Alarm Management Analysis Using Machine Learning

Team 5

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Introduction

This report presents an end-to-end data analytics process to manage and classify industrial alarms, focusing on chattering behavior and predicting alarm durations using machine learning models including Logistic Regression, Decision Trees, and XGBoost.

Load Required Libraries

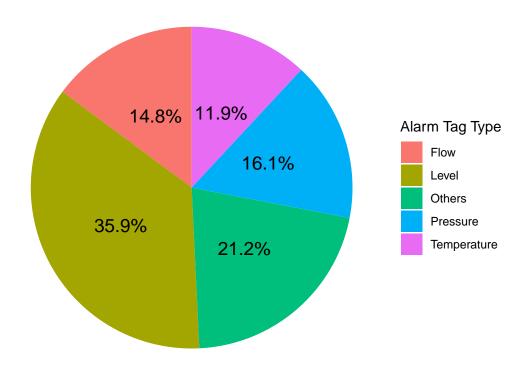
```
library(readxl)
library(tidyverse)
library(RColorBrewer)
library(gridExtra)
library(grid)
library(caret)
library(rpart)
library(rpart)
library(pROC)
library(e1071)
library(Metrics)
```

Load and Preview Dataset

```
data <- read excel("IM009B-XLS-ENG.xlsx")</pre>
head(data)
## # A tibble: 6 x 20
##
     SO
               ATD
                      CHB
                              M 'Alarm Tag Type'
                                                  Flow Level Pressure Temperature
             <dbl> <dbl> <dbl> <chr>
                                                   <dbl> <dbl>
                                                                               <dbl>
     <chr>>
                                                                   <dbl>
## 1 XI-3057
                        0
                              6 Others
                                                       0
                                                                       0
                                                                                   0
                 0
                                                             0
## 2 XI-3057
                              7 Others
                                                       0
                                                             0
                                                                       0
                                                                                   0
                        0
                                                       0
                                                             0
                                                                       0
                                                                                   0
## 3 XI-3057
                  0
                              7 Others
## 4 XI-3057
                             10 Others
                                                             0
                                                                       0
                                                                                   0
## 5 XI-3057
                        0
                             10 Others
                                                             0
                                                                       0
                                                                                   0
## 6 XI-3058
                 0
                        0
                              6 Others
                                                                                   0
## # i 11 more variables: Others <dbl>, H <chr>, 'Hour:0-6' <dbl>,
       'Hour:7-12' <dbl>, 'Hour:13-18' <dbl>, 'Hour:19-24' <dbl>, Week <chr>,
       '1st Week' <dbl>, '2nd week' <dbl>, '3rd week' <dbl>, '4th week' <dbl>
```

EDA – Alarm Tag Type (Pie Chart)

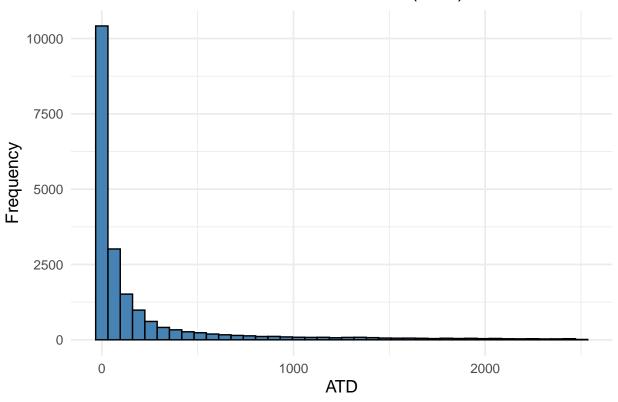
Distribution of Alarm Tag Types



EDA – Distribution of ATD

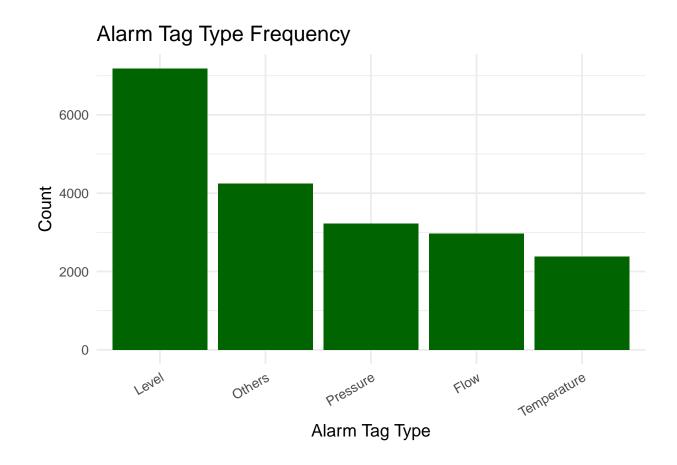
```
ggplot(data, aes(x = ATD)) +
  geom_histogram(fill = "steelblue", color = "black", bins = 40) +
  labs(title = "Distribution of Active Time Duration (ATD)", x = "ATD", y = "Frequency") +
  theme_minimal(base_size = 13)
```

Distribution of Active Time Duration (ATD)



EDA – Alarm Tag Type Frequency

```
alarm_counts <- data %>% count(`Alarm Tag Type`) %>% arrange(desc(n))
ggplot(alarm_counts, aes(x = reorder(`Alarm Tag Type`, -n), y = n)) +
   geom_bar(stat = "identity", fill = "darkgreen") +
   labs(title = "Alarm Tag Type Frequency", x = "Alarm Tag Type", y = "Count") +
   theme_minimal(base_size = 13) +
   theme(axis.text.x = element_text(angle = 30, hjust = 1))
```

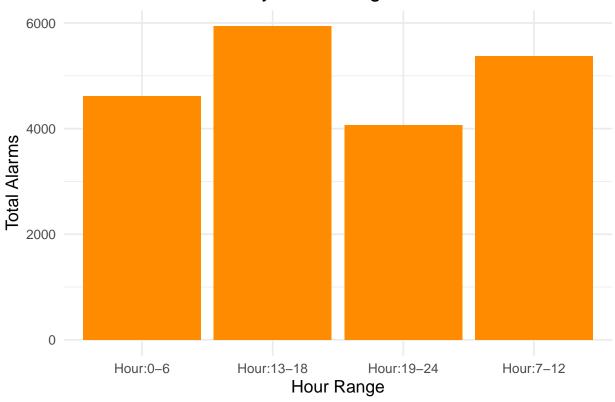


EDA – Hour-Based Alarm Analysis

```
hour_data <- data %>%
  select(`Hour:0-6`, `Hour:7-12`, `Hour:13-18`, `Hour:19-24`) %>%
  pivot_longer(cols = everything(), names_to = "Hour_Range", values_to = "Count") %>%
  group_by(Hour_Range) %>% summarise(Total_Alarms = sum(Count, na.rm = TRUE))

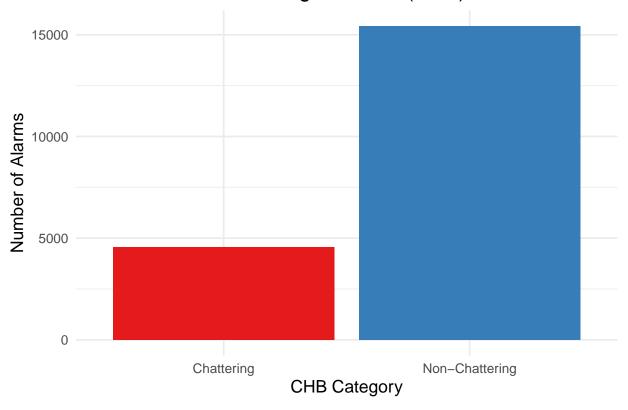
ggplot(hour_data, aes(x = Hour_Range, y = Total_Alarms)) +
  geom_bar(stat = "identity", fill = "#FF8C00") +
  labs(title = "Total Alarm Counts by Hour Range", x = "Hour Range", y = "Total Alarms") +
  theme_minimal(base_size = 13)
```

Total Alarm Counts by Hour Range



EDA – CHB (Chattering Behavior)

Distribution of Chattering Behavior (CHB)



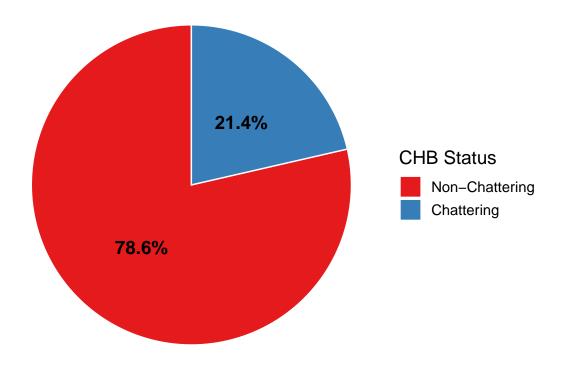
CHB in "Others" Alarm Type – Pie Chart

```
others_data <- data %>% filter(`Alarm Tag Type` == "Others")

others_chb_dist <- others_data %>%
    count(CHB) %>%
    mutate(
    CHB = factor(CHB, labels = c("Non-Chattering", "Chattering")),
    percent = round(n / sum(n) * 100, 1),
    label = pasteO(percent, "%")
)

ggplot(others_chb_dist, aes(x = "", y = n, fill = CHB)) +
    geom_bar(stat = "identity", width = 1, color = "white") +
    coord_polar(theta = "y") +
    scale_fill_manual(values = c("Non-Chattering" = "#e41a1c", "Chattering" = "#377eb8")) +
    geom_text(aes(label = label), position = position_stack(vjust = 0.5), size = 5, color = "black", font
    labs(title = "CHB Distribution in 'Others' Alarm Type", fill = "CHB Status") +
    theme_void(base_size = 14) +
    theme(plot.title = element_text(hjust = 0.5, size = 18, face = "bold"))
```

CHB Distribution in 'Others' Alarm Type



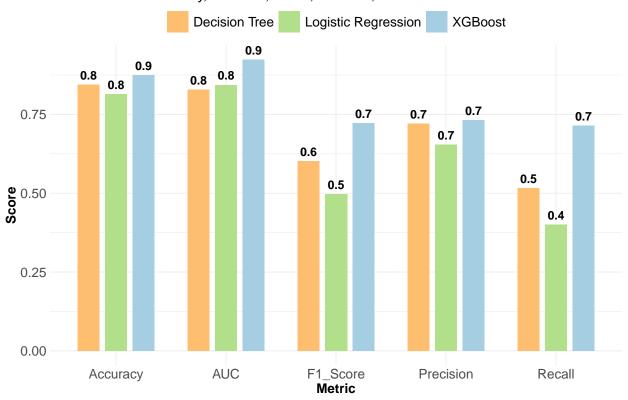
CHB Classification – Model Training and Evaluation

```
data_clean <- data %>%
  select(ATD, CHB, M, `Alarm Tag Type`, H) %>%
  drop na() %>%
  mutate(CHB = as.factor(CHB), `Alarm Tag Type` = as.factor(`Alarm Tag Type`))
set.seed(42)
train_index <- createDataPartition(data_clean$CHB, p = 0.7, list = FALSE)</pre>
train_data <- data_clean[train_index, ]</pre>
test_data <- data_clean[-train_index, ]</pre>
log_model <- glm(CHB ~ ., data = train_data, family = "binomial")</pre>
log_probs <- predict(log_model, newdata = test_data, type = "response")</pre>
log_preds <- ifelse(log_probs > 0.5, 1, 0)
log_roc <- roc(as.numeric(as.character(test_data$CHB)), as.numeric(log_probs))</pre>
tree_model <- rpart(CHB ~ ., data = train_data, method = "class")</pre>
tree_preds <- predict(tree_model, test_data, type = "class")</pre>
tree_probs <- predict(tree_model, test_data)[,2]</pre>
tree_roc <- roc(as.numeric(as.character(test_data$CHB)), as.numeric(tree_probs))</pre>
train_matrix <- model.matrix(CHB ~ . -1, data = train_data)</pre>
test_matrix <- model.matrix(CHB ~ . -1, data = test_data)</pre>
```

```
xgb_train <- xgb.DMatrix(data = train_matrix, label = as.numeric(train_data$CHB) - 1)</pre>
xgb_test <- xgb.DMatrix(data = test_matrix)</pre>
xgb_model <- xgboost(data = xgb_train, nrounds = 50, objective = "binary:logistic", verbose = 0)</pre>
xgb_probs <- predict(xgb_model, xgb_test)</pre>
xgb_preds <- ifelse(xgb_probs > 0.5, 1, 0)
xgb_roc <- roc(as.numeric(as.character(test_data$CHB)), xgb_probs)</pre>
get_metrics <- function(true, pred, probs, roc_obj) {</pre>
  cm <- confusionMatrix(as.factor(pred), as.factor(true), positive = "1")</pre>
  tibble(
    Accuracy = cm$overall["Accuracy"],
    Precision = cm$byClass["Precision"],
    Recall = cm$byClass["Recall"],
    F1_Score = cm$byClass["F1"],
    AUC = as.numeric(pROC::auc(roc_obj))
  )
}
results <- bind_rows(
  get_metrics(test_data$CHB, log_preds, log_probs, log_roc) %>% mutate(Model = "Logistic Regression"),
  get_metrics(test_data$CHB, tree_preds, tree_probs, tree_roc) %% mutate(Model = "Decision Tree"),
  get_metrics(test_data$CHB, xgb_preds, xgb_probs, xgb_roc) %>% mutate(Model = "XGBoost")
results_long <- results %>%
  pivot longer(cols = -Model, names to = "Metric", values to = "Score")
ggplot(results_long, aes(x = Metric, y = Score, fill = Model)) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.75), width = 0.6) +
  geom_text(aes(label = round(Score, 1)), position = position_dodge(width = 0.75), vjust = -0.6, size =
  scale_fill_manual(values = c("Logistic Regression" = "#b2df8a", "Decision Tree" = "#fdbf6f", "XGBoost
  labs(title = "CHB Classification - Model Performance Comparison", subtitle = "Accuracy, Precision, Re
  theme_minimal(base_size = 6) +
  theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 11),
        plot.subtitle = element_text(hjust = 0.5, size = 10, face = "italic"),
        axis.title = element_text(size = 10, face = "bold"),
        axis.text = element_text(size = 10),
        legend.position = "top",
        legend.title = element_blank(),
        legend.text = element_text(size = 10))
```

CHB Classification – Model Performance Comparison

Accuracy, Precision, Recall, F1 Score, and AUC across Models

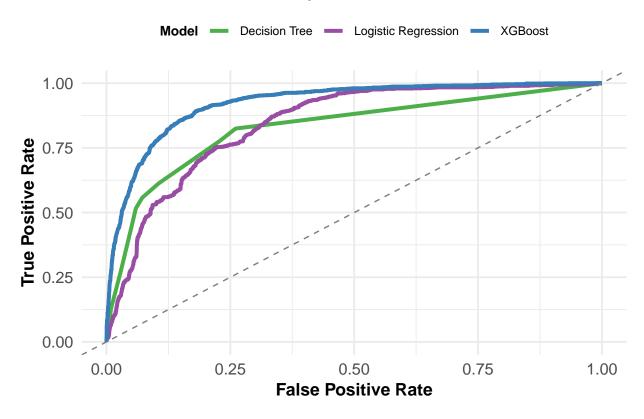


ROC Curve – CHB Classification

```
log_df <- data.frame(FPR = rev(1 - log_roc$specificities), TPR = rev(log_roc$sensitivities), Model = "L</pre>
tree_df <- data.frame(FPR = rev(1 - tree_roc$specificities), TPR = rev(tree_roc$sensitivities), Model =</pre>
xgb_df <- data.frame(FPR = rev(1 - xgb_roc$specificities), TPR = rev(xgb_roc$sensitivities), Model = "X</pre>
roc_combined <- bind_rows(log_df, tree_df, xgb_df)</pre>
ggplot(roc_combined, aes(x = FPR, y = TPR, color = Model)) +
  geom_line(size = 1.4) +
  geom_abline(linetype = "dashed", color = "gray50") +
  scale_color_manual(values = c("XGBoost" = "#377eb8", "Decision Tree" = "#4daf4a", "Logistic Regression
  labs(
    title = "ROC Curve Comparison - CHB Classification",
    x = "False Positive Rate",
    y = "True Positive Rate",
    color = "Model"
  ) +
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
    axis.title = element_text(size = 13, face = "bold"),
    axis.text = element text(size = 12),
    legend.title = element_text(size = 10, face = "bold"),
```

```
legend.text = element_text(size = 9),
legend.position = "top"
)
```

ROC Curve Comparison – CHB Classification



ATD Prediction and Residual Analysis

This section compares linear regression and XGBoost regressor models in predicting the Active Time Duration (ATD). It also includes residual analysis to evaluate prediction accuracy across the range of ATD values.

```
# Load additional library
library(Metrics)

# Prepare the data
data_clean_reg <- data %>%
    select(ATD, CHB, M, `Alarm Tag Type`, H) %>%
    drop_na() %>%
    mutate(`Alarm Tag Type` = as.factor(`Alarm Tag Type`))

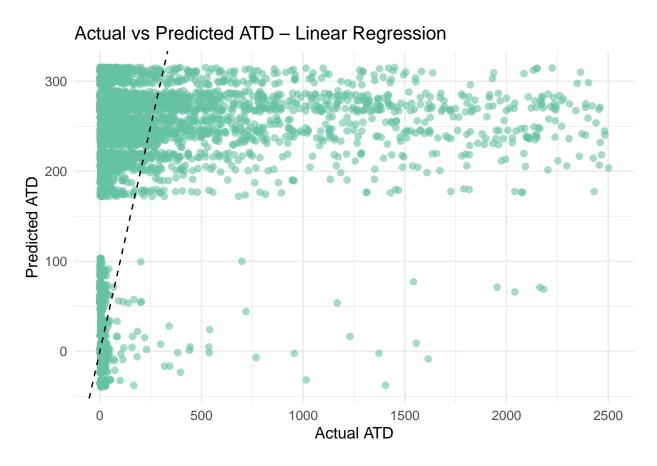
# Split into training and test sets
set.seed(123)
train_index <- createDataPartition(data_clean_reg$ATD, p = 0.7, list = FALSE)
train_data <- data_clean_reg[train_index, ]
test_data <- data_clean_reg[-train_index, ]</pre>
```

```
# Train Linear Regression
linear_model <- lm(ATD ~ ., data = train_data)</pre>
linear_preds <- predict(linear_model, newdata = test_data)</pre>
# Train XGBoost Regressor
train_matrix_reg <- model.matrix(ATD ~ . -1, data = train_data)</pre>
test_matrix_reg <- model.matrix(ATD ~ . -1, data = test_data)</pre>
xgb_train_reg <- xgb.DMatrix(data = train_matrix_reg, label = train_data$ATD)</pre>
xgb_test_reg <- xgb.DMatrix(data = test_matrix_reg)</pre>
xgb_model_reg <- xgboost(data = xgb_train_reg, nrounds = 50, objective = "reg:squarederror", verbose =</pre>
xgb_preds <- predict(xgb_model_reg, xgb_test_reg)</pre>
# Evaluation
rmse_linear <- rmse(test_data$ATD, linear_preds)</pre>
rmse_xgb <- rmse(test_data$ATD, xgb_preds)</pre>
mae_linear <- mae(test_data$ATD, linear_preds)</pre>
mae_xgb <- mae(test_data$ATD, xgb_preds)</pre>
cat("Linear Regression - RMSE:", round(rmse_linear, 2), " MAE:", round(mae_linear, 2), "\n")
## Linear Regression - RMSE: 407.53 MAE: 240.02
cat("XGBoost Regressor - RMSE:", round(rmse_xgb, 2), " MAE:", round(mae_xgb, 2), "\n")
## XGBoost Regressor - RMSE: 404.03 MAE: 231.82
```

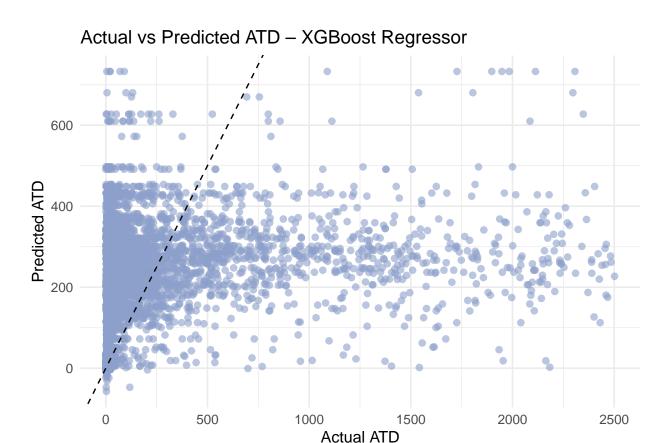
Actual vs Predicted Plots

```
# Combine predictions
results_plot <- data.frame(
    Actual = test_data$ATD,
    Linear_Regression = linear_preds,
    XGBoost = xgb_preds
)

# Linear Regression Plot
ggplot(results_plot, aes(x = Actual, y = Linear_Regression)) +
    geom_point(color = "#66c2a5", alpha = 0.6, size = 2) +
    geom_abline(slope = 1, intercept = 0, linetype = "dashed", color = "black") +
    labs(title = "Actual vs Predicted ATD - Linear Regression", x = "Actual ATD", y = "Predicted ATD") +
    theme_minimal(base_size = 12)</pre>
```



```
# XGBoost Regressor Plot
ggplot(results_plot, aes(x = Actual, y = XGBoost)) +
   geom_point(color = "#8daOcb", alpha = 0.6, size = 2) +
   geom_abline(slope = 1, intercept = 0, linetype = "dashed", color = "black") +
   labs(title = "Actual vs Predicted ATD - XGBoost Regressor", x = "Actual ATD", y = "Predicted ATD") +
   theme_minimal(base_size = 12)
```



Residual Plot

```
# Residual analysis for XGBoost
residuals <- test_data$ATD - xgb_preds</pre>
ggplot(data.frame(Actual = test_data$ATD, Residual = residuals),
       aes(x = Actual, y = Residual)) +
  geom_point(color = "royalblue", alpha = 0.6, size = 2) +
 geom_hline(yintercept = 0, linetype = "dashed", color = "black", linewidth = 1) +
 labs(
   title = "Residual Plot - XGBoost Regressor",
   subtitle = "Residuals (Actual - Predicted) across actual ATD values",
   x = "Actual ATD",
   y = "Residuals"
  theme_minimal(base_size = 12) +
 theme(
   plot.title = element_text(size = 14, face = "bold", hjust = 0.5),
   plot.subtitle = element_text(size = 11, hjust = 0.5),
   axis.title = element_text(size = 12),
   axis.text = element_text(size = 10)
```

Residual Plot - XGBoost Regressor

