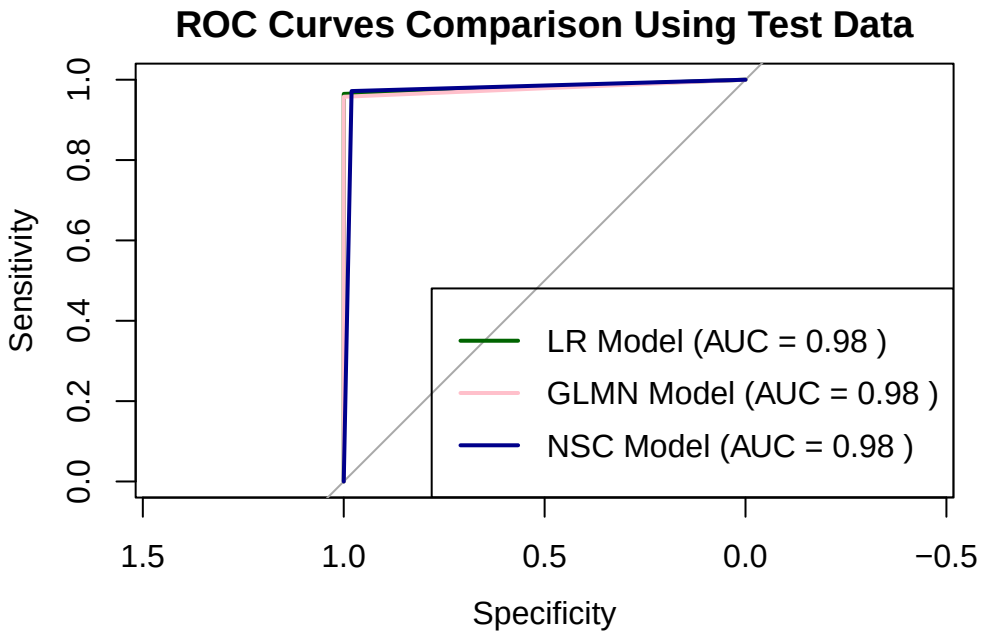
```
roc_test_glmn <- roc(response = as.factor(test_org$Fire.Alarm),
                     predictor = as.numeric(glmn_predictions$Fire.Alarm))
```

```
Setting levels: control = No, case = Yes
Setting direction: controls < cases
```

```
roc_test_nsc <- roc(response = as.factor(test_org$Fire.Alarm),
                     predictor = as.numeric(nsc_predictions$Fire.Alarm))
```

```
Setting levels: control = No, case = Yes
Setting direction: controls < cases
```

```
auc_test_lr <- auc(roc_test_lr)
auc_test_glmn <- auc(roc_test_glmn)
auc_test_nsc <- auc(roc_test_nsc)

# Plot ROC curve
plot(roc_test_lr, col = "darkgreen", main = "ROC Curves Comparison Using Test Data", lwd = 2)
plot(roc_test_glmn, col = "pink", add = TRUE, lwd = 2)
plot(roc_test_nsc, col = "darkblue", add = TRUE, lwd = 2)
legend("bottomright", legend = c(paste("LR Model (AUC =", round(auc_test_lr, 2), ")"),
                                 paste("GLMN Model (AUC =", round(auc_test_glmn, 2), ")"),
                                 paste("NSC Model (AUC =", round(auc_test_nsc, 2), ")")),
       col = c("darkgreen", "pink", "darkblue"), lwd = 2)
```




```
# Model's ROC score
lrFit_ROC <- round(lrFit$results$ROC,3)
glmnmodel_ROC <- round(glmnmodel$results$ROC,3)
nscFit_ROC <- round(nscFit$results$ROC,3)

# Confusion matrix train accuracy score
lrCM_train_accuracy <- 0.924
glmnCM_train_accuracy <- 0.926
nscCM_train_accuracy <- 0.930

# Confusion matrix test AUC score
lrCM_AUC <- round(auc(roc_test_lr),3)
glmnCM_AUC <- round(auc(roc_test_glmn),3)
nscCM_AUC <- round(auc(roc_test_nsc),3)

# Confusion matrix test accuracy score
lrCM_test_accuracy <- round(lrCM_test$overall["Accuracy"],3)
glmnCM_test_accuracy <- round(glmnCM_test$overall["Accuracy"],3)
nscCM_test_accuracy <- round(nscCM_test$overall["Accuracy"],3)

# Confusion matric test class balanced accuracy score
lrCM_test_bal_accuracy <- round(lrCM_test$byClass["Balanced Accuracy"],3)
glmnCM_test_bal_accuracy <- round(glmnCM_test$byClass["Balanced Accuracy"],3)
nscCM_test_bal_accuracy <- round(nscCM_test$byClass["Balanced Accuracy"],3)
```

```r
# Adjust nscFit_ROC
nscFit_ROC_adjusted <- nscFit_ROC[1]

# Now, create the data frame with adjusted nscFit_ROC
results_table <- data.frame(
  Model = c("LR", "Penalized LR",
            "NSC"),
  ROC_Score = c(lrFit_ROC, glmnmodel_ROC, nscFit_ROC_adjusted),
  Train_Accuracy = c(lrCM_train_accuracy, glmnCM_train_accuracy,
                     nscCM_train_accuracy),
  Test_AUC = c(lrCM_AUC, glmnCM_AUC, nscCM_AUC),
  Test_Accuracy = c(lrCM_test_accuracy, glmnCM_test_accuracy,
                    nscCM_test_accuracy),
  Test_Balanced_Accuracy = c(lrCM_test_bal_accuracy,
                             glmnCM_test_bal_accuracy,
                             nscCM_test_bal_accuracy))

# Create a gt table
results_table |> gt() |>
  tab_header(title = "Model Comparison",
             subtitle = "Comparison of performance metrics for different models") |>
  cols_label(Model = "Model",
             ROC_Score = "Model ROC",
             Train_Accuracy = "Train Accuracy",
             Test_AUC = "Test AUC",
             Test_Accuracy = "Test Accuracy",
             Test_Balanced_Accuracy = "Test Balanced Accuracy")
```

**Model Comparison**

Comparison of performance metrics for different models

| Model | Model ROC | Train Accuracy | Test AUC | Test Accuracy | Test Balanced Accuracy |
|---|---|---|---|---|---|
| LR | 0.981 | 0.924 | 0.982 | 0.990 | 0.982 |
| Penalized LR | 0.981 | 0.926 | 0.979 | 0.988 | 0.979 |
| NSC | 0.969 | 0.930 | 0.976 | 0.978 | 0.976 |