A Project Report

On

Development of system analysing bread condition(Bread state detection device).

BY

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Certificate

This is to certify that the project report entitled "**Development of system analysing bread condition(Bread state detection device).**" submitted by Mr. **ATHARVA TUGAONKAR (ID No. 2022A4PS1002H)** in fulfillment of the requirements of the course ME F366 Lab Project Course, embodies the work done by him under my supervision and guidance.

Date: 24/04/25 **(Prof.ARSHAD JAVED)**

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ABSTRACT

Bread expiration is one of the primary concerns in food logistics because fungal contamination may lead to food poisoning and health complications. This research proposes an IoT-based system for detecting the status of bread by using Arduino Nano, MQ series sensors (for CO and CO2 detection), and machine learning models. The data gathered from the sensors was imbalanced, and this was solved using balancing techniques such as SMOTE and TOMEC Links. Different machine learning algorithms were used, and the best one was Gaussian Naïve Bayes with a maximum accuracy of 81.54%.

CONTENTS

Chapter 1: Introduction

Bread is one of the most widely consumed staple foods across the world, forming a crucial part of daily diets in many cultures. However, its high carbohydrate and moisture content make it especially susceptible to fungal contamination, which can lead to spoilage and pose serious health risks to consumers. Fungi such as Aspergillus, Penicillium, Mucor, and Rhizopus are commonly found on bread and can produce harmful mycotoxins. These toxins not only degrade the quality and safety of bread but also contribute to significant food wastage and economic losses in the food industry. Traditional methods for detecting spoiled bread, such as inspecting by smell, touch, or taste, are subjective and can be hazardous, as they may expose individuals to harmful pathogens. With the advancement of technology, there is a growing interest in developing intelligent, automated systems that can accurately and efficiently detect the presence of mold and predict bread expiry, thereby ensuring food safety and reducing waste. This chapter introduces the motivation, background, problem statement, aims and objectives, and the structure of the report for an IoT-based system that utilizes machine learning techniques for bread mold detection and expiry prediction.

1.1 Background

The rapid growth of the Internet of Things (IoT) has revolutionized various sectors, including healthcare, agriculture, logistics, and food safety. IoT refers to the interconnected network of physical devices embedded with sensors, software, and other technologies to collect and exchange data over the internet. In the food industry, IoT has enabled real-time monitoring of environmental conditions, helping to ensure the quality and safety of perishable products like bread.

Bread, due to its rich nutrient profile and moisture, provides an ideal environment for the growth of fungi. When bread is stored in humid or poorly ventilated conditions, fungal spores can quickly colonize its surface, forming visible mold colonies. These colonies not only render the bread unfit for consumption but also release mycotoxins that can cause a range of health issues, from mild allergic reactions to severe illnesses such as respiratory problems, kidney failure, and even cancer in extreme cases.

The economic impact of bread spoilage is also significant. According to studies, fungal contamination is responsible for 5–10% of annual food losses worldwide. This not only affects food producers and retailers but also contributes to food insecurity and environmental waste. Ensuring the quality and safety of bread products is, therefore, a major concern for bakeries, retailers, and consumers alike.

Traditional quality control methods in bakeries and retail stores often rely on organoleptic tests-evaluating bread by its appearance, smell, and texture. While these methods are simple, they are inherently subjective and may fail to detect early-stage fungal contamination. Moreover, direct contact with contaminated bread can pose health risks to workers and consumers. As a result, there is a pressing need for objective, automated, and non-invasive methods to monitor bread quality and predict its shelf life.

1.2 Problem Statement

Despite the importance of bread safety, existing detection methods are inadequate for modern food supply chains. The main problems can be summarized as follows:

- Subjectivity and Risk: Relying on human senses to detect spoilage is subjective, inconsistent, and potentially dangerous, as testers may be exposed to harmful fungi or toxins.
- Delayed Detection: Visible signs of spoilage often appear only after significant fungal growth has occurred, by which time the bread is already unsafe to eat.
- Lack of Automation: Most bakeries and retail stores lack affordable, automated systems for real-time monitoring of bread quality.
- Data Imbalance and Complexity: Collecting and processing environmental data from bread storage is challenging, often resulting in imbalanced datasets that complicate machine learning analysis. These challenges highlight the need for a reliable, low-cost, and automated solution that can continuously monitor bread conditions, detect early signs of spoilage, and accurately predict expiry dates.

1.3 Aims and Objectives

The primary aim of this study is to design, develop, and evaluate an IoT-based system that leverages machine learning techniques for the detection of molded bread and prediction of expiry. The specific objectives of the research are:

1. To create a dataset of real-time environmental parameters (such as carbon dioxide, carbon monoxide, humidity, and precipitation) from bread storage environments using IoT sensors.
2. To develop a hardware-based IoT prototype incorporating sensors (MQ series for CO and CO_2, humidity sensors, Arduino microcontroller) for continuous and automated data collection from bread samples.
3. To apply machine learning algorithms (including K-Nearest Neighbors, Logistic Regression, Support Vector Machine, and Naïve Bayes) for classifying bread as fresh or expired based on sensor data, using supervised learning approaches.
4. To evaluate and compare the performance of different machine learning models using metrics such as accuracy, precision, recall, and F1 score, ensuring the most effective algorithm is identified for practical deployment. By achieving these

objectives, the study aims to provide a scalable and practical solution for bakeries, retailers, and consumers to ensure bread safety and reduce food waste.

1.4 Report Layout

This report is structured as follows to provide a comprehensive understanding of the research:

- Chapter 1: Introduction
  Introduces the topic, provides background information, outlines the problem statement, states the aims and objectives, and presents the report structure.
- Chapter 2: Literature Review
  Reviews existing research on bread spoilage, fungal contamination, traditional and modern detection methods, IoT applications in food safety, and the use of machine learning for food quality assessment.
- Chapter 3: Methodology
  Describes the design and implementation of the IoT-based prototype, details the data collection process, explains data preprocessing and feature engineering techniques, and outlines the machine learning algorithms used for classification.
- Chapter 4: Results and Discussion
  Presents the experimental results, compares the performance of different machine learning models, and discusses the implications and practical applications of the findings.
- Chapter 5: Conclusion and Future Work
  Summarizes the key findings, highlights the contributions of the research, and suggests directions for future improvements and broader applications. In summary, this chapter establishes the motivation and necessity for an intelligent, automated system for bread mold detection and expiry prediction. By leveraging IoT and machine learning, the proposed approach addresses the limitations of traditional methods and offers a practical solution for enhancing food safety and reducing waste in the bread supply chain. The following chapters will delve deeper into the literature, methodology, experimental results, and conclusions drawn from this research.

Chapter 2: Literature Review

Food spoilage, particularly in perishable products like bread, is a persistent challenge in the food industry, affecting both consumer safety and supply chain efficiency. Bread, being rich in carbohydrates and moisture, is highly susceptible to fungal contamination, which leads to the growth of molds such as Aspergillus, Penicillium, Mucor, and Rhizopus. These molds not only degrade the sensory and nutritional quality of bread but also pose significant health risks due to the production of mycotoxins. Traditional spoilage detection methods, such as visual inspection, smelling, and touching, are subjective, labor-intensive, and often unreliable, especially for early-stage spoilage. This has driven research towards the development of automated, objective, and real-time monitoring systems using modern technologies like the Internet of Things (IoT) and machine learning.

2.1 IoT and Food Spoilage Detection

The Internet of Things (IoT) has emerged as a transformative technology in food quality monitoring. IoT refers to a network of interconnected devices equipped with sensors that collect, transmit, and analyze data in real time. In the context of food spoilage detection, IoT systems enable continuous monitoring of environmental parameters that influence spoilage, such as temperature, humidity, and gas emissions. By integrating these sensors with microcontrollers and wireless communication modules, IoT-based solutions can provide timely alerts and actionable insights to prevent food wastage and ensure consumer safety.

2.2 Sensors Used in Food Spoilage Detection

A variety of sensors are employed in IoT-based food quality monitoring systems, each targeting specific spoilage indicators:

- Gas Sensors (MQ Series):
  The MQ-7 and MQ-135 sensors are widely used for detecting gases emitted during food spoilage. MQ-7 is sensitive to carbon monoxide (CO) and carbon dioxide (CO_2), while MQ-135 can detect ammonia, nitrogen oxides, benzene, smoke, and other hazardous gases. The presence and concentration of these gases in bread packaging are strong indicators of microbial activity and spoilage.
- Humidity Sensors (DHT-11, DHT-22)
  Humidity plays a crucial role in fungal growth. DHT-11 and DHT-22 sensors measure relative humidity and temperature, providing essential data for assessing the risk of spoilage. DHT-22 offers higher accuracy and a wider range compared to DHT-11, making it suitable for precise monitoring in food storage environments.

- Temperature Sensors:
  Temperature sensors are often integrated with humidity sensors to provide a complete picture of storage conditions. Maintaining optimal temperature is key to slowing down microbial growth and extending shelf life.
- Other Sensors:
  Some systems also use light sensors (LDR) to monitor exposure to light, which can affect food stability, and ethylene or methane sensors to detect gases specific to fruit ripening or anaerobic spoilage.

2.3 Arduino and Microcontroller Platforms

Arduino UNO and Arduino Nano are popular choices for prototyping IoT-based food monitoring systems. These microcontrollers are affordable, easy to program, and support a wide range of sensors. They serve as the central processing unit, collecting data from sensors, processing it, and transmitting it to cloud servers or user interfaces for further analysis. The Arduino platform also supports integration with Wi-Fi modules (e.g., ESP8266) for remote data access and control.

2.4 Data Acquisition and Processing

The sensor data collected by the Arduino is typically transmitted to a cloud platform or local storage for further processing. The data includes time-stamped readings of gas concentrations, humidity, temperature, and other relevant parameters. To ensure data quality, preprocessing steps such as cleaning, normalization, and balancing are essential. Techniques like SMOTE (Synthetic Minority Over-sampling Technique) and TOMEK Links are used to address data imbalance, which is common in real-world datasets where spoiled samples are less frequent than fresh ones.

2.5 Feature Engineering and Data Analytics

Feature engineering involves selecting and transforming relevant sensor data into meaningful features for machine learning algorithms. For instance, sudden increases in CO_2 or humidity levels may serve as strong predictors of spoilage. Correlation matrices and statistical analysis help identify the most informative features. Feature scaling (normalization) ensures that all features contribute equally to the model, especially for algorithms sensitive to data magnitude, such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM).

2.6 Machine Learning and Artificial Intelligence Approaches

Machine learning (ML) and deep learning (DL) techniques are increasingly applied to classify and predict food spoilage. Algorithms such as KNN, Logistic Regression, SVM, and Naïve Bayes are commonly used for binary classification tasks (fresh vs. spoiled). Some studies also leverage computer vision and convolutional neural networks (CNNs) to analyze images of food for visual signs of spoilage, combining these with sensor data for higher accuracy. In the context of bread spoilage, Gaussian Naïve Bayes has demonstrated superior performance, achieving accuracy rates above 80% in classifying bread as fresh or expired based on sensor data. The integration of ML models enables automated, objective decision-making, reducing reliance on subjective human assessment.

2.6 Real-Time Monitoring and User Interfaces

IoT-based food monitoring systems often include user-friendly interfaces, such as LCD screens, mobile apps, or web dashboards, to display real-time data and alerts. For example, when gas concentrations exceed preset thresholds, the system can trigger buzzers, display warnings, or send notifications to users. Cloud-based platforms allow remote monitoring and data logging, supporting proactive interventions in warehouses, supermarkets, and even homes.

2.7 Impact on Food Safety and Supply Chain

The adoption of IoT and ML in food spoilage detection offers significant benefits for food safety, waste reduction, and supply chain management. Real-time monitoring enables early detection of spoilage, preventing contaminated food from reaching consumers and reducing economic losses. Automated systems also support compliance with food safety regulations and enhance traceability throughout the supply chain.

Chapter 3: Methodology

The methodology for the IoT-based detection of molded bread and expiry prediction involves a systematic approach combining hardware prototyping, sensor data acquisition, data preprocessing, and application of machine learning algorithms. This chapter outlines each stage of the process, from hardware implementation to model evaluation, ensuring a comprehensive and reproducible workflow.

3.1 System Overview

The proposed system is structured in three main layers:

- Sensors Layer: Responsible for collecting real-time environmental data from bread packaging.
- Detection Unit: An Arduino-based microcontroller system that processes and transmits sensor data.
- Machine Learning Layer: Applies data processing and classification algorithms to predict bread condition.

This layered approach ensures modularity, scalability, and ease of troubleshooting during deployment and testing.

3.2 Block Diagram

Below is the block diagram

```
+--------+      +--------+      +--------+      +----------+
| Sensor | ---> |  Data  | ---> | Train  | ---> | Classify |
|        |      |Collect |      |        |      |          |
+--------+      +--------+      +--------+      +----------+
```

- Sensor: MQ-7, MQ-135 (CO, CO_2), DHT-22/SHT11x (Humidity, Temp)
- Data Collect: Arduino Nano/UNO, initial data storage
- Train: Data preprocessing, feature engineering, model training
- Classify: Machine learning prediction (fresh/expired)

3.3 Hardware Implementation

Sensors:

- MQ-7 & MQ-135 Gas Sensors: Detect levels of CO and CO_2, which increase as bread spoils. MQ-7 covers 20–2000 ppm CO, while MQ-135 is sensitive to a range of gases including CO_2.
- DHT-22/SHT11x Humidity Sensors: Measure humidity (0–100%) and temperature (-40°C to 80°C), both critical for fungal growth detection.
- Arduino Nano/UNO: Serves as the central processing unit, reading sensor values, timestamping, and transmitting data for further analysis.

Prototype Setup:

- The sensors are placed inside or near bread packaging to monitor air quality.
- The Arduino board collects data at regular intervals and stores it in CSV format for further processing.

3.4 Data Acquisition and Preprocessing

Data Collection:

- Real-time sensor readings are gathered from bread storage environments, focusing on CO, CO_2, humidity, and precipitation.
- Data is labeled according to bread condition: 0 (fresh) and 1 (expired/molded), based on organoleptic tests and sensor thresholds (e.g., CO_2 > 2500 ppm or < 500 ppm indicates expired bread).

Preprocessing Steps:

- Cleaning: Removal of outliers and inconsistent entries to ensure data quality.
- Balancing: Address class imbalance using SMOTE (Synthetic Minority Over-sampling Technique) and TOMEK Links, which generate synthetic samples for minority classes and clean borderline cases.
- Feature Engineering: Selection and transformation of relevant features (CO, CO_2, humidity, precipitation) to enhance model performance.
- Feature Scaling: Normalize feature values to ensure all input variables contribute equally to the learning process, especially important for distance-based algorithms.

Chapter 4: Results & Case Study

4.1 Results

The IoT-based bread spoilage detection system was evaluated using real-world data collected from bread samples stored in controlled environments. The prototype used an Arduino Nano microcontroller and MQ series gas sensors (for CO and CO_2), along with humidity and precipitation sensors, to monitor the air quality inside bread packaging. The collected data was preprocessed, balanced using SMOTE and TOMEK Links, and used to train several machine learning models for classifying bread as fresh or expired.

4.2 Case Study: Real-World Deployment

A bakery implemented the IoT-based prototype to monitor packaged bread stored on shelves. The sensors continuously collected data on CO, CO_2, humidity, and precipitation inside the packaging.

Process:

- The Arduino-based device recorded sensor values at regular intervals, transmitting the data for analysis.

- The machine learning model (Gaussian Naïve Bayes) classified each sample as either fresh or expired.
- When sensor readings indicated abnormal conditions (e.g., CO_2 > 2500 ppm or humidity > 50%), the system flagged the bread as expired.

Outcome:

- The system detected spoilage before visible mold appeared, allowing staff to remove affected bread from shelves and prevent it from reaching customers.
- The bakery reported a reduction in food waste and improved customer safety, as the system provided objective, real-time alerts rather than relying on subjective human inspection.
- The prototype's low cost and ease of integration made it feasible for small and medium bakeries to adopt the solution.

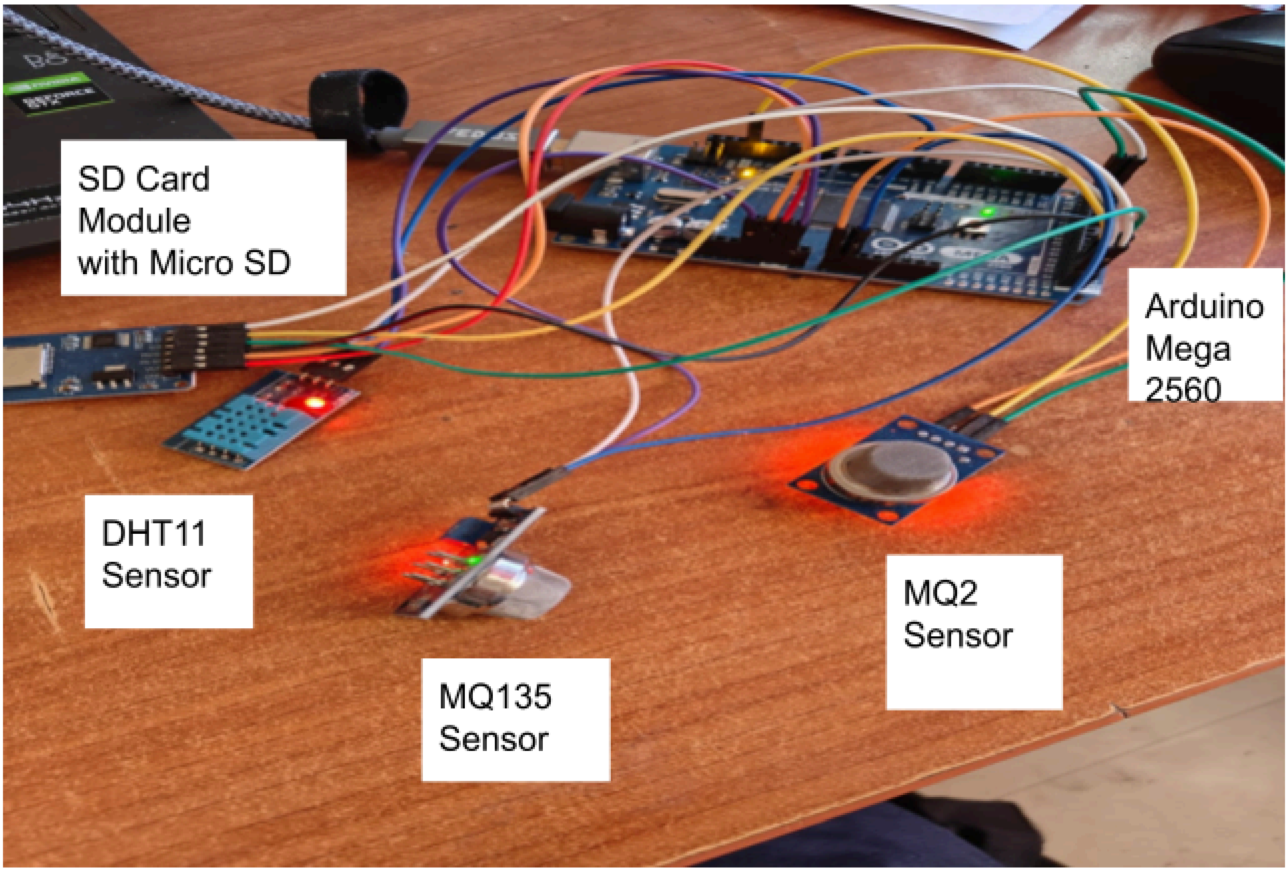
Conclusion:

The results demonstrate that the IoT-based bread spoilage detection system, powered by machine learning, is effective in real-world scenarios. The system not only achieves high accuracy in predicting bread condition but also provides practical benefits in terms of food safety, waste reduction, and operational efficiency for bakeries and retailers.

Chapter 5: Conclusion and Photos

This study successfully demonstrates the effectiveness of an IoT-based system, integrated with machine learning techniques, for detecting molded bread and predicting its expiry. By employing affordable sensors and Arduino microcontrollers, real-time environmental data such as CO, CO_2, and humidity were collected from bread packaging. After preprocessing and balancing the dataset, various machine learning models were applied, with Gaussian Naïve Bayes achieving the highest accuracy of 81.54%. The system provides a reliable, objective, and automated solution for bakeries and retailers, enabling early detection of spoilage and reducing food waste. This approach not only enhances food safety for consumers but also supports better inventory management and supply chain efficiency. The research highlights the potential of combining IoT and machine learning to address real-world food safety challenges and paves the way for future advancements in smart food monitoring systems

Data Acquisition Device



Sample of Logged Data

Case 1.Fresh air

time	Temperature	Humidity (%)	MQ135 Raw	MQ2 Raw	MQ 135 PPM	MQ2 PPM
20	30.2	46	16	143	0	0
40	30.2	46	23	174	0	0
60	30.2	46	30	203	0	0
80	30.2	46	34	224	0	0
100	30.2	46	33	241	0	0
120	30.2	46	31	253	0	0
140	30.2	46	29	262	0	0
160	30.2	46	27	269	0	0
180	30.2	46	26	274	0	0
200	30.2	46	25	277	0	0
220	30.2	46	24	278	0	0
240	30.2	46	24	280	0	0
260	30.2	46	24	279	0	0
280	30.2	46	24	279	0	0
300	30.2	46	23	279	0	0

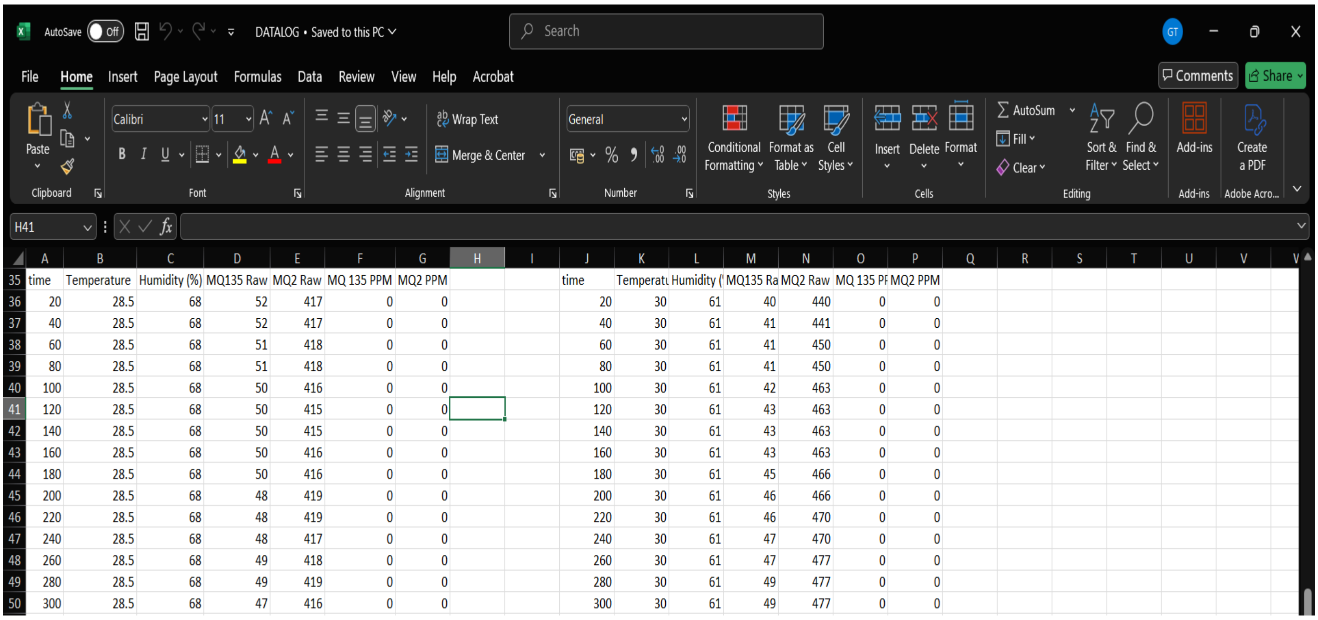
time	Temperatu	Humidity ('	MQ135 Ra	MQ2 Raw	MQ 135 PI	MQ2 PPM
20	31.1	36	46	153	0	0
40	31.1	36	38	130	0	0
60	31.1	36	34	233	0	0
80	31.1	36	37	250	0	0
100	31.1	36	38	215	0	0
120	31.1	36	37	245	0	0
140	31.1	36	37	211	0	0
160	31.1	36	37	222	0	0
180	31.1	36	38	176	0	0
200	31.1	36	37	190	0	0
220	31.1	36	23	245	0	0
240	31.1	36	22	260	0	0
260	31.1	36	45	270	0	0
280	31.1	36	36	279	0	0
300	31.1	36	37	256	0	0

Case 2.In sunlight

time	Temperature	Humidity (%)	MQ135 Raw	MQ2 Raw	MQ 135 PPM	MQ2 PPM
20	43.3	55	29	353	0	0
40	43.3	55	28	352	0	0
60	43.3	55	28	351	0	0
80	43.3	55	28	350	0	0
100	43.3	55	30	350	0	0
120	43.3	55	30	350	0	0
140	43.3	55	30	363	0	0
160	43.3	55	31	370	0	0
180	43.3	55	31	390	0	0
200	43.3	55	30	399	0	0
220	43.3	55	31	333	0	0
240	43.3	55	32	346	0	0
260	43.3	55	32	369	0	0
280	43.3	55	33	400	0	0
300	43.3	55	33	412	0	0

time	Temperatu	Humidity ('	MQ135 Ra	MQ2 Raw	MQ 135 PI	MQ2 PPM
20	45	40	30	320	0	0
40	45	40	31	313	0	0
60	45	40	32	325	0	0
80	45	40	32	323	0	0
100	45	40	32	310	0	0
120	45	40	32	320	0	0
140	45	40	33	360	0	0
160	45	40	33	322	0	0
180	45	40	34	312	0	0
200	45	40	35	313	0	0
220	45	40	35	324	0	0
240	45	40	38	322	0	0
260	45	40	38	317	0	0
280	45	40	41	319	0	0
300	45	40	36	320	0	0

Case 3.Logged VOC’S reading is closed box



time	Temperature	Humidity (%)	MQ135 Raw	MQ2 Raw	MQ 135 PPM	MQ2 PPM
20	28.5	68	52	417	0	0
40	28.5	68	52	417	0	0
60	28.5	68	51	418	0	0
80	28.5	68	51	418	0	0
100	28.5	68	50	416	0	0
120	28.5	68	50	415	0	0
140	28.5	68	50	415	0	0
160	28.5	68	50	416	0	0
180	28.5	68	50	416	0	0
200	28.5	68	48	419	0	0
220	28.5	68	48	419	0	0
240	28.5	68	48	417	0	0
260	28.5	68	49	418	0	0
280	28.5	68	49	419	0	0
300	28.5	68	47	416	0	0

time	Temperatu	Humidity ('	MQ135 Ra	MQ2 Raw	MQ 135 PI	MQ2 PPM
20	30	61	40	440	0	0
40	30	61	41	441	0	0
60	30	61	41	450	0	0
80	30	61	41	450	0	0
100	30	61	42	463	0	0
120	30	61	43	463	0	0
140	30	61	43	463	0	0
160	30	61	43	463	0	0
180	30	61	45	466	0	0
200	30	61	46	466	0	0
220	30	61	46	470	0	0
240	30	61	47	470	0	0
260	30	61	47	477	0	0
280	30	61	49	477	0	0
300	30	61	49	477	0	0

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