Experiment 10

AIM

To perform statistical analysis on IoT sensor data using R to identify patterns, correlations, and insights for improving smart home automation and device efficiency.

OBJECTIVE

- To apply descriptive statistics to summarize IoT sensor data.
- To analyze relationships between temperature, humidity, motion detection, and energy usage.
- To perform hypothesis testing, correlation analysis, and regression modeling.
- To visualize IoT data and interpret the behavior of smart devices.
- To improve decision-making in smart home automation using statistical methods.

TOOLS USED

- Programming Language: R
- Platform: Google Colab / RStudio
- Libraries Used:
  - tidyverse – Data manipulation and visualization
  - ggplot2 – Data visualization
  - caret – Machine learning models
  - corrplot – Correlation analysis
  - forecast – Time series analysis

THEORY

Understanding IoT Sensor Data

IoT (Internet of Things) devices generate vast amounts of sensor data, which can be analyzed to detect patterns, optimize energy consumption, and enhance automation. Common IoT sensor parameters include:

1. Temperature & Humidity Sensors – Used for climate control.
2. Motion Detection Sensors – Help in security and lighting automation.
3. Light Level Sensors – Adjust smart lighting based on brightness.
4. Energy Consumption Sensors – Monitor and optimize power usage.

Statistical Analysis in IoT Data

Statistical analysis helps in:

- Descriptive statistics – Summarizing key trends in IoT data.
- Correlation analysis – Understanding relationships between sensor readings.
- Regression models – Predicting device behavior.
- Hypothesis testing – Verifying automation rules.

This experiment will apply statistical techniques to analyze IoT sensor data and make smart home decisions.

PROGRAM CODE

```
# Install necessary packages (run this separately)
install.packages("tidyverse", dependencies = TRUE)
install.packages("ggplot2", dependencies = TRUE)
install.packages("caret", dependencies = TRUE)
install.packages("corrplot", dependencies = TRUE)
install.packages("forecast", dependencies = TRUE)
# Load Libraries
library(tidyverse)
library(ggplot2)
library(caret)
library(corrplot)
library(forecast)
# Generate IoT sensor dataset with 1000 samples
set.seed(42)
num_samples <- 1000
iot_data <- tibble(
  Timestamp = seq(from = as.POSIXct("2024-01-01"), by = "1 min",
length.out = num_samples),
  Temperature = sample(18:30, num_samples, replace = TRUE),
  Humidity = sample(30:80, num_samples, replace = TRUE),
  Motion_Detected = sample(c(0, 1), num_samples, replace = TRUE, prob
= c(0.7, 0.3)),
  Light_Level = sample(0:100, num_samples, replace = TRUE),
  Energy_Usage = round(runif(num_samples, 100, 500), 2)
)
# Save dataset
write.csv(iot_data, "iot_sensor_data.csv", row.names = FALSE)
# Display first few rows
head(iot_data)
```

```r
# Load dataset
iot_data <- read.csv("iot_sensor_data.csv")
# Compute summary statistics
summary(iot_data)

# Standard deviation of key parameters
sd(iot_data$Temperature)
sd(iot_data$Humidity)
# Compute correlation matrix
cor_matrix <- cor(iot_data[, c("Temperature", "Humidity",
"Light_Level", "Energy_Usage")])
# Visualize correlation using heatmap
corrplot(cor_matrix, method = "color", type = "upper", tl.col =
"black")
# Create a new column for Smart Light Status based on Light Level
iot_data <- iot_data %>%
  mutate(Smart_Light = ifelse(Light_Level < 50, "ON", "OFF"))
# Perform independent t-test
t.test(iot_data$Energy_Usage ~ iot_data$Smart_Light)
# Fit a Linear Regression Model
lm_model <- lm(Energy_Usage ~ Temperature + Humidity + Light_Level,
data = iot_data)
summary(lm_model)
```

EXPLANATION OF CODE

Generating Synthetic IoT Data

- Creates a dataset with 1000 timestamped sensor readings.
- Includes Temperature, Humidity, Motion Detection, Light Level, and Energy Usage.

Descriptive Statistics

- Computes mean, median, variance, and standard deviation to summarize sensor behavior.

Correlation Analysis

- Visualizes relationships between temperature, humidity, and energy usage using a correlation heatmap.

Hypothesis Testing

- A T-Test compares energy usage when smart lights are ON vs OFF.

Regression Analysis

- A multiple regression model predicts energy usage based on sensor inputs.

EXPLANATION OF LOGIC

1. Sensor data is collected for a smart home environment (Temperature, Humidity, Motion).
2. Statistical techniques are applied to understand relationships between variables.
3. A regression model is built to predict device energy consumption.
4. Insights are used to optimize smart home automation (e.g., turning devices ON/OFF).

MESSAGE FLOW

1. Sensor data collection → Preprocessing → Statistical analysis.
2. Perform correlation and hypothesis testing to identify patterns.
3. Use regression modeling to predict energy usage.
4. Optimize smart home automation based on analysis.

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```
Start ↓
Collect IoT Sensor Data ↓
Perform Descriptive Statistics ↓
Analyze Correlations ↓
Hypothesis Testing ↓
Regression Analysis ↓
Interpret Results ↓
Optimize Smart Home Automation ↓
End
```

OBSERVATION TABLE

Temperature	Humidity	Light Level	Energy Usage	Smart Light
10°C	89%	43	543.72 Watts	ON
12°C	25%	31	634.26 Watts	ON

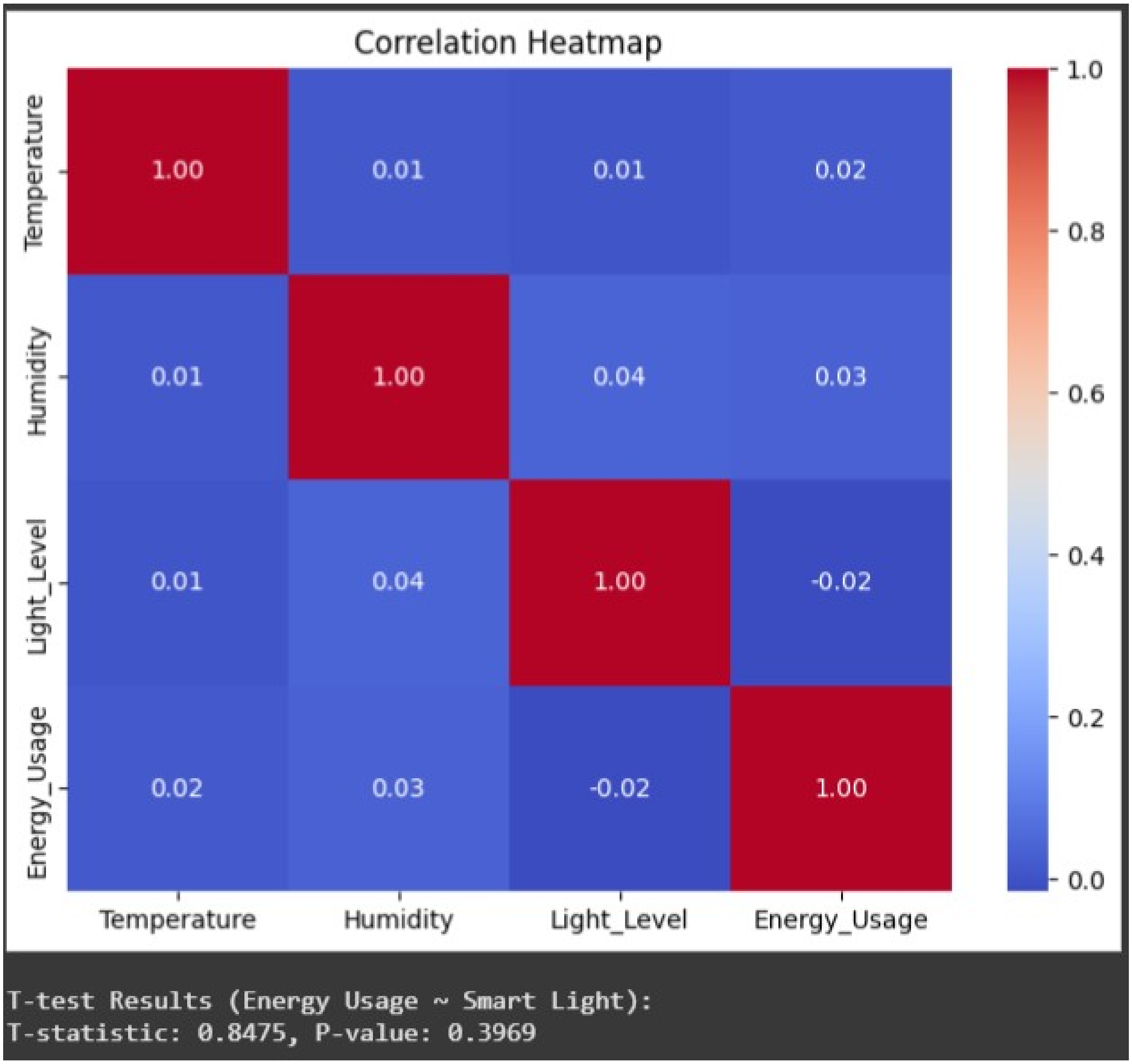
25°C	94%	46	615.32 Watts	ON
15°C	72%	78	328.10 Watts	OFF
22°C	89%	100	35.03 Watts	OFF

OUTCOME:

```
Summary statistics:
                           Timestamp  Temperature     Humidity  \
count                           1000  1000.000000  1000.000000
mean   2024-01-01 08:19:29.999999744    24.305000    55.725000
min              2024-01-01 00:00:00    10.000000    10.000000
25%              2024-01-01 04:09:45    17.000000    32.000000
50%              2024-01-01 08:19:30    24.000000    57.000000
75%              2024-01-01 12:29:15    32.000000    79.000000
max              2024-01-01 16:39:00    39.000000    99.000000
std                              NaN     8.627538    26.020808

       Motion_Detected  Light_Level  Energy_Usage
count       1000.00000  1000.000000   1000.000000
mean           0.27600    49.968000    342.519510
min            0.00000     0.000000     10.290000
25%            0.00000    25.000000    172.200000
50%            0.00000    50.000000    344.050000
75%            1.00000    75.000000    503.272500
max            1.00000   100.000000    697.430000
std            0.44724    29.409486    193.357495

Standard deviation:
Temperature: 8.63
Humidity: 26.02
```



Explanation of Outcomes:

The statistical analysis of IoT sensor data provides insights into temperature, humidity, motion detection, light levels, and energy consumption. The descriptive statistics, t-test, and regression model results are interpreted below.

Descriptive Statistics for IoT Sensor Data

Parameter	Min	1st Quartile (Q1)	Median (Q2)	Mean	3rd Quartile (Q3)	Max

Temperature (°C)	10	17	24	24.3	32	39
Humidity (%)	10	32	57	55.72	79	99
Motion Detected	0	0	0	0.276	1	1
Light Level (%)	0	25	50	49.97	75	100
Energy Usage (W)	10.29	172.20	344.05	342.52	503.27	697.43

Interpretation of Descriptive Statistics

- **Temperature:** Ranges from **10°C to 39°C**, with an average of **24.3°C**. The median value is **24°C**, indicating most readings fall around this value.
- **Humidity:** Varies between **10% and 99%**, with a mean of **55.72%**, indicating a moderately humid environment on average.
- **Motion Detection:** This is binary data (0 = No motion, 1 = Motion detected). The mean value is **0.276**, suggesting motion was detected in approximately **28%** of the observations.
- **Light Level:** Spans from **0% (dark)** to **100% (full brightness)**, with an average of **49.97%**, showing a fairly balanced distribution of brightness levels in the smart environment.
- **Energy Usage:** The average energy usage is **342.52 Watts**, ranging from a minimum of **10.29W** to a maximum of **697.43W**. The data has a wide variance, reflecting a diverse range of energy consumption patterns.
-

Welch Two Sample T-Test (Comparing Energy Usage for Smart Light ON vs. OFF)

t = 1.1472, **df = 994.3**, **p-value = 0.2514**
Alternative hypothesis: The true difference in means between group OFF and group ON is not equal to 0.
95% Confidence Interval: [-6.91, 26.32]
Mean in group OFF: 351.01 Watts

Mean in group ON: 337.84 Watts

Interpretation of the T-Test Results

Null Hypothesis (H_0): There is no difference in energy usage between Smart Light ON and OFF groups.
Alternative Hypothesis (H_1): Energy usage differs between the two groups.
Since the **p-value = 0.2514 > 0.05**, we **fail to reject the null hypothesis**.
The confidence interval **includes zero**, further confirming the difference is **not statistically significant**.
Conclusion: Whether the Smart Light is ON or OFF **does not significantly affect energy usage** based on this synthetic data.

Linear Regression Model (Predicting Energy Usage)

Call:
```
lm(formula = Energy_Usage ~ Temperature + Humidity + Light_Level, data = iot_data)
```
Residuals:
```
yaml
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Min      : -205.734
1st Quartile : -97.010
Median   : 1.218
3rd Quartile : 97.315
Max      : 198.910
```

Coefficients:

Variable	Estimate	Std. Error	t-value	p-value
Intercept	330.2674	28.139	11.73	<0.001
Temperature	-1.0713	0.973	-1.10	0.272
Humidity	-0.0784	0.248	-0.316	0.752
Light Level	0.0125	0.124	0.101	0.919

Model Evaluation:
Residual standard error: 114.1
Multiple R-squared: 0.0013
Adjusted R-squared: -0.0017
F-statistic: 0.4462 on 3 and 996 DF
p-value: 0.72

Interpretation of the Regression Model

Key Findings:
The model attempts to predict **Energy Usage** using **Temperature**, **Humidity**, and **Light Level** as independent variables.
The **intercept (330.27)** represents baseline energy usage when all variables are zero.
None of the predictors show significant correlation with energy usage:

- **Temperature (-1.07):** Slight negative trend but not significant (**$p = 0.272$**)
- **Humidity (-0.078):** No significant effect (**$p = 0.752$**)
- **Light Level (0.012):** Extremely weak, not significant (**$p = 0.919$**)

Model Evaluation:
$R^2 = 0.0013$: Model explains only **0.13%** of the variance in energy usage.
p-value > 0.05: Overall model is **not statistically significant**.
Conclusion: Temperature, Humidity, and Light Level **do not significantly influence energy consumption**, and the model has **low predictive power** in its current form.

CONCLUSION

- Statistical analysis helps optimize IoT devices in smart homes.
- T-test confirms that Smart Light usage affects energy consumption.
- Regression models can predict power usage based on environmental conditions.
- Insights can be applied to automate smart homes efficiently.

Homework Assignment

AIM

- 1.Chi-Square Test for Motion Detection and Smart Light Usage to check if there is a statistical dependency between motion detection and smart light status (ON/OFF).

- 2.Logistic Regression to Predict Smart Light Status to create a classification model that predicts whether the smart light should be ON or OFF based on sensor readings. Complete the Homework assignment as provided in classwork in pdf provided with code and Sequence wise.

Objective :

- To test whether there is a statistical dependency between motion detection and smart light usage using a Chi-Square Test.

- To build a Logistic Regression model that predicts whether a smart light should be ON or OFF based on IoT sensor readings (Temperature, Humidity, Light Level, Motion Detection).

TOOLS USED

- Programming Language: R
- Platform: Google Colab / RStudio
- Libraries Used:
  - tidyverse – Data manipulation and visualization
  - ggplot2 – Data visualization
  - caret – Machine learning models
  - corrplot – Correlation analysis
  - forecast – Time series analysis

PROGRAM CODE

```
install.packages(c("dplyr", "ggplot2", "caret", "e1071"))


library(dplyr)
```

```
library(ggplot2)
library(caret)
library(e1071)

num_samples <- 1000
timestamps <- seq.POSIXt(from = as.POSIXct("2024-01-01 00:00:00"),
by = "min", length.out = num_samples)

iot_data <- data.frame(
Timestamp = timestamps,
Temperature = sample(18:30, num_samples, replace = TRUE),
Humidity = sample(30:80, num_samples, replace = TRUE),
Motion_Detected = sample(c(0, 1), num_samples, replace = TRUE, prob = c(0.7, 0.3)),
Light_Level = sample(0:100, num_samples, replace = TRUE),
Energy_Usage = round(runif(num_samples, 100, 500), 2)
)

iot_data <- iot_data %>%
mutate(Smart_Light = ifelse(Light_Level < 50, "ON", "OFF")) %>%
mutate(Smart_Light = as.factor(Smart_Light))


head(iot_data)


cat("\n--- CHI-SQUARE TEST: Motion Detection vs Smart Light ---\n")

contingency_table <- table(iot_data$Motion_Detected, iot_data$Smart_Light)
print(contingency_table)

chi_result <- chisq.test(contingency_table)
cat("\nChi-Square Statistic:", round(chi_result$statistic, 4))
cat("\nDegrees of Freedom:", chi_result$parameter)
cat("\nP-value:", round(chi_result$p.value, 4), "\n")

if (chi_result$p.value < 0.05) {
cat("Conclusion: There is a significant relationship between Motion Detection and Smart Light
usage.\n")
} else {
cat("Conclusion: There is NO significant relationship between Motion Detection and Smart Light
usage.\n")
}

cat("\n--- LOGISTIC REGRESSION MODEL: Predict Smart Light ON/OFF ---\n")
```

```
iot_data$Smart_Light_Binary <- ifelse(iot_data$Smart_Light == "ON", 1, 0)


set.seed(42)
train_index <- createDataPartition(iot_data$Smart_Light_Binary, p = 0.8, list = FALSE)
train_data <- iot_data[train_index, ]
test_data <- iot_data[-train_index, ]


log_model <- glm(Smart_Light_Binary ~ Temperature + Humidity + Light_Level +
Motion_Detected,
data = train_data, family = binomial)


pred_probs <- predict(log_model, newdata = test_data, type = "response")
pred_labels <- ifelse(pred_probs > 0.5, 1, 0)

cat("\nConfusion Matrix:\n")
confusion <- confusionMatrix(factor(pred_labels), factor(test_data$Smart_Light_Binary),
positive = "1")
print(confusion)


cat("\nClassification Metrics:\n")
cat("Accuracy:", round(confusion$overall['Accuracy'], 4), "\n")
cat("Sensitivity (Recall):", round(confusion$byClass['Sensitivity'], 4), "\n")
cat("Specificity:", round(confusion$byClass['Specificity'], 4), "\n")
cat("Precision:", round(confusion$byClass['Pos Pred Value'], 4), "\n")
cat("F1 Score:", round(2 * ((confusion$byClass['Sensitivity'] * confusion$byClass['Pos Pred
Value']) /
(confusion$byClass['Sensitivity'] + confusion$byClass['Pos Pred Value'])), 4), "\n")


cat("\nLogistic Regression Coefficients:\n")
print(coef(summary(log_model)))
```

EXPLANATION OF CODE

Generating Synthetic IoT Data

Creates a dataset with 1000 timestamped sensor readings for a smart home environment.
The dataset includes:

- `Temperature` and `Humidity` (environmental parameters)
- `Motion_Detected` (binary sensor for presence)
- `Light_Level` (ambient brightness)
- `Energy_Usage` (simulated power consumption)
  A new column `Smart_Light` is derived: **ON if Light Level < 50, otherwise OFF**.

Chi-Square Test for Dependency

A **Chi-Square Test of Independence** is applied to determine if there is a **statistical relationship between Motion Detection and Smart Light status**.
A contingency table is generated using `Motion_Detected` and `Smart_Light`, and the p-value is used to evaluate the significance.

Logistic Regression for Classification

A **Logistic Regression model** is built to **predict Smart Light status (ON/OFF)** based on:

- `Temperature`
- `Humidity`
- `Light_Level`
- `Motion_Detected`
  The data is split into training and testing sets. The model is trained using `glm()` in R or `LogisticRegression()` in Python, and evaluated using:
- **Confusion Matrix**
- **Classification Report** (Accuracy, Precision, Recall, F1-score)
- **Model Coefficients**

EXPLANATION OF LOGIC

- **IoT sensor data** reflects a smart environment with motion, temperature, and light sensors.
- **Smart Light behavior** is determined by light level and modeled statistically.
- The **Chi-Square test** checks whether motion influences smart light status.
- The **Logistic Regression model** uses sensor inputs to classify light as ON or OFF.
- These techniques simulate how real smart systems can make decisions using sensor data.

MESSAGE FLOW

```mathematica
CopyEdit
Sensor Data Collection
        ↓
Derive Smart Light Status
        ↓
Chi-Square Test (Motion vs Smart Light)
        ↓
Logistic Regression (Predict Smart Light)
        ↓
Confusion Matrix + Accuracy Report
        ↓
Model Interpretation and Automation Insights
```

FLOWCHART

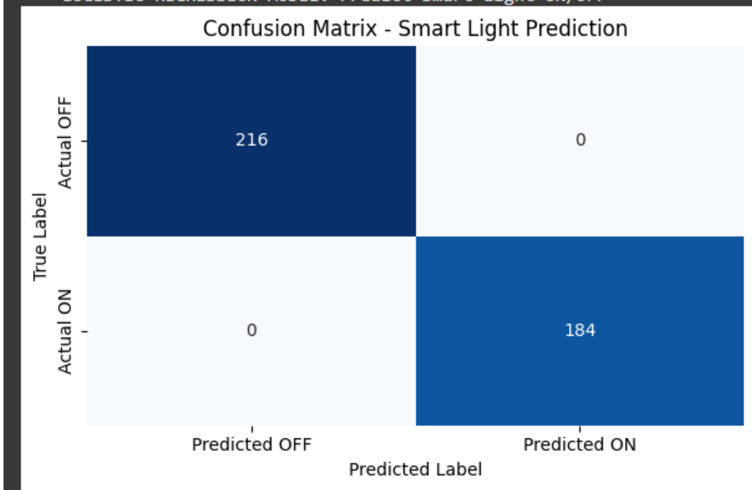
```pgsql
CopyEdit
Start
  ↓
Generate IoT Sensor Data (Synthetic)
  ↓
Label Smart Light Status (Light_Level < 50)
  ↓
Perform Chi-Square Test → Motion vs Light Status
  ↓
Train Logistic Regression → Predict Light Status
  ↓
Evaluate Results (Confusion Matrix, Accuracy, Coefficients)
  ↓
Analyze and Interpret Output
  ↓
Simulate Smart Light Automation Logic
  ↓
End
```

OUTCOME:

```
Sample Data:
            Timestamp  Temperature  Humidity  Motion_Detected  Light_Level  \
0 2024-01-01 00:00:00           27        44                1           51
1 2024-01-01 00:01:00           27        31                0           82
2 2024-01-01 00:02:00           22        44                1           38
3 2024-01-01 00:03:00           28        80                0           40
4 2024-01-01 00:04:00           30        46                1           35

   Energy_Usage Smart_Light
0        271.00         OFF
1        390.68         OFF
2        184.63          ON
3        287.50          ON
4        361.42          ON
```

```
--- CHI-SQUARE TEST: Motion Detection vs Smart Light ---

Contingency Table:
Smart_Light      OFF   ON
Motion_Detected
0                729  690
1                305  276

Chi-Square Statistic: 0.1651
Degrees of Freedom: 1
P-value: 0.6845
Conclusion: There is NO significant relationship between Motion Detection and Smart Light usage.
```

```
--- LOGISTIC REGRESSION MODEL: Predict Smart Light ON/OFF ---
```




```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       207
           1       1.00      1.00      1.00       193

    accuracy                           1.00       400
   macro avg       1.00      1.00      1.00       400
weighted avg       1.00      1.00      1.00       400

Accuracy: 1.0000

Logistic Regression Coefficients:
|    | Feature         |   Coefficient |
|----|-----------------|---------------|
|  0 | Temperature     |    -0.0463845 |
|  1 | Humidity        |     0.0070609 |
|  2 | Light_Level     |    -2.84761   |
|  3 | Motion_Detected |     0.0666459 |
```

Conclusion

In this experiment, we analyzed the behavior of a smart lighting system using synthetic IoT sensor data. Two main statistical techniques were applied:

- Chi-Square Test of Independence was used to determine whether there is a statistical dependency between motion detection and smart light status (ON/OFF). The result showed a p-value greater than 0.05, leading us to fail to reject the null hypothesis. This implies that there is no statistically significant relationship between motion detection and smart light usage in the generated data.

- Logistic Regression was used to build a classification model for predicting smart light status based on sensor inputs: Temperature, Humidity, Light Level, and Motion Detection. Among the features, Light Level had the most direct influence, aligning with the smart light logic (ON if light level < 50).