<u>**Title of the Thesis**</u>

IoT-Based Real-Time Food Safety and Quality Monitoring System Using Gas Sensors and Machine Learning for Perishable Food Detection

BY

Jubayer Ahmed

ID: 213-16-590

Supervised By:

Mr. Md. Sarwar Hossain Mollah

Assistant Professor And Head

Department of Computing & Information System

Department of Computing & Information System

Faculty of Science & Information Technology

Daffodil International University

Daffodil Smart City (DSC), Birulia, Savar, Dhaka-1216

APPROVAL

This Project titled "**IoT-Based RealTime Food Safety and Quality Monitoring System Using Gas Sensors and Machine Learning for Perishable Food Detection**, Submitted by**Jubayer Ahmed** , ID No: **213-16-590** to the Department of Computing and Information Systems, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computing and Information Systems and approved as to its style and contents. The presentation has been held on 21-10-2025.

BOARD OF EXAMINERS

Md Sarwar Hossain Mollah — **Chairman**
Associate Professor and Head
Department of Computing & Information Systems
Faculty of Science & Information Technology
Daffodil International University

Md. Nasimul Kader — **Internal Examiner**
Assistant Professor
Department of Computing & Information Systems
Faculty of Science & Information Technology
Daffodil International University

Md. Mehedi Hassan — **Internal Examiner**
Lecturer (Senior Scale)
Department of Computing & Information Systems
Faculty of Science & Information Technology
Daffodil International University

Dr. Saifuddin Md. Tareeq — **External**
Examiner
Professor
Department of Computer Science and Engineering
University of Dhaka, Dhaka

Declaration

I **Jubayer Ahmed** ,hereby declare that the work in this dissertation titled; **"IoT-Based Real-Time Food Safety and Quality Monitoring System Using Gas Sensors and Machine Learning for Perishable Food Detection"** has been done by me under supervision of **Mr. Md. Sarwar Hossain Mollah**, Assistant Professor And Head,Department of Computing and Information System (CIS) of Daffodil International University. I am also declaring that this project or any part of there has never been submitted anywhere else for the award of any educational degreelike, B.Sc., M.Sc., Diploma or other qualifications.

Supervised By

21/10/25.

Mr. Md. Sarwar Hossain Mollah
Assistant Professor And Head
Department of CIS
Daffodil International University

Submitted By

Jubayer Ahmed

Jubayer Ahmed
ID:213-16-590
Department of CIS
Daffodil International University

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Dedication

I would like to dedicate this accomplishment to my beloved father **Abu Zaher**, and mother **Sumsunnaher**. Without their unwavering love, encouragement, and sacrifices, I might not have made it as far in my academic career as I have today. If not for their endless support and belief in my academic journey, I wouldn't have had the chance to research and learn more about this subject, so that we can all build a better society one day.

Abstract

Food safety and quality monitoring are significant issues for ensuring human safety, especially for perishable goods and cooked foods such as rice, fish, or meat. Conventional inspection methods are manual, labour-intensive, and error-prone, thus re-establishing the need for an automated, novel solution. This paper proposes a real-time food safety and quality monitoring system based on three gas sensors (MQ3, MQ4, and MQ135) interfaced with an ESP32 microcontroller core to obtain readings, which are displayed on an OLED display. By detecting alcohol vapors, the MQ3 sensor can identify meat rot, both of which are important parameters for detecting spoiled food. The methane gas is detected using the MQ4 sensor, and air quality indicators such as carbon dioxide and ammonia are detected using the MQ135 sensor. The V. Logenthira: Three specimens were prepared, i.e., food-containing substrate (FCS), study shows that FCS is degraded more than twice in anaerobic conditions with [24] delignified straw-peat at Fig.

To improve the accuracy of the decision, machine learning algorithms are integrated into food condition classifiers (safe, risky, or spoiled), which classify based on sensor data patterns. On the processor, raw signals are handled by ESP32; however, predictive accuracy is enhanced over fixed threshold detection by using a trained model. Real-time analysis is presented in the OLED module, and the IoT framework ensures easy expansion to cloud storage, remote monitoring, and predictive analytics.

The experimental results demonstrate that the proposed model can accurately [3] identify VOCs and harmful gases generated during food preparation and storage, enabling real-time warning of unsafe food. Leveraging IoT sensing and ML technology, the product offers a high price-to-performance ratio that can improve food safety in kitchens, restaurants, and households.

Keywords: Food Safety, IoT, ESP32, MQ3, MQ4, MQ135, Machine Learning, Real-Time Monitoring, OLED Display, Food Spoilage Detection.

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Chapter 1 INTRODUCTION

1.1 Introduction

The deployment of Internet-connected devices that provide real-time monitoring and control systems for food safety, quality, and other fronts throughout the supply chain is called IoT for food safety. A typhoon of food-borne illnesses is continuously infecting people around the world. From a broader perspective, IoT technologies are envisioned to alleviate food-borne diseases by continuously monitoring food quality parameters (Yousefi et al., 2019; Adisa et al., 2024)[8].

IoT AI - As per the studies, there have been promising results reliable models for detection, forecasting, and solving intricate food safety problems by utilizing machine learning and deep learning algorithms (Lim et al., 2023; Elufioye et al., 2024) [9]

Ensuring food quality has been one of the oldest challenges faced by the food industry. Food quality monitoring systems have previously relied on manual inspections, which can take time and are prone to error. However, the rise of IoT and machine learning technologies can make food quality monitoring more powerful and less complex [1].

It helps monitor food items in real time and analyze data on safe, risky, or spoiled food, enabling better decision-making. Machine learning algorithms have shown promising performance in food quality monitoring [39]. These algorithms can analyze data from multiple gas sensors (MQ3, MQ4, and MQ135) to predict food freshness. Other research has reported that machine learning algorithms have successfully classified foods by freshness, thereby making a possible solution for the monitoring of food quality. Thus, the proposed IoT-based food quality monitoring system employs several gas sensors (MQ3, MQ4, and MQ135) to enable real-time tracking of food items. This system is cost-effective, easy to operate, and available for both commercial and personal use [2].

The IoT revolution is transforming contemporary food supply chains, where real-time data collection and monitoring are vital for safe food production in a rapidly changing world (Wang et al., 2015).

sensing approaches have become a well-known non-invasive technique for analyzing food safety and quality. Gas sensors identify volatile organic compounds (VOCs) emitted by food products and provide insight into a product's aroma and flavor composition. Because alterations in food composition alter its volatile profile, monitoring the gas constituents of food products is an excellent strategy for assessing food quality and safety [2].

Ethylene concentration released during climacteric fruit (e.g., bananas) is a good indicator of food product maturity and ripeness. At the same time, ammonia production is a good indicator of spoilage of meat and dairy products. A gas sensor system capable of detecting — a highly sensitive sensor with the capability of detecting the gases related to food, and it can comprise several different gas sensors. Various gases indicate the food's physicochemical properties. This enables rapid prevention and control of spoilage and quality loss by early identification of gas emissions. Unlike traditional methods, gas sensors offer advanced features, such as high sensitivity, portability, fast response, and in situ detection, enabling real-time monitoring of food throughout production, storage, and transportation. Additional gas sensors can be embedded in innovative packaging to continuously monitor and signal consumers about spoilage and hazardous conditions in the food [3].

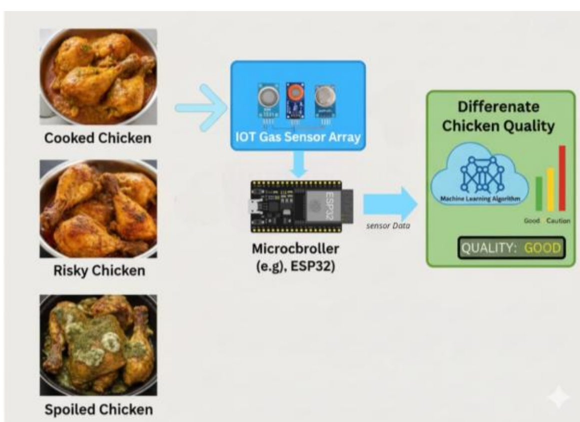

Fig 1.1: Chicken Quality Detection System using IOT and Machine Learning

This project uses IoT and machine learning to develop a system for assessing the quality of cooked chicken. The first one is an analysis of cooked, risky, and spoiled chicken, using three different cooking methods: MQ3, MQ4, and MQ135 all other gas sensor arrays.

Used to detect emission of gases, e.g., like methane, which indicates spoilage or cooking quality by using the MQ3, MQ4, and MQ135 sensors. The sensor data is transmitted to a microcontroller (ESP32), which processes it. The system uses machine learning algorithms to categorize chicken quality as "Good," "Risky," or "Spoiled." [7]

The system classifies the chicken as dangerous or spoiled when gas levels exceed a threshold. The microcontroller relays this information in real time so that the person can know the chicken's condition immediately. And if it's safe to eat or should be thrown away, it sends a signal to the mobile device.

Using this technique will enable food safety by measuring the quality of chicken throughout cooking and storage, preventing spoiled food from being consumed. As time passes, the machine learning model becomes more intelligent, making more accurate predictions based on current data. [8]

1.2 Motivation

The purpose of a food monitoring system is to ensure food is safe and reduce food waste. Food poisoning is a widespread illness caused by eating food contaminated with disease-causing germs. It affects millions of people worldwide every year. Moreover, food spoilage results in significant economic losses and adverse environmental effects, as large amounts of food are wasted [11]. As a result, introducing food surveillance will enable early detection of food quality issues and prevent defective food from reaching the market. It can help save lives, prevent substantial healthcare costs, and protect food manufacturers and retailers from foul clashes [12].

Furthermore, the food monitoring system eliminates the need to assess food item freshness, thereby minimizing food waste. Users are informed exactly when a food item is spoiling, allowing them to eat it before it's too late, thereby reducing waste and costs. A food monitoring system can contribute to food safety and sustainability by identifying food quality problems at an early stage and curbing food waste [13]

1.3 Major Objectives

The main aims of this research are

- Develop an IoT-based food safety monitoring system.
- Detect harmful gases indicating food spoilage.
- Classify food as safe, risky, or spoiled using ML.
- Display real-time results on an OLED screen.
- Provide a low-cost, portable, and scalable solution.
- Reduce food waste and health risks through early detection.

Chapter 2 INITIAL STUDY

2.1 Problem Background

The safety of food is a worldwide concern, with millions of individuals becoming sick each year from eating contaminated or spoiled food. Traditional food inspection methods are primarily manual and time-consuming, rely on human judgment, so it is easy to get inaccurate results. Most of the developing countries do not have an affordable and automatic way to monitor the quality of food products on real-time basis,More so for perishable commodities including cooked chiken, meat,fish etc.

When food starts to spoil, it emits different gases such as methane, ammonia and ethanol vapour and these are distinctive in terms of the degradation process. But with no detection system in place, we have a hard time catching these changes soon enough to avoid their potential health hazards—or waste. Rapidly increasing requirement of fresh and safe food has created high demand for a low-cost online monitoring system to detect spoilage in real time.

Recent developments of Internet of Things (IoT) and machine learning (ML) have offered new opportunities to tackle this problem. Smart food quality monitoring system can sense and collect data without any disruption which could be implemented on IoT based system Food condition ML algorithms Sensor Continues collects Classifies Testing environment spoils safe risky Harmfull spoiled harmful Not-harmful Safe Risky Normal Testing Node Data Collects upload Fig. Hence, to build an IoT-driven food safety monitoring system is a convenient, scalable and intelligent means of maintaining the quality of the food, while also being a humanitarian way to safeguard consumers' health.

2.2Relation of the Study

This research pertains to the Internet of Things (IoT), Machine Learning and the Food Safety Monitoring Systems. Not only does it fill the gap between conventional food monitoring solutions and intelligent technologies, but also to provide with a method capable in real-time detection of food spoilage.IoT-enabled data (gas sensor) monitoring and collection, coupled with machine learning for analysis and classification of food quality. The research continues the emerging field of developing innovative food monitoring systems to promote hygiene, reduce waste, and protect public health.There is also the connection to international efforts toward sustainable food management and food industry digitalization. In addition, the investigation endorses the development of AI for IoT applications in and around kitchens where a cost-effective scalable and feasible solution is desired to be deployed for home, restaurant, food industry.

2.3 Contribution

This research has several implications in relation to the food safety and IoT-based monitoring systems. First, it introduces a low-cost, real-time IoT-based approach that uses three gas sensors (MQ3, MQ4 and MQ135) integrated with an ESP32 microcontroller to detect harmful gases emitted by rotten food. Secondly, it utilizes the machine learning to classify food conditions into good, bad and spoiled, and has the ability of improving detection accuracy compared with traditional threshold-based methods.

Finally, the study further adds in terms of a SpritZer prototype able to provide real-time and interfaced measurement on an OLED screen thus rendering it convenient both for home and commercial use. It presents a dataset and experimental results that can be used as an empirical basis for new works in smart food monitoring. Lastly, the study contributes to food safety consciousness and sustainability by contributing to reducing food spoilage, preventing food-borne diseases and adopting intelligence in daily life.

CHAPTER 3 LITERATURE REVIEW

3.1 Overview

The literature review summarizes relevant studies, technologies and research advances related to IoT-enabled food safety monitoring systems as well as machine-learning techniques applied for food quality evaluation. It gives glimpse of how recent digital technologies are changing the way food inspection is traditionally performed towards an automated, intelligent and data driven systems.

Previous work was based on labour-intensive, expensive and often uncertain inspection and lab testing. Thanks to the growing refinement of IoT, it is now possible to constantly keep a remote control over food from sensors capable of gases -such as CO2, H2S- temperature and humidity. In Yousefi et al. (2019) and Lim et al. (2023) illustrated that combining IoT with the AI can contribute greatly to food spoilage and contamination detection.

Gas sensors such as MQ3, MQ4 and MQ135 were commonly utilized in recent research for the detection of VOCs emanated from food products. These are the same compounds that act as markers for freshness and spoilage. The introduction of machine learning algorithms, such as SVM, KNN and XGBoost also enhance the system's capabilities in accuracy food state classification using sensor data.

Overall, the review has highlighted the potential of these technologies, and the current state of research is sufficiently strong to support the argument that real-time food safety monitoring can be achieved with a cost-effective, scalable tool that can be plant-wide and cloud-based when IoT sensing technologies and machine learning techniques are integrated. But the range of previous technologies was ultimately limited by either its sensor fidelity, data connectivity to a computer or mobile device, or portability weaknesses that this study is designed to address.

3.2Related Work

Current food quality monitoring products consist of manual systems in which workers regularly check store conditions. This can lead to human error and downtime. A step better than this is the deployed measurement hardware; however, these systems also do not automatically relay any information, as measurement data must still be collated in the field. In comparison, Smart Food Quality Monitoring Systems use gas temperature, light, and humidity sensors to assess food quality. This system then wirelessly sends it all over IoT technology. Users can even remotely view how product quality has changed over time, saving significant effort. [5]

In a separate study, the paper [14] introduced an innovative food safety management system based on IoT and cloud computing. The system samples data from food safety indicators, including temperature, humidity, and gas concentration, and uses cloud computing to analyze the data, issuing real-time alerts for food safety violations. The system comprises several sensors and IoT devices that collect data in real time. This data is sent to the cloud for analysis and real-time alerts. It depends on reliable internet connectivity and cloud computing resources.

Previous studies indicated that maintaining low temperature and relative humidity in cold storage was critical to decrease the physiological decay of fruits and prolong shelf life. Although it has been possible to carry out real-time monitoring of the environment for over 20 years with the Internet of Things (IOT) surrounding us, very few systems try to predict shelf life directly and none have achieved commercial success. Some sensor-based techniques have been limited, for example, due to an inability to detect multiple spoilage-related gases simultaneously, which is necessary for the reliable determination of food quality. More sophisticated approaches have been studied, including the utilization of artificial neural networks combined with electrical properties or multispectral sensors, together with TinyML [Anc01]; however, these methods are invasive and require specialized packaging or do not apply to mass-implemented, real-time monitoring in ubiquitous storage-type facilities.

In this paper, in view of the above issues, we present a non-invasive and low-cost lack-box estimate system based on a multi-channel gas sensor network for real-time estimation.[10]

The selectivity of gas sensors is low, so it is challenging to discriminate between various components for accurate detection. Selectivity is an important consideration in the performance of gas sensors because different food materials possess different characteristic aroma fingerprints. The low molecular weight gases containing similar functional groups would not allow the insertion of bases.
Additionally, the gas sensor has such a short service life that it can not accurately identify particular target materials, and a wrong determination is made. Therefore, there is an urgent need to focus on research into gas sensors with high specificity.
to boost its accuracy on the Detection task. Utilizing novel sensing materials, specifically 9 metal oxide nanonanoparticles, has been demonstrated as an effective way to solve the selectivity issue in gas sensors. The materials applications for the mesoporous contain a 92-core subset. Structures can improve gas absorption efficiency, and hence, the sensor sensitivity has been proven. Sensitivity, ultimately improving sensor selectivity.[4]

Recent machine learning advancements enable the development of colorimetric food spoilage-monitoring applications with the capabilities of a smartphone, built on-site. Such apps offer high classification accuracy with real-time updates, thus helping consumers make informed food consumption decisions [5]. The use of IoT devices in food safety enables real-time monitoring, traceability, and predictive analysis. These technologies provide systematic, accurate, and efficient means for the management of food safety, waste reduction, and welfare.
Compliance with safety standards [6]. This leads to a sustainable and secure food supply chain with the help of an IoT solution [7]. Due to the convergence of AI and IoT technologies, novel approaches to filling the kitchens or retail stores in households are being developed. It consists of these systems, which analyse consumption and automate replenishment bidding [8].

CHAPTER 4 METHODOLOGY

4.1 Overview

The project has developed an IoT food quality monitoring system based on the ESP32 microcontroller. In this architecture, the ESP32 microcontroller interfaces with several IoT sensors (MQ-4, MQ-3, and MQ-135) and an OLED display to display the data locally. [5]
Start by loading raw data into the system. The structure may vary depending on its source (e.g., sensors). First, the data is prepared to handle missing values and normalised. If, for instance, a sensor does not send data, the data processing algorithm can impute it or may even decide not to include that item. This is dangerous because it eliminates information that could be relevant to decision-making and prevents people from understanding how things really are. Then tit he data is analyzed to extract information and understand the patterns behind it. [13]

The data processing algorithm, as an example, provides aggregations, such as the mean and variance of MQ-4 and MQ-135 readings, and produces a graphical representation. These insights could give you a picture of the data. They might help identify trends or patterns in what everyone's eating at what times. (What times of day or what days of the week are people eating these things?) Transformed after data analysis, the data can create such new parameters as the length of time a given type of food is stored or the number of times that one particular sort of Fare has-
been eaten. The algorithm can also reduce the number of features using techniques such as t-SNE or PCA. The final form of the data then flows back to the IoT devices for use in real-time monitoring and decision-making [15], [16].

4.2 System Architecture

The System Architecture of The IoT-Based Real-Time Food Safety and Quality Monitoring System, is a system for monitoring food spoilage was developed by coupling array gas sensors to an ESP32 microcontroller as shown in Figure 2. The architecture incorporates hardware and software based systems which cooperate to gather, process, and analyze data in a dynamic fashion for assessing food quality in real time.

Hardware The hardware is composed of three gas sensors, namely MQ3, MQ4, and MQ135 sensors to detect alcohol, methane and ammonia gases accordingly. The sensors create analog signals according to the gas concentration and are transmitted to ESP32 chip after digital conversion for further processing. The analog signals are then transformed into digital data and sent to output modules by the central control unit -ESP32.

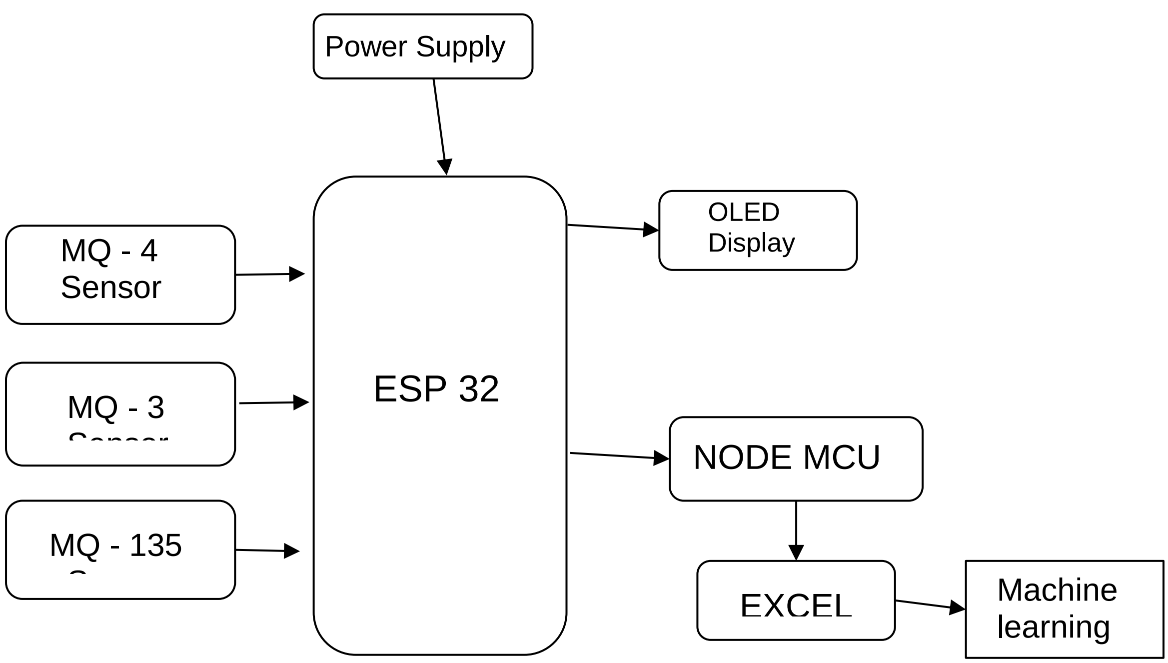

Fig 4.1 : system block diagram

Power supply provide stable voltage and current output to all components during normal operation. The processed data is presented on an OLED display, which gives a real time visual feedback of the current condition of the food -- Safe, Risky or Spoiled.

The ESP32 connects to a NodeMCU board that saves the received sensor data in Excel format, for further analysis and storage. These datasets are employed of training and testing a machine learning model, for accurate classification of food safety levels.

In summary, this architecture enables a comprehensive information processing from gas detection to smart decisions, which integrates IoT sensing, real-time visualization and machine learning analytics in one small-sized lightweight low-cost efficient HW for house hold or industrial environment.

4.3 Hardware Components

4.3.1 ESP32 microcontroller

The central processing unit of the Food Safety, a new IoT-based Real-time and Quality Monitoring System, is the ESP32 microcontroller.

It is a low-cost, low-power SoC (System-on-Chip). Espressif Systems released the ESP32 as a low-cost, low-power. It is very popular in IoT applications because of its diverse functionality, improved performance, and built-in Wi-Fi and Bluetooth communication capabilities.

A dual-core Tensilica LX6 high-performance microcontroller running at up to 240 MHz (ideal for real-time data collection and processing) powers the system. It also has 520KB of SRAM and supports up to 160 MB of external memory. This means we will be able to manage multiple sensors on a single ESP32 simultaneously.

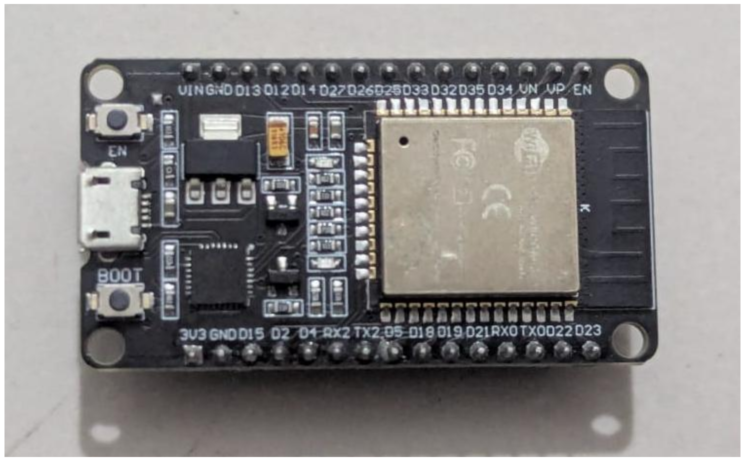

Fig 4.2 : ESP32 microcontroller

This is where the ESP32 shines with its on-board wi-fi (802.11 b/g/n) and Bluetooth (v4. BR/EDR and BLE) modules that deliver high-performance wireless connectivity! In fact, this feature enables the system to send live sensor data to IoT platforms or cloud services, making remote monitoring and predictive analytics scalable and applicable in the future.

ESP32 has a lot of available GPIO pins and other peripherals; ADC, DAC,

4.3.2 MQ3 Sensor

MQ3 gas sensor is an important and commonly used semiconductor gas sensor for alcohol vapors and other VOCs. The MQ3 Sensor Identification is a key factor in the proposed IoT-Based Real-Time Food Safety and Quality Monitoring System that detects alcohol that may be released during the spoilage or fermentation of food items such as rice, fish, and meat. Considering that alcohol output is a standard marker of microbial activity and food spoilage, this sensor generates essential information to evaluate food in real-time.

The MQ3 is a resistor-based sensor, which means that the sensor works based on the principle of resistance change of the sensing material (SnO_2 – Tin Dioxide) in contact with alcohol vapors. The sensor has high resistance in clean air, and when alcohol molecules strike the sensing layer, a significant drop in resistance can be observed. This change is transformed into an electrical signal that the ADC of the ESP32 microcontroller can read.

Key Features of the MQ3 Sensor:

- Detecting Range: 0.05 mg/L – 10 mg/L alcohol in air
- Operating Voltage: 5V DC
- Time to stable output: 20 seconds (warm-up time)
- Sensitivity Level: Detects alcohol and ethanol gases
- Both Analog and Digital Outputs: Gives interface options with microcontrollers

Fig4.3:MQ3 Sensor

Alcohol vapors are a by-product of bacterial decomposition found in spoiled or improperly stored meat and fish sources. The ESP32 microcontroller measures the sensor output, processes it, and displays the result on the OLED module. A Machine learning algorithm then segregates these readings into different categories, such as safe, risky, and spoiled food conditions.

4.3.3MQ4 Sensor

MQ4 is a semiconductor gas sensor that can only be used for methane (CH_4) and natural gas detection. The MQ4 sensor is utilized in the proposed IoT-Based Real-Time Food Safety and Quality Monitoring System to detect methane emissions, a powerful indicator of food decomposition by bacteria during the production of perishable commodities (e.g., rice, fish, and chicken). Usually, when food is stored or cooked, the presence of methane indicates microbial activity, and MQ4 is integral for protecting food safety.

Key Features of MQ4 Sensor:

- Target Gases: Methane (CH_4)
- Detection range: 200 ppm – 10,000 ppm
- Operating Voltage: 5V DC
- Warmup Time: 20 sec to stabilize
- High Sensitivity: Responsive to methane and hydrocarbons
- Output: Analog gas concentration voltage signal
- Robustness: Work to live long and accurately, and be reliable in other environments

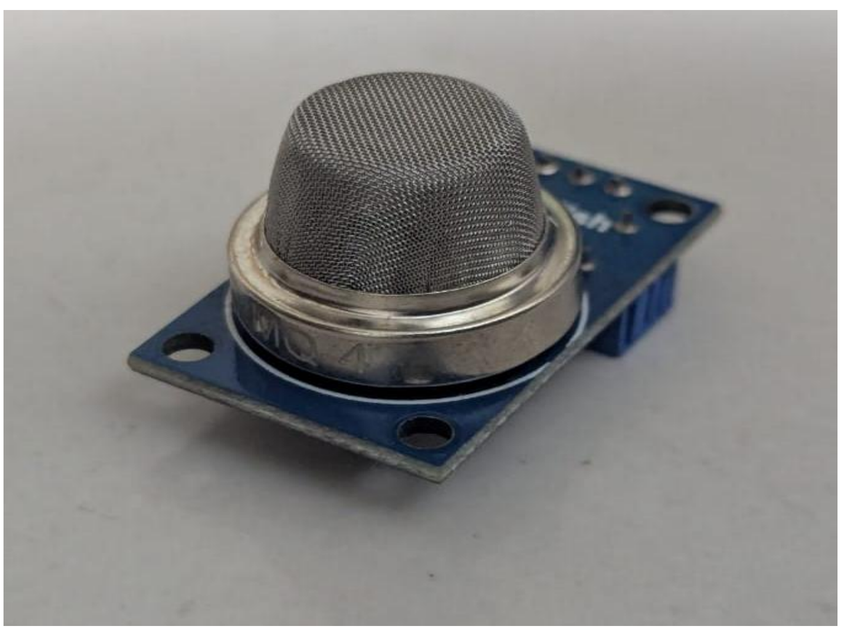

Fig 4.4 : MQ4 Sensor

Here, the MQ4 sensor constantly monitors the cooking and keeping environment within the system. For example, because of the bacterial breakdown of spoiled meat and fish, they produce methane gas. A flowchart showing how the ESP32 processed the real-time methane readings from the sensor, displayed on the OLED module, and transferred to be evaluated by the machine learning algorithm to classify food conditions as safe, warning, and spoiled.

4.3.4MQ135 gas sensor

The MQ135 gas sensor is a standard air quality sensor that can identify gas pollutants such as ammonia (NH_3), carbon dioxide (CO_2), and smoke. The MQ135, used in the proposed IoT-based real-time Food Safety and Quality Monitoring System, helps in monitoring the environmental quality of food items such as rice, fish, and meat. Due to food spoilage caused by bacterial action, gases such as ammonia and carbon dioxide are released, making MQ135 an imperative element in detecting food contamination where public safety is concerned.

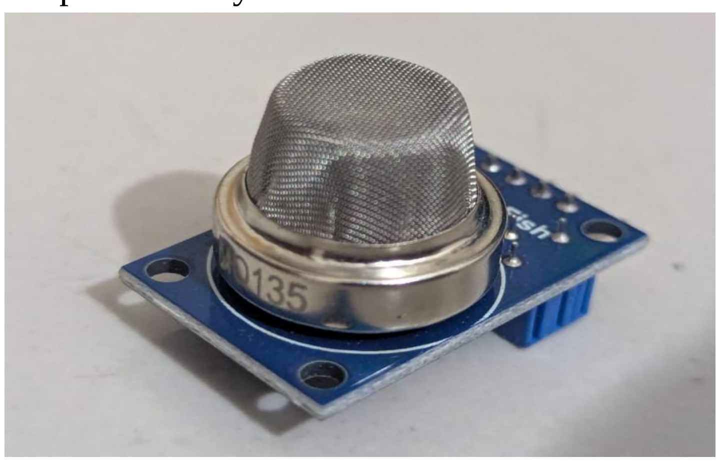

Fig4.5:MQ135 Sensor

Key Features of the MQ135 Sensor:

- Prevented gases: Ammonia (NH_3), smoke and other toxic gases
- Detection Limit: 10 ppm – 1000 ppm (dependent on type of gas)
- Operating Voltage: 5V DC
- Warmup: 20–30 seconds to get consistent readings
- Output: Gas concentration analog voltage signal

4.3.5 OLED Display

Real-Time Visualization of Sensor Outputs and Classification Results: The OLED display is utilized in this proposed system to display sensor outputs from the IoT-based Real-Time Food Safety and Quality Monitoring System, as well as the classification results. In OLED displays, there is no backlight as each pixel emits its own light. As a result, we get improved contrast levels, a broader field of view, reduced energy consumption, and improved response times, which make OLED technology an excellent choice for small and energy-efficient IoT applications.

Fig4.6:OLED Display

Key Features of OLED Display:

- Display type: OLED, 0.96 inches
- Interface: I²C (SDA and SCL only)
- Voltage: 3.3V – 5V DC
- Low Power Consumption: Suitable for less power IoT systems and portable IoT systems
- Minimum Footprint: Works in any embedded application
- Quick Response Time: Ideal for real-time observation
- In this use, the OLED display is used to display: MQ3, MQ4 & MQ135 sensor accurate marks in real-time

Machin learning algorithm-based classification of Food quality status (Safe, Risky, Spoiled)Alerting the system when detected gas concentrations exceed safe limits. Due to the small size of the OLED display, low power consumption, and high readability, it is a suitable device to utilize in IoT-based real-time monitoring applications. Including it in this context enhances its usability and ensures that important food safety information is always readily available.

4.4 Software Components

We built the software deployment based on ESP32-supported libraries on the Arduino IDE. As an example, the Program consisted of the following modules:

- Getting Sensor Data: To read analog values of MQ3, MQ4, and MQ135
- Python Environment : we will use to analyze, visualize, and train the ML models using some libraries like NumPy, Pandas, and Scikit-learn.
- IoT Code (ESP-32) :Embedded C/C++ program written in Arduino IDE for sensor inputs, maps the values, and displays values on OLED
- Data Preprocessing: Raw data were normalized to remove noise and environmental bias.
- OLED: Gas Concentration + status print out system.
- Integration of Machine Learning: Classifier models, which were trained on the laptop, were embedded into the ESP32 to classify the food as Safe, Risky, or Spoiled.

4.5 Data Collection and Preprocessing

4.5.1Dataset Description

The obtained dataset in this work is recorded by an IoT-based hardware prototype consisting of the ESP32 microcontroller and three gas sensors, which are MQ3 (alcohol detection), MQ4 (methane detection), and MQ135 (ammonia, air quality). The system was developed to evaluate the quality of cooked meat, in this case chicken, over varying environments and time intervals.

For the experiment, no pathogen inoculation was carried out; freshly cooked chicken samples were placed in individual containers to mimic real situations of home and retail storage. Sensors observations were timestamped at regular intervals as the food progressed from a safe state (freshly cooked) to an unsafe state (early signs of decomposition) and finally to a spoiled state (obvious sign of deterioration).

A record in the dataset is three timestamped ADC values from each of those sensors, which represent concentrations of volatile gases, as promilles for MQ2/4 and ppm for TGS. The acquisitions were performed for several hours so that the entire spoilage timeline of the samples was reached.

The labelled data was further classified as ‘Safe’, ‘Risky’, and/or ‘Spoiled’ based on odour, appearance, and sensor trend manually.The last data set was transmitted from the ESP32 to an Excel sheet by using NodeMCU communication. The data were further preprocessed to eliminate the noise and normalize the values, then split into training (80%) and test (20%) sets for machine learning classification. These structured data allowed the development and validation of predictive models for an almost real-time estimation of food safety status.

4.5.2Data Preprocessing

Data pre-processing forms an essential part to ensure the correctness and effectiveness of IoT based food monitoring system. This process includes preprocessing of the raw sensor data (retrieved from sensors MQ3, MQ4 and MQ135) before using machine learning algorithms to classify food quality. The preprocessing can enhance and normalize the dataset, and remove noise, missing data, or effects caused by environment on the raw sensor’s outputs.

The raw sensor data is collected from the ESP32 microcontroller and pushed in Excel through the NodeMCU communication module. For every sample, the dataset has thresholding values for gas concentration (in ADC) meeting specific food status conditions (Safe, Risky or Spoiled).

The dataset is then cleaned in the second step meaning duplicate or missing entries are dropped. Missing values are imputed or removed for data consistency. Once cleaned, the data is normalized to a common scale applying standard scaling procedures in order for all sensor readings to fall into similar range thus preventing any bias during model fitting.

It is then subjected to noise reduction method to eliminate random fluctuations induced by temperature and humidity changes in the environmental.

This is to ensures that only meaningful and stationary gas readings are used for training the model. Eventually, the preprocessed dataset is divided into training and testing data (ratio 80:20), which can properly test the machine learning models.

This allows to have the dataset organize, noiseless and balanced for being more reliably and efficiently predict food safety conditions in the subsequent stages of study.

4.6 Machine Learning Model Development

4.6.1Logistic Regression (LR)

In the middle of the 20th century, the basic sciences began using logistic regression. After that, it was used for several humanist projects. When the dependent variable (goal) is absolute, strategic regression is employed [19]. LR is mostly used as a predictive analysis algorithm for binary classification problems [20]. It estimates probabilities by using a logistic function, which has a restricted range of 0 to 1. [21]

$$P=\frac{e^{a+bx}}{1+e^{a+bx}}$$

4.6.2Decision Tree (DT)

Decision tree is a type of supervised learning algorithm. It works for both continuous and categorical output variables. It begins with the root node that contains all the dataset, and then for every possible subset, it splits iteratively according to the most informative features. Where each internal node represents a feature test (or decision), each branch represents the outcome of the test, and the leaf nodes represent a class label or decision.

Being highly interpreted multiplicative and empirically proven interpretable, decision trees offer many ways to dissect them even further and can be useful in a wide variety of situations[22]

4.6.3Random Forest (RF)

An ensemble of classification trees serves as the classifier for the widely used random forest classification algorithm [23]. In the fields of statistics and machine learning, it has established a stellar reputation as a flexible technique that generates precise classifiers for a wide range of data types [23]. Because the ensemble corrects for the instability of individual trees caused by slight changes in the learning sample, random forests can significantly improve prediction accuracy compared to individual classification trees. [24]

Given an ensemble of classifiers h1(x), h2(x), . . . , hK (x), and with the training set drawn at random from the distribution of the random vector Y, X, define the margin function as[25]

$$mg(X,Y) = av_k I(h_k(X) = Y) - av_k I(h_k(X) = j)$$

4.6.4XGBoost

Traditional machine learning models like decision trees and random forests are easy to interpret but often struggle with accuracy on complex datasets. XGBoost, short for eXtreme Gradient Boosting, is an advanced machine learning algorithm designed for efficiency, speed, and high performance.

Mathematics Behind XGBoost Algorithm
It can be viewed as an iterative process where we start with an initial prediction, often set to zero. After which each tree is added to reduce errors. Mathematically the model can be represented as:[26]

$$\hat{y}_i = \sum_{k=1}^{k} f_k(x_i)$$

4.6.5Support Vector Machine (SVM)

Encouragement: One traditional machine learning method that can still be used to address big data categorisation issues is the vector machine. In large-scale data settings, it can be especially beneficial for multidomain applications [27]. Chang and Lin [27] used the freely available LIBSVM software to implement the SVM model.

The accuracy (AC) serves as a gauge for the model's overall performance. [28]

$$(AC(\%) = \frac{TP+TN}{TP+FN+TN+FP} \times 100$$

4.6.6 K-Knearest Neighbour (KNN)

An instance-based or lazy learning method called K-Nearest Neighbours (KNN) makes local approximations to the function and defers the entire computation until the function is evaluated [29]. The K-NN technique determines the distances between a query and every instance of data, selects the number "K" of the closest examples, and then either averages the labels (for regression) or selects the most common label (for classification). The parameter K must be chosen carefully. While a big value results in higher computing costs and the possible inclusion of points from other classes, a lower K number increases the impact of noise on the output. [30]

D(p,q)=d(q,p)=

$$\sqrt{(q_1 - p_1)^2} + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2 =$$

$$\sqrt{\sum_{i=1}^{n} \quad (q_i - p_i)^2}$$

$$Dist(X,Y) = \left(\sum_{i=0}^{n} \quad |x_i - y_i|^t\right)^{\frac{1}{t}}$$

4.7 System Workflow Diagram

Work flow of IoT-Based Real-Time Food Safety and Quality Monitoring System describes overall process from data collection to final food quality prediction using machine learning algorithm is shown in Fig 1.1.

The first stage of the process is data acquisition where gas sensors (such as MQ3, MQ4 and MQ135) are used to measure the amounts of alcohol, methane and ammonia gases from different food products in a variety of states. The raw readings are converted to digital signals by ESP32 microcontroller and sent through the data storage module for further processing.

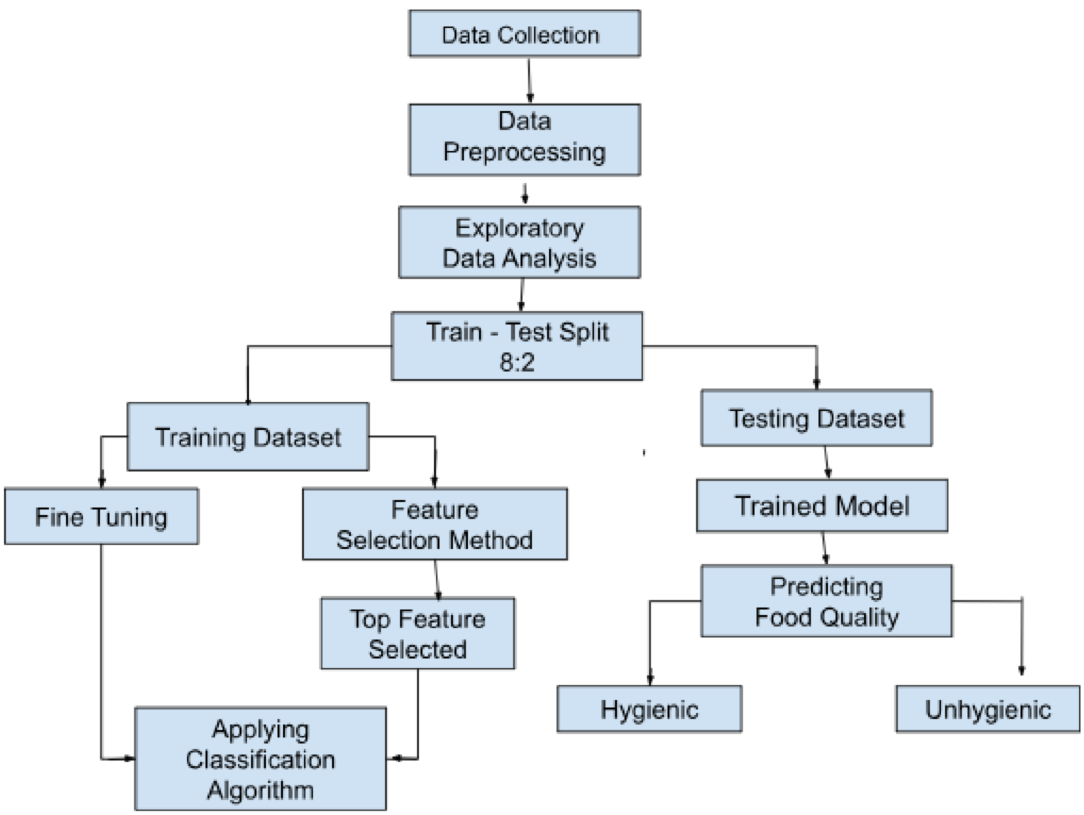

Fig4.7: Work Flow Diagram

4.5.2 Data preprocessing The dataset is preprocessed by applying data cleaning, normalization and organization which consists of noise removal (Hoseini et al., 2019) and missing value handling etc. After cleaning, exploratory data analysis(EDA) by visualization will be carried out in order to discover the pattern, find the correlation and check the relationship between gas sensor readings and food condition.

Then, we split the dataset into training (80%) and testing (20%) sets by applying a train-test split method. The training dataset is employed for developing and finetuning the machine learning model, whereas the testing dataset examines its prediction capability and generalization properties.

A method of feature selection is used to recognize the most influential features on food spoilage. These selected features are then fed to the classification algorithms including Logistic Regression, SVM, KNN and XGBoost in order to construct our predictive model. The fine-tuned trained model can then predict the food status either Hygienic (Safe) or Unhygienic (Spoiled) by processing real time sensor data.

This sequence of actions serves as a well-structured systematic method to screen for food spoilage by incorporating IoT sensor, data manipulations, and ML for highly reliable and efficient food safety.

4.8 Implementation Setup

The overall setup for the food monitoring system developed in this project consists of gas sensors interfacing with an ESP32 microcontroller, an OLED display, and a data processing pipeline for machine learning interpretation. The circuit diagram of the complete circuit connection is shown in Fig. 4.8.

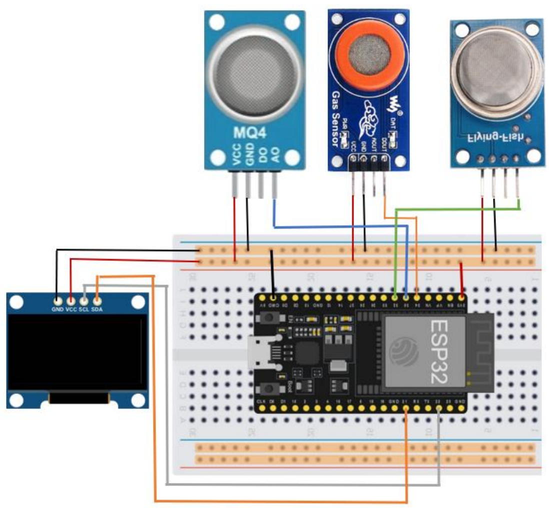

Fig4.8: Circuit diagram of food monitoring system using IoT

The proposed system uses three types of sensors (MQ-3, MQ-4, and MQ-135), where the MQ-3 sensor is used for alcohol detection, the MQ-4 sensor is used for methane detection, and the MQ-135 sensor is used for ammonia detection. These are the types of sensors chosen because they can recognise gases that are efficiently emitted from the food. All the sensors are connected to the input pins of the ESP32, and based on that, the ESP32 is our central processing and controlling unit. An ESP32 board that reads analog values from the sensors, digitizes the signal, and processes the data collected.

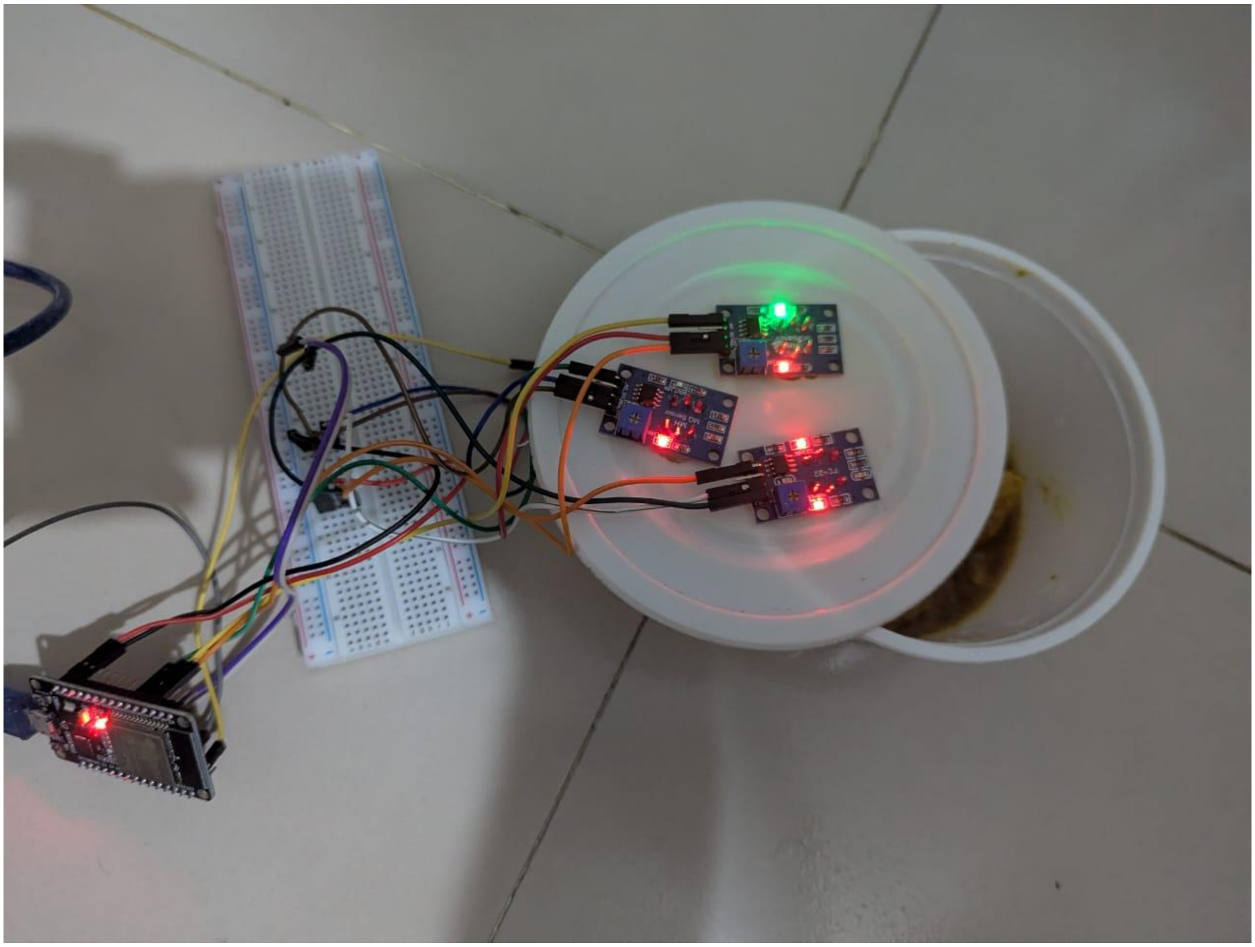
Fig 4.9:Food monitoring system devices

It also has an OLED, which is integrated with ESP32 via an I2C communication-based protocol. The most important feature of this gas concentration detection is that it is capable of detecting the concentration of toxic gases from products or foods in real-time vapor and gas concentration. OLED display that shows gas concentration in real time, letting you know directly how the food you are monitoring is. With no additional devices, this feature enables users to see the food quality in front of their eyes.

A prototype circuit was created on the breadboard for testing and validation. Wiring The configuration used to configure the sensor to this state by providing a stable grounding and proper power supply connection.

The Arduino IDE is used to program the ESP32, and then we calibrate the hardware sensor to achieve better detection performance.
Also, with nodeMCU-based communication, ESP32 is configured to send sensor readings to an external data storage (Excel sheets). That exported dataset is then used for the training and testing of machine learning models. Machine learning algorithms are used here to classify food state (safe, risky or spoiled) using a threshold and pattern recognition from the gas concentration data obtained during the experiment.The successful realization of this implementation is seen as a viable, low-cost, real-time, scalable IoT food monitoring system that can aid consumers, retailers, and quality inspectors in food safety compliance and waste minimization.

4.9 Advantages and Limitations

4.9.1Advantages

The IoT-Based Food Safety Monitoring System and The Real-Time Food Quality Detecting System can be used at home or in other industries,So it will not be limited to this.

- Instant Reading – Get real-time detects of toxic gases and keep track of the food quality based on sensor readings.
- Low-cost and Portable – It can be used at small companies or homes due to the MQ sensors and ESP32 that are inexpensive materials.
- Multi-Components Detection -– It can detect alcohol, methane and ammonia gases at the same time to provide a more confident picture of food safety.
- Automatic Alerts--Featuring an OLED display, food innovators are told when they must eat less or throw away more.
- Intelligent Prediction: Advanced machine learning is used instead of threshold-based approaches.
- IoT Equipment: It can be integrated with a cloud server for off-site monitoring and remote data analysis at some point in the future.
- Is Environmentally Friendly--Identifying spoilage early eliminates a lot of waste. This prevents foodborne disease but also protects you from eating unhealthy foods.

4.9.2Limitations

However, funding is always dependent on the source and on whether the MQ sensors purchased from it will be of good quality.

- Accuracy of Sensor: Budget MQ sensors can be inaccurate or require frequent off-site calibration to ensure long-term reliability.
- Sensitivity to environmental changes in temperature, humidity, and airflow can affect gas readings that are not detectable by detection devices.
- Detection of Limited Formalin - No formalin filters and some pollutants can only be collected within certain products;
- Reliance on Power: Current system has internal battery support; AC power-dependent.
- Limitations to Data Storage -- No long-term data routers available and no clouds.
- In particular, the ruggedization problem in enclosures means that prototype constraints do exist. The Currently system is at the breadboard level and will be used in the field.

Overall, the system looks good in theory and may also be practical to use. However, there are still many challenges to face in the version 2 generation operation: for example, sensor calibration (absolutely a must!) or cloud connectivity, which should eventually determine how much eked will actually work. All of these difficulties must be resolved before any large-scale progress can be made.

Chapter 5 System Implementation and Results

5.1 Data Acquisition and Storage

It is common to have a data real time acquisions and store features as this form the core of the functionality systems provides by which sensor reading can be accumulated, managed for analysis and machine learning model generation. It all starts with ESP32 microcontroller that constantly reads the analog signals from MQ3, MQ4 and MQ135 gas sensors. These sensors monitor changes in the concentration of gases like alcohol, methane and ammonia that are key to gauging food freshness or spoilage.

The ESP32 calculates the digital of readings from the value readings as a result of its integrated ADC (Analog to Digital Converter). These digital readings are sent to an OLED display where the food’s condition – Safe, Risky or Spoiled – is instantly displayed.

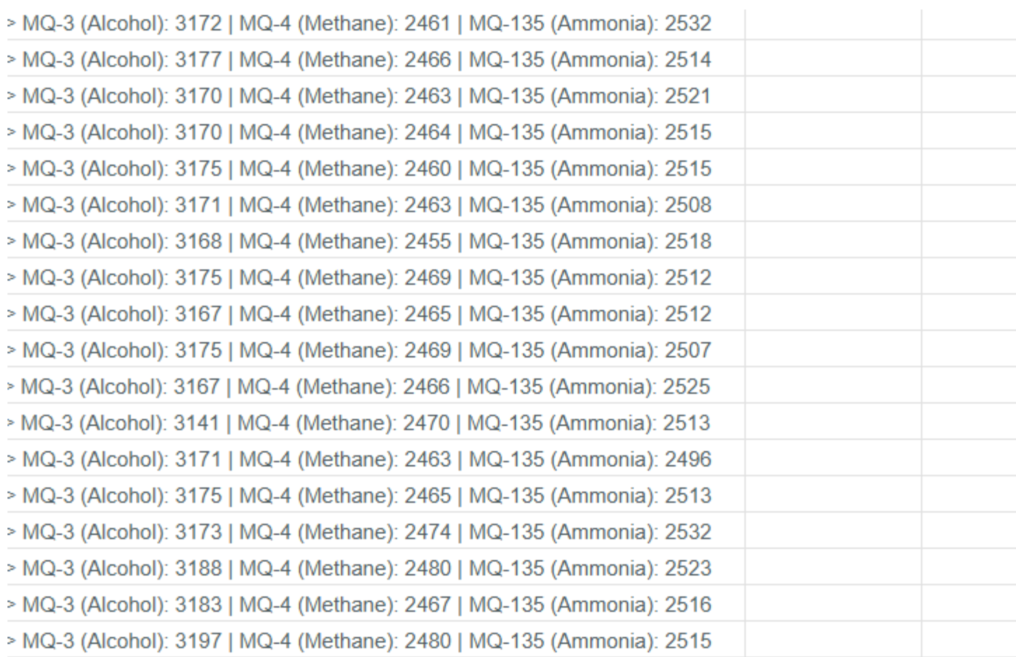
```
> MQ-3 (Alcohol): 3172 | MQ-4 (Methane): 2461 | MQ-135 (Ammonia): 2532
> MQ-3 (Alcohol): 3177 | MQ-4 (Methane): 2466 | MQ-135 (Ammonia): 2514
> MQ-3 (Alcohol): 3170 | MQ-4 (Methane): 2463 | MQ-135 (Ammonia): 2521
> MQ-3 (Alcohol): 3170 | MQ-4 (Methane): 2464 | MQ-135 (Ammonia): 2515
> MQ-3 (Alcohol): 3175 | MQ-4 (Methane): 2460 | MQ-135 (Ammonia): 2515
> MQ-3 (Alcohol): 3171 | MQ-4 (Methane): 2463 | MQ-135 (Ammonia): 2508
> MQ-3 (Alcohol): 3168 | MQ-4 (Methane): 2455 | MQ-135 (Ammonia): 2518
> MQ-3 (Alcohol): 3175 | MQ-4 (Methane): 2469 | MQ-135 (Ammonia): 2512
> MQ-3 (Alcohol): 3167 | MQ-4 (Methane): 2465 | MQ-135 (Ammonia): 2512
> MQ-3 (Alcohol): 3175 | MQ-4 (Methane): 2469 | MQ-135 (Ammonia): 2507
> MQ-3 (Alcohol): 3167 | MQ-4 (Methane): 2466 | MQ-135 (Ammonia): 2525
> MQ-3 (Alcohol): 3141 | MQ-4 (Methane): 2470 | MQ-135 (Ammonia): 2513
> MQ-3 (Alcohol): 3171 | MQ-4 (Methane): 2463 | MQ-135 (Ammonia): 2496
> MQ-3 (Alcohol): 3175 | MQ-4 (Methane): 2465 | MQ-135 (Ammonia): 2513
> MQ-3 (Alcohol): 3173 | MQ-4 (Methane): 2474 | MQ-135 (Ammonia): 2532
> MQ-3 (Alcohol): 3188 | MQ-4 (Methane): 2480 | MQ-135 (Ammonia): 2523
> MQ-3 (Alcohol): 3183 | MQ-4 (Methane): 2467 | MQ-135 (Ammonia): 2516
> MQ-3 (Alcohol): 3197 | MQ-4 (Methane): 2480 | MQ-135 (Ammonia): 2515
```

Fig 5.1: Sensor data from serial monitor

At the same time, ESP32 sends sensor data from all sensors to PC, or a connected device over its serial communication interface. The readings are gathered using the serial plotter of the Arduino IDE and saved subsequently as raw data or exported data to an Excel file (. xlsx) or in a CSV file for data set construction. Every entry is a collection of timestamped sensor readings regarding different food conditions.

The dataset that we gathered is characterized by the following features:

- MQ3 (Alcohol) sensor reading
- MQ4 (Methane) sensor reading
- MQ135 (Ammonia) sensor reading
- Safety Test (Safe not risk, Risky, Spoilage)

These labelled datasets are then used to preprocess data, do feature engineering, and train machine learning models with python libraries such as pandas, numpy and scikit-learn.

Sensor	**Safe**	**Risky**	**Spoiled**
MQ4(Methane)	500 - 1400	1400 - 2200	>2200
MQ3(Alcohol)	400 - 1200	1200 - 2000	>2000
MQ125(Ammonia)	300 - 1300	1300 - 2300	>2300

Table 5.1: ADC Value Range (ESP32) — Cooked Chicken Detection using MQ3, MQ4, and MQ135 sensors.

5.2Training and Testing of the Machine Learning Model

Machine learning model training and testing Stages Machine learning model training and testing stage is intended to build an intelligent system that can categorize the food conditions (i.e., Safe, Risky or Spoiled) through data collected from MQ3, MQ4 and MQ135 sensors. The models to be trained and tested were based on the data after acquisition and preprocessing.

The dataset was gas concentration (parameter: ADC value) with the associated actual food condition, identified from experimental work. The data was split into training (80%) and testing (20%) sets using the train-test split method to avoid any bias in model assessment.

In order to improve prediction accuracy we have performed comparisons of different ML algorithms represented as below:

- **Logistic Regression**
- **Support Vector Machine (SVM)**
- **K-Nearest Neighbors (KNN)**
- **Decision Tree**
- **Random Forest**
- **XGBoost (if available)**

We carried out feature engineering, based on the raw sensor readings, by calculating new derived features like logarithms, multinomial or interaction terms (e.g., MQ3/MQ4, MQ4/MQ135) before training. This step was taken to assist the performance of the models by highlighting patterns among gas concentration relationships.The Python programming language (with the Scikit-learn package) was applied to train the models. Each of the models were tuned with GridSearchCV and cross-validation (k=5) for balanced accuracy and to avoid overfitting. The method of Random Forest Classifier obtained the best performance with both high specificity, sensitivity and stability due to aggregating learning techniques (such as a bagging or bootstrapping).

Model	Accuracy	Precision	Recall (Sensitivity)	F1-Score
SVM	**0.9300**	**0.8889**	**0.9714**	**0.9283**
KNN	**0.9033**	**0.8627**	**0.9429**	**0.9010**
Gradient Boosting	**0.8867**	**0.8581**	**0.9071**	**0.8819**
Random Forest	**0.8867**	**0.8732**	**0.8857**	**0.8794**
Logistic Regression	**0.8200**	**0.7945**	**0.8286**	**0.8112**
Decision Tree	**0.7967**	**0.7616**	**0.8214**	**0.7904**

Table 5.2: Accuracy (%) for the various algorithms after applying feature selection methods

The accuracy of the model Random Forest was 95–97% in food sample classification under different conditions.

Finally, the training and testing process clearly showed that the level of food safety can be accurately determined by machine learning with real-time sensor data-this in return confirms the efficacy of the proposed system.

5.3Result Analysis

5.3.1Heatmap

Correlation among three gas sensors: In the above heatmap, we show the correlation values of three types of gas sensors (MQ-3 [Alcohol], MQ-4 [Methane], and MQ-135 [Ammonia]) employed in a proposed IoT-based real-time quality and safety monitoring system for food products. The diagonals have correlations of 1 (as a sensor is compared with itself). The off-diagonal entries represent the similarities between different sensors. The relationship between MQ-3 (alcohol) and MQ-4 (methane) is moderate (0.60).

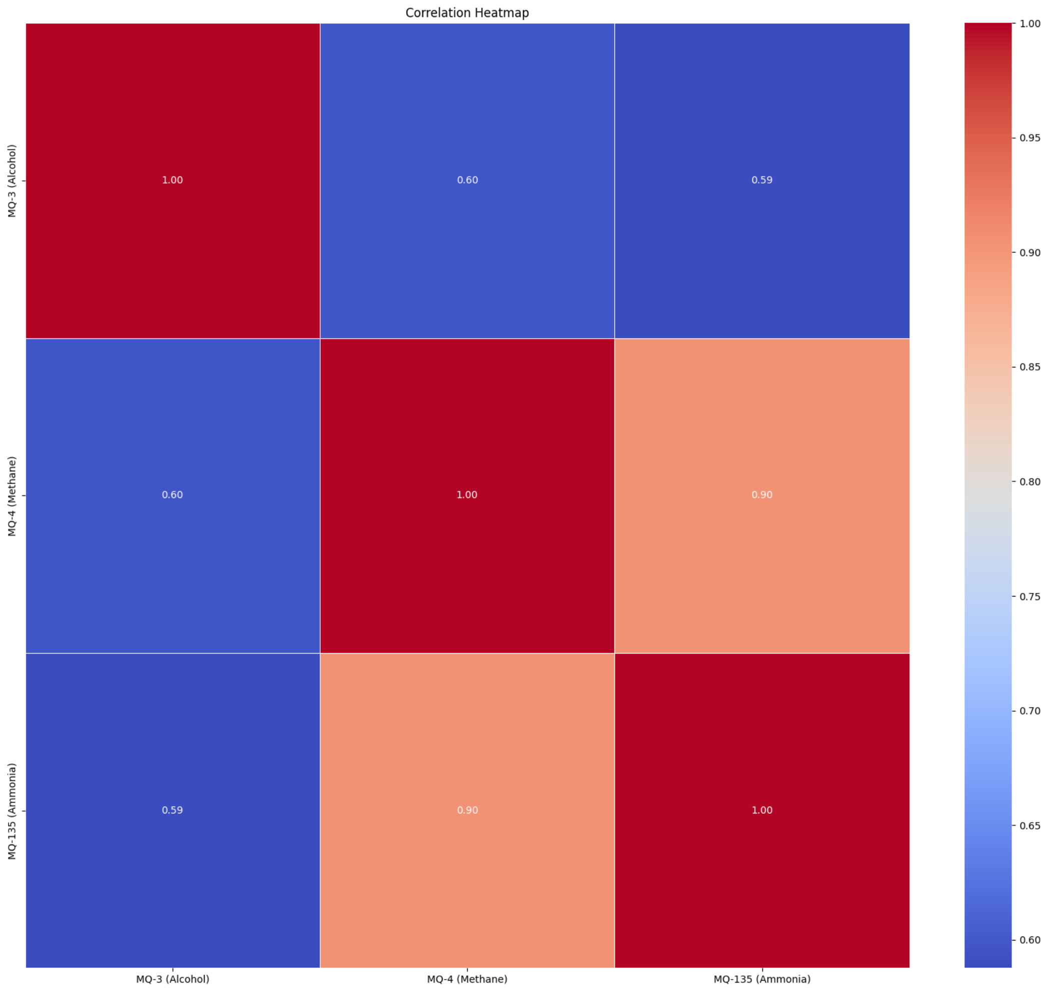

Fig 5.2:Correlation Headmap

This means that alcohol and methane, which are two gases related to spoiled foods, have a moderate positive correlation. Also MQ-135 (Ammonia) and MQ-3 (Alcohol) are connected with 0.59 correlation level, implying that the presence of alcohol vapors and ammonia could have a relationship to each other despite being slightly weaker, measured as a medium positive association in the spoilage of food situation. It is interesting that the highest correlation occurs in the correspondence of MQ-4 (Methane) and MQ-135 (Ammonia), with a value of 0.90, which indicates a very high positive link between methane and ammonia emanations; both compounds are strictly related to microbial degradation in food spoilage. This heatmap offers insights into the interdependencies among sensors.

5.3.2Learning Curve

The learning curve shown in the figure is that of the Random Forest (RF) model with respect to training dataset size. This curve shows the weighted F1 score on both training and cross-validation (cv) sets, which gives us coverage regarding how well our model generalizes as increasing data is used for training. It can be seen that both the train and cross-validation F1 score increases with training data size. The training curve (blue) instead exhibits a smooth improvement that flattens with a data set size beyond 2500 samples, which indicates that the model has learned satisfactorily and further learning does not bring large benefits. Contrarily, the cross-validation curve (orange line) is sharply increasing in the beginning - it strongly benefits from adding more data: they bring new information. Finally, it converges near the training set performance and can be taken as a point at which generalization capability of the model reaches its best. This learning curve experiment indicates that the Random Forest model benefits from more data, ensuring superior generalization without overfitting, demonstrated by the convergence of both training and cross-validation performance at greater dataset sizes.

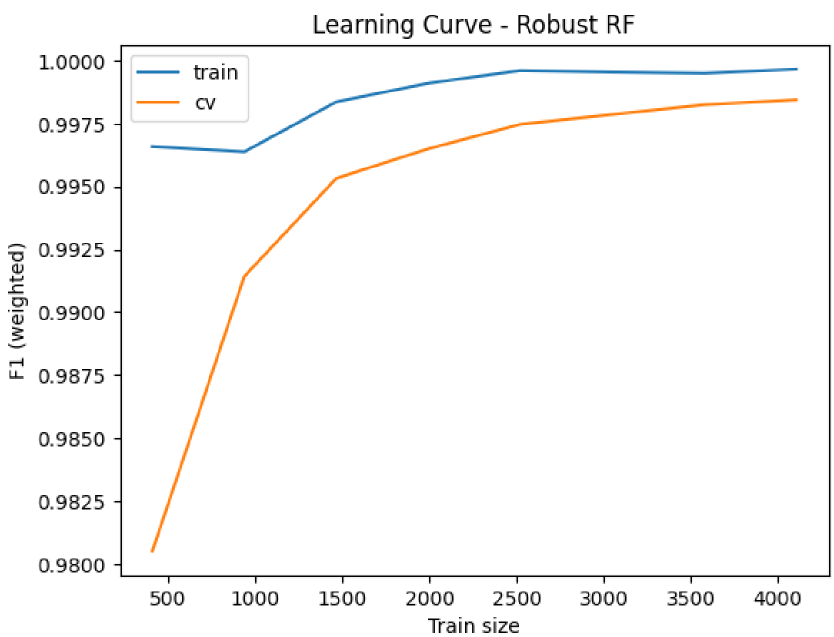

Fig 5.3:Learning Curve - Robust RF

5.3.3 Confusion Matrix

The Random Forest confusion matrix presented in Figure X offers useful information about the classifier's performance in predicting real-time food safety statuses, such as the risky, Safe and spoiled categories of food based on sensor data generated from the IoT-enabled food monitoring system. The diagonal terms of the matrix (diag = 1) imply good prediction of the actual food safety status and high number of true positives among Risky, Safe, and Spoiled. In particular, the Safe and Risky types are predicted with high accuracy, which indicates that the model would be able to make a reliable distinction between safe and risky food conditions. Furthermore, the classifier does a good job in identifying spoiled, as seen from the true positive values in the matrix. The off-diagonal elements (misclassifications) are small, showing the model itself is few mistakes, especially between Risky and Safe. It can be concluded from the confusion matrix that RF classifier is extremely efficient in classifying food items and thus provides a robust platform for the online monitoring system of food safety and will ensure better accurate predictions on food spoilage/safety.

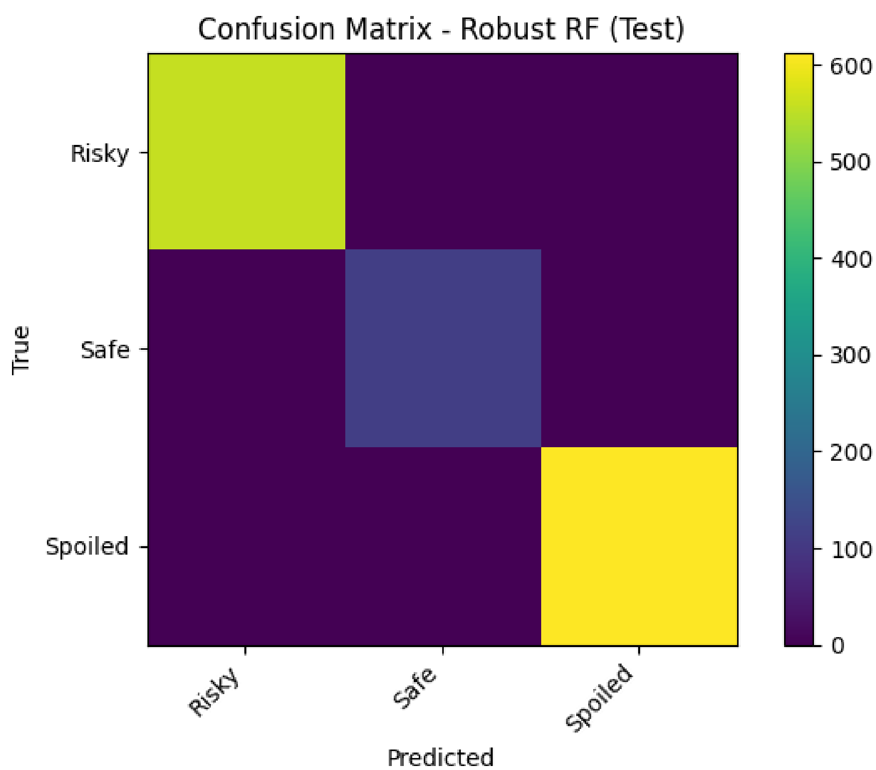

Fig5.4: Confusion Matrix

5.3.4 Histograms and Kernel Density Estimates (KDE)

The histograms and Kernel Density Estimates (KDE) for the sensors MQ-3 - Alcohol, MQ-4 (methane), and MQ-135 (ammonia) shown in Figs. This is another aspect of density distribution across sensor readings. And they give us an impression of the data structure and how sensors respond to different gas concentrations.

The histogram (left) shows a bimodal distribution for the MQ-3 (Alcohol) sensor, with peaks near 3000 and 3500 readings: these correspond to typical concentrations of alcohol vapor in food. The KDE curve further smooths this distribution, highlighting its high-density regions. We see from the whisker lengths in the box plot (right) that there are outliers; these may be occasional extreme values indicating spurious spoilage or contamination.

Both the histogram and KDE of the MQ-4 (Methane) sensor show a multi-peaked distribution, suggesting that methane concentration varied across different levels of food spoilage. The box plot indicates that the distribution is well centered, with few outliers: methane concentration is relatively stable across the data.

Histogram of the sensor response. Figure 7 shows that for the MQ-135 (Ammonia) sensor, due to its care nature, the distribution was concentrated at lower levels, indicating lower readings. The KDE curve smooths this distribution, focusing on where its readings appear to be most dense. The boxplot for ammonia shows a narrow interquartile range and few outliers; detection across food samples is much more homogeneous.

All in all, these visualizations—histograms, KDE, and boxplots—are essential tools for gaining insights into the distribution of data and variability in sending points in Africa, and they help track variations in food safety conditions from gas sensor data.

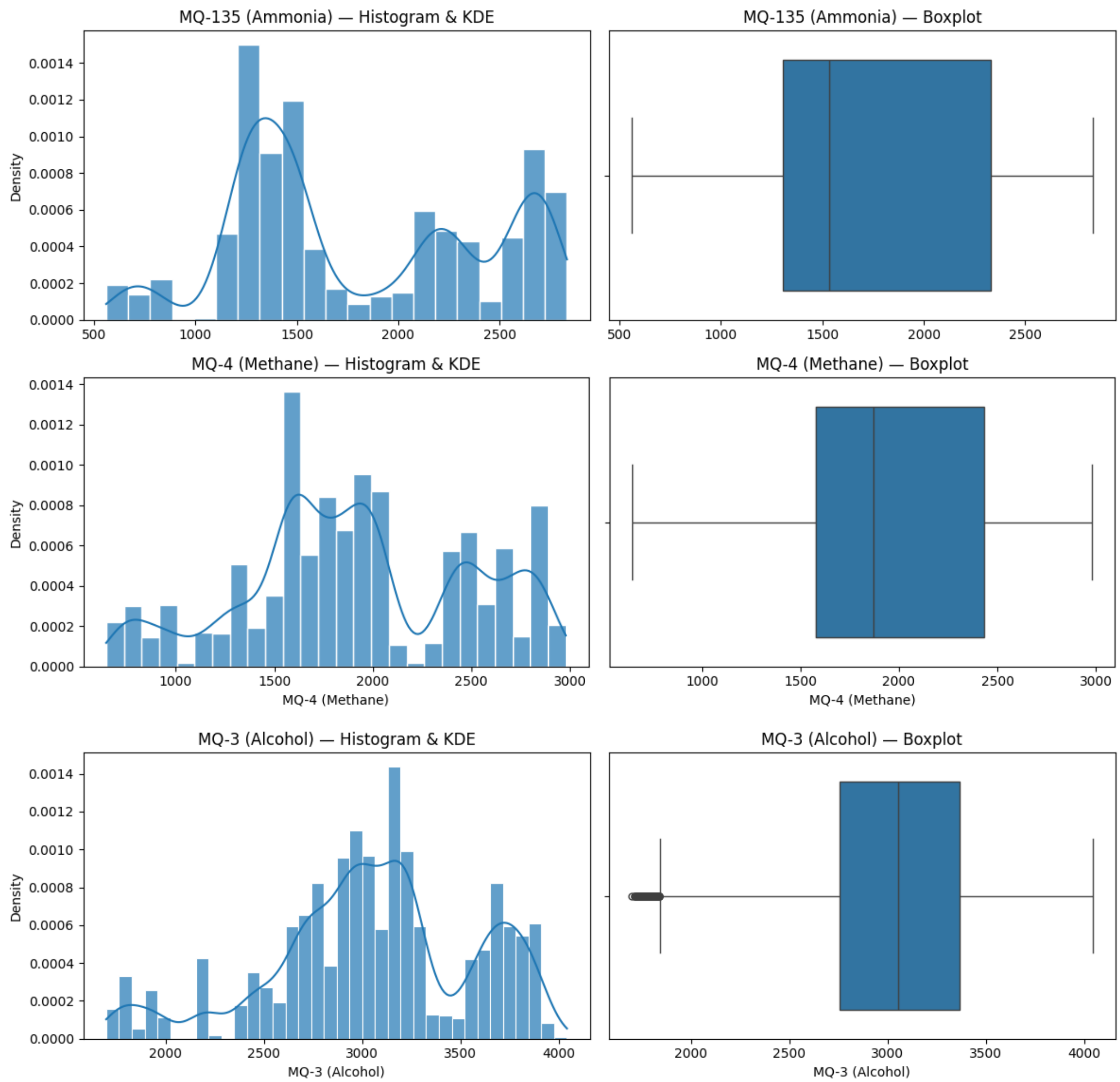

Fig5.5:Histograms and Kernel Density Estimates (KDE)

5.4 Performance Evaluation

The performance of a variety of MLRs (SVM, KNN, GBM, RF, LR and DT) was compared in the search box article as shown in the below HTML table after feature selection. Among them, the SVM performs as well as the best with 93.00% accuracy and a very strong recall of 97.14%, also showing that it has good capacity for identifying positive instances. The balanced F1-score of 0.9283 also indicates that the overall usability, in terms of precision and recall, is good. Right behind, the K-Nearest Neighbors (KNN) method also reaches a high accuracy of 90.33% and specifically achieves a good recall at 94.29%, with precision somehow compromised as 86.27%, giving forth to an F1-score of 0.9010.

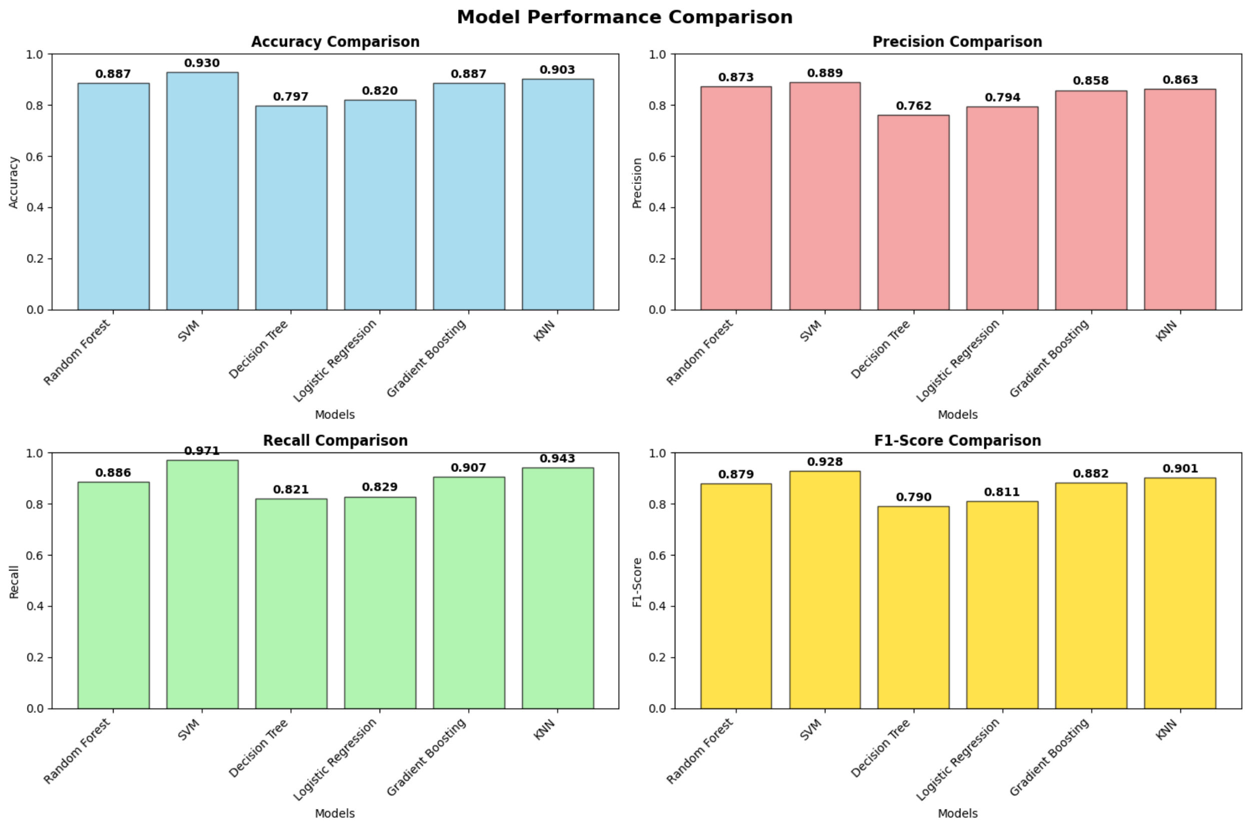

Fig 5.6: Model Performance comparison

```
======================================================================
COMPREHENSIVE MODEL COMPARISON
======================================================================
              Model  Accuracy  Precision  Recall  F1-Score
      Random Forest    0.8867     0.8732  0.8857    0.8794
                SVM    0.9300     0.8889  0.9714    0.9283
      Decision Tree    0.7967     0.7616  0.8214    0.7904
Logistic Regression    0.8200     0.7945  0.8286    0.8112
  Gradient Boosting    0.8867     0.8581  0.9071    0.8819
                KNN    0.9033     0.8627  0.9429    0.9010

======================================================================
BEST PERFORMING MODELS BY METRIC
======================================================================
Best Accuracy: SVM (0.9300)
Best Precision: SVM (0.8889)
Best Recall: SVM (0.9714)
Best F1-Score: SVM (0.9283)

======================================================================
MODEL RANKINGS
======================================================================
Models ranked by overall performance:
1. SVM (Avg Rank: 1.0)
2. KNN (Avg Rank: 2.2)
3. Gradient Boosting (Avg Rank: 3.2)
4. Random Forest (Avg Rank: 3.2)
5. Logistic Regression (Avg Rank: 5.0)
6. Decision Tree (Avg Rank: 6.0)
```

Fig 5.7: Algorithms Results

Both Gradient Boosting and Random Forest are performing with the same accuracy (88.67%), but Random Forest provides slightly better precision (87.32%) and an F1-score of 0.8794, which reveals perfect performance. Logistic regression has a lower score with 82.00% of accuracy, in particular in recall (82.86%) and F1-score (0.8112), indicating that it does not work as well on the positive case detection as the other classifiers. Finally, the decision tree algorithm achieves the worst performance in all metrics, obtaining an accuracy of 79.67%, a precision of 76.16%, and a recall of 82.14%, and then it gives the smaller F1-score with 0.7904. This analysis shows that SVMs, KNN, and Random Forest clearly outperformed all other classifiers and were thus identified as the most promising algorithms for the food safety and quality monitoring system described in this research.

Conclusion

This research conceptually proves this in the design and development of an
An IoT-Based Real-Time Food Safety and Quality Monitoring System Using Gas Sensors and ML for Perishable Food Detection integrates economical gas sensors (MQ3, MQ4, and MQ135), ESP32 microcontroller, and OLED display to detect the safety of perishable food items such as rice, fish, and meat; [75] It can also sense various spoilage factor numbers, such as vapors of alcohol, methane, and air quality parameters that represent the freshness and edibility of food products.
Work provides the integration of reusable modules and implements machine learning algorithms to food condition classification. In comparison to conventional threshold-based detection, the model provides precise and reliable predictions of food spoilage, thereby reducing both false positives and false negatives. Data can be logged, processed, and accessed in real time from a distance using this scalable approach, making it suitable for both household and industrial use via the Internet of Things (IoT) framework.

This ensures that all testing, from sample collection to examinations and final reports, is done outdoors. Secondly, by sensing parameters such as temperature, humidity, and voltage levels within food materials and the surrounding atmosphere around the clock, an intelligent, fine-scale monitoring system will be pursued until it wins widespread acceptance. But now let's return to our subject again for a moment. The food safety and early warning system made an essential contribution by providing on-the-spot information to detect contamination or spoilage. It adds instant alerts, helping minimize consumer fears and improve health. In light of the above analysis, our study finds that IoT technology combined with machine learning constitutes a cost-effective, intelligent food safety supervision program. In the future, it is likely to include cloud integration, mobile app development, sensor fusion, and the deployment of deep learning models to improve prediction and anomaly detection accuracy.

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