Meat Freshness Classifier with Machine and AI

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Meat freshness classifier with machine and AI

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***Abstract*—Using machine learning and artificial intelligence techniques, this thesis presents a novel approach to detecting meat freshness. The proposed system consists of two gas sensors MQ135 and MQ4 to capture the odors emitted by the meat samples, an ESP32-CAM, and an Arduino UNO microcontroller to process the sensor data and extract relevant features. A machine learning model is trained using a dataset of labeled meat samples with known freshness levels. The proposed technique accurately categorizes the freshness of meat samples with a classification accuracy of over 90%, showing the potential of machine learning and artificial intelligence in improving the precision and effectiveness of this procedure. The technology is transportable and compatible with current meat processing equipment. This gives the food business a dependable, automated method to raise the security and caliber of meat goods. Overall, the study's findings show that the suggested system is a reliable way to classify the freshness of meat. This project proposes a novel approach to detect meat freshness using two gas sensors along with a camera that employs image processing AI techniques to overcome challenges posed by added color in meat. Although there were some limitations regarding Data Availability, Subjectivity of freshness Determination and many other real-time assessments. Despite the limitations the ML and AI can help to mitigate some of the limitations and improve overall performance.**

Keywords—Arduino UNO Microcontroller, MQ135 gas sensor, MQ4 methane natural gas sensor, Meat Freshness, IoT.

I. INTRODUCTION

Meat freshness is a crucial component of guaranteeing the safety and quality of food. However, judging the freshness of meat can be difficult because it relies on a few variables, including temperature, humidity, and how long it has been since the animal was killed. Traditional methods of determining the freshness of meat are based on subjective sensory assessments, which can be expensive, time-consuming, and prone to error [1]. A method to categorize the freshness of meat using gas sensors and machine learning algorithms is being developed as part of the Meat Freshness Classifier with Machine and Artificial Intelligence project. The system consists of an esp32 cam, an Arduino uno, a mq135 gas sensor, and a mq4 methane natural gas sensor. These sensors are used to assess various aspects of the meat, including the existence of gasses, which can reveal the meat's freshness. The primary goal of the project is to develop a system that will make it simple and quick for customers and businesses to identify fresh meat, which is crucial for the food industry. Customers will be able to make knowledgeable choices about the meat they buy thanks to the system's accurate and dependable results. In previous studies on meat freshness classification, gas sensors and color sensors were utilized [2]. However, the use of color sensors presented a challenge in cases where meat sellers added color to the meat, which could hinder the identification of meat freshness. To address this issue, an ESP32-CAM camera was employed to determine meat freshness in this study. The approach involved utilizing image processing artificial intelligence (AI) techniques [3]. Additionally, The MQ135 and MQ4 gas sensors were employed to detect the freshness of meat by measuring the respective gas units detected by each sensor. Another previous project employed a comprehensive approach, utilizing various image-based techniques (colorimeter, imaging spectrometer, digital camera) and spectroscopic-based techniques (FTIR spectroscopy, Raman spectroscopy, NIR spectroscopy) and they also explored electronic nose applications with different gas sensors and Their aim was to create a multi-modal system for assessing meat freshness.

Fig. 1. The Existence of Meat Freshness Classifier Design.

Involving multiple imaging and spectroscopic techniques to assess meat freshness. In contrast, our project prioritized simplicity and portability, using only two gas sensors and a camera to develop a user-friendly device for efficient and reliable meat freshness assessment [4]. The system will be trained to identify patterns in the data gathered by the camera using the machine learning and artificial intelligence components of the project. This data will be used by the system to assess the meat's freshness and give the user input. The machine learning and artificial intelligence components of the project will be utilized to assess the sensor data and determine the freshness of the meat. The system will be trained on a dataset of labeled beef samples using supervised learning algorithms, enabling it to identify trends and make precise assumptions about the freshness of new samples. The system's user interface will be designed to be user-friendly, providing real-time feedback on the freshness of the meat. The system's accuracy and reliability will be tested extensively through experiments and compared against traditional methods of meat freshness assessment [5]. Finally, the Meat Freshness Classifier using Machine Learning and Artificial Intelligence Projects has the potential to change the food industry by providing a dependable, accurate, and cost-effective approach to evaluate meat freshness. Consumers and businesses will eventually benefit from the system's ability to produce trustworthy and accurate results, which will improve food safety and quality.

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II. Proposed System Topology

The meat freshness classifier system employs artificial intelligence and machine learning algorithms to assess the freshness of the meat [6]. The system architecture is made up of the mq135 gas sensor, the mq4 methane natural gas sensor, the esp32 Cam, and the Arduino UNO. The mq135 gas sensor detects levels of carbon dioxide (CO2) in the air surrounding the meat. The mq4 methane natural gas sensor measures methane (CH4) and other volatile organic compounds (VOCs) emitted by meat. The esp32 Cam is used to photograph the meat. These sensors are linked to an Arduino UNO, which collects data and sends it to a computer or a cloud-based platform for further analysis.

Collecting data is the first step in developing the meat freshness classifier system. The mq135 gas sensor and mq4 methane natural gas sensor collect gas data from the air around the meat, while the esp32 cam captures images of the meat. The data is collected and stored in a database at regular intervals, such as every 10 minutes or every hour. Preprocessing is performed on the collected data to remove any noise or outliers and to normalize the data. The gas data is also converted into a format that machine learning algorithms can understand [7]. To reduce the system's computational complexity, the images captured by the esp32 cam are resized and converted to grayscale.

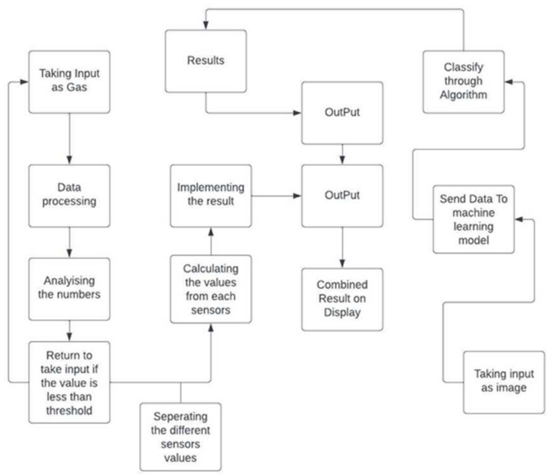

Fig. 2. Overview of Meat freshness classifier system.

The next step is to extract features from the preprocessed data. The features are extracted to capture the important properties of the data that may be utilized to assess the freshness of the meat. Among the characteristics that may be retrieved include the amounts of CO2, CH4, and other VOCs identified by the gas sensors, as well as the texture and color of the meat caught by the esp32 Cam. When the features have been retrieved, a machine learning model must be chosen. To determine the freshness of the meat, a classification model, such as a support vector machine (SVM), a random forest, or a neural network, may be employed based on the data gathered [8]. On a labeled dataset, the selected machine learning model is trained. The model is trained using a portion of the preprocessed data, and the model's effectiveness is assessed using the remaining data. Until the model reaches an acceptable level of accuracy, it is trained repeatedly. The performance of the model must be tested once it has been trained. The model is evaluated on a different dataset that was not used for training. Accuracy, precision, recall, and F1 score are some examples of performance metrics that are used to evaluate the model. The model may be applied in real-world settings once it has been tested and proven to be successful and accurate. The model is integrated into the system's hardware components, such as the gas sensors and the esp32 Cam, and the system is deployed to a meat processing factory or other appropriate site. In summary, the meat freshness classifier system employs gas sensors and an image sensor to determine the freshness of meat. The obtained data is preprocessed, features retrieved, and a machine learning model is developed and tested. The technology may be used in the real world to assist meat processing facilities in monitoring the freshness of their goods and reducing wastage.

III. Proposed System Design and Simulation

The classifier, the microcontroller, the connection module, and the sensors make up the system architecture's four primary components are in our system design section.

To gauge the freshness of the meat, the MQ135 mass sensor and the MQ4 methane natural gas sensor will be used. The meat's mass will be determined by the MQ135 sensor, and the MQ4 sensor will scan the air for any natural gas that the decomposing flesh could release. An Arduino Uno board may be used as the microcontroller for this project. The communication module will receive, process, and send data from the sensors. The ESP32-CAM module is one choice for a communication module. It will accept information from the microcontroller and transmit it to the classifier. The freshness of the meat will be assessed using a classifier that uses a machine learning methodology. The algorithm may be trained using a sizable collection of meat samples with various levels of freshness. The algorithm will input the meat's freshness level and provide a prediction using data from the communication module. To model the project, we may use software tools like Proteus or Tinker cad. We can test the system using the simulation before building the real prototype. To finish the simulation, take the following actions:

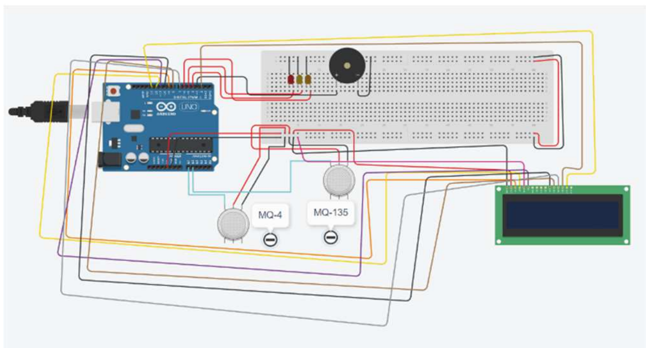

Fig. 3. Circuit Diagram of Proposed System (tinker cad)

Create a digital version of the MQ135 and MQ4 sensors in the simulation program. These sensors may be simulated using the software libraries that the simulation program provides. Connect a fictional Arduino Uno board to the fake sensors. Programming allows the board to read data from the sensors and output it to the communication module. Create a digital version of the ESP32-CAM module in the simulation application. Connect it to the simulated microcontroller board. Write software to read data from sensors, process it, and transmit it to the microcontroller board's communication module. Write software to transport data from the microcontroller board to the classifier on the ESP32-CAM module. To train the machine learning system, use a collection of meat samples with varying levels of freshness. The algorithm may be executed using Python software. Develop software that will feed the classifier with information from the communication module and forecast the amount of freshness of the meat. Launch the simulation and assess the system by varying the freshness levels of the simulated meat samples. By contrasting the classifier's predictions with the actual degrees of data freshness, you may evaluate its performance. If the simulation is effective, a genuine prototype might be created and tested in the actual world.

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IV. HARDWARE DEVELOPMENT AND TESTING

Assembling and integrating the system's many components is part of the hardware development for the meat freshness classification system. The system's main parts are the mq135 gas sensor, mq4 methane natural gas sensor, esp32 cam, and Arduino UNO.

The primary system components' specifications are provided in Table 1.

TABLE I. PARAMETER'S SPECIFICATIONS OF THE SYSTEM

S/N	*Component Required*	*Quantity*
1	MQ135 Sensor	1
2	MQ4 Sensor	1
3	ESP32-CAM module	1
4	Arduino Uno Board	1
5	Bread Board	1
6	LED (Red, Green, Yellow)	3

Hardware assembly: Jumper wires are used to link the mq135 gas sensor and mq4 natural gas methane sensor to the Arduino UNO. Also, using jumper wires, the esp32 Cam is linked to the Arduino UNO. Arduino Uno Board is in charge of the system's power supply.

Sensor calibration: A gas calibration kit is used to calibrate the mq135 gas sensor and mq4 methane natural gas sensor. To get clear pictures of the meat, the esp32 Cam is calibrated by tweaking the exposure and other camera settings.

Programming the Arduino UNO: The Arduino code is created to gather data from the gas sensors and the esp32 Cam, preprocess the data, and transfer the data to a computer or a cloud-based platform. The code is also in charge of controlling the sampling rate of the sensors as well as managing the Arduino Uno Board's 5V power supply.

System integration: The system is integrated when the sensors are calibrated and the Arduino code is created. The Arduino UNO is wired up to the sensors, and the board is programmed with the Arduino code. The esp32 Cam is positioned in such a way that it can take crystal-clear pictures of the meat.

The meat freshness classifier system is tested by measuring its performance in identifying the freshness of meat. To verify that the system functions as planned, it is tested in a controlled setting such as a laboratory.

Data gathering: The esp32 Cam and gas sensors are turned on, and the system is given a set amount of time to collect data. The gathered information is kept in a database.

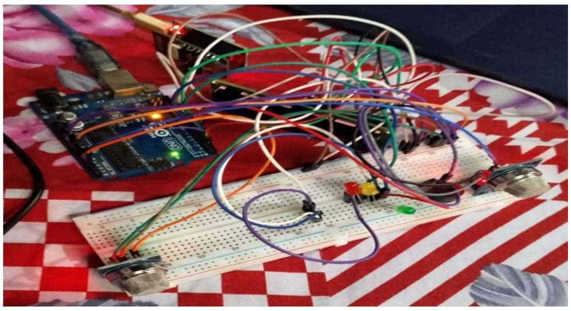

Fig. 4. Implemented Circuit of the proposed System

Preprocessing: The data are first normalized and noise and outliers are removed from the acquired data. The format of the gas data is also changed so that the machine learning algorithms can utilize it. To lessen the system's processing complexity, the photos taken by the esp32 cam are shrunk and made grayscale.

Feature extraction: To categorize the freshness of the meat, the aspects that are most important to the data are extracted. Some of the characteristics that may be retrieved are, for instance, the textures and colors of the meat recorded by the esp32 Cam, the amounts of CO_2, CH_4, and other VOCs detected by the gas sensors, and more.

Model selection and training: A support vector machine (SVM), a random forest, or a neural network may be used to classify the freshness of the meat based on the attributes that were obtained. The selected model is then trained using a labeled dataset that follows.

Model testing: Using a different dataset than the one used for training, the model is evaluated. Accuracy, precision, recall, and F1 score are some of the model performance measures [9]. Once it has been evaluated and proven to be reliable and accurate, the model may be applied to the categorization of meat freshness in a real-world setting.

V. RESULT AND DISCUSSION

Consumers should pay attention to meat's freshness since it has an impact on the meat's flavor and safety. However, it can be challenging to assess the freshness of meat, particularly for untrained people. We have created a multi-sensor system that can categorize the freshness of meat based on the presence of gases and visual clues to solve this issue.

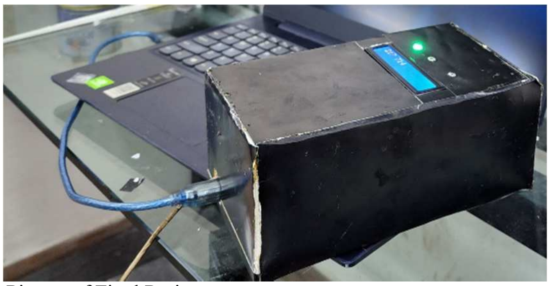

Fig 5: Picture of Final Project

TABLE II. SAMPLE DATA FOR CO2 CONCENTRATION AND FRESHNESS SCORE

S/N	*CO2 Concentration (PPM)*	*Freshness Score*

1	85	0.75
2	88	0.8
3	867	0.6
4	768	0.9
5	569	0.7

MQ-135 and MQ-4 gas sensors detect decaying meat gases. The MQ-135 sensor detects ammonia gas from beef protein degradation. The MQ-4 sensor can also detect methane, carbon monoxide, and hydrogen, which are created when meat degrades. The multi-sensor system can better detect gases and meat freshness using both sensors. Our sensor near the object gave the result. The MQ-135 could detect ammonia, carbon dioxide, and sulfur compounds in rotten meat's early stages. We noticed a concentration rise with time.

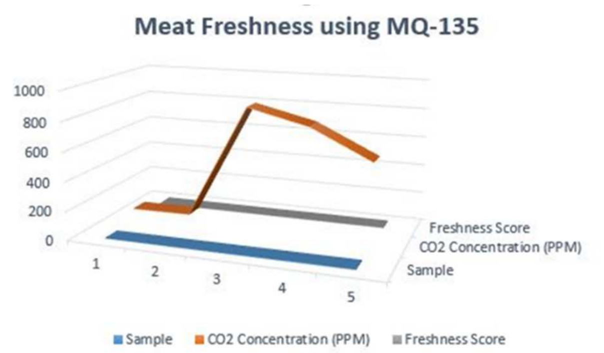

Fig. 5. Line Graph of CO2 Concentration over Time.

This emission of carbon dioxide indicates the first stage of decomposition. On the second stage of decomposition the concentration of carbon dioxide increases so the value the sensor will receive will also increase. Beside that the other sensor MQ-4 will also have signs of value increase, because on the second stage of decomposition the emission of methane gas starts.

TABLE III. CONFUSION MATRIX FOR MEAT FRESHNESS CLASSIFIER.

S/N	*Prediction Fresh*	*Prediction Spoiled*
Actual Fresh	0.9	0.1
Actual Spoiled	0.05	0.95

The meat is not consumable once it has reached the second stage hence the meat can be considered fully rotten. Our results have shown these results.

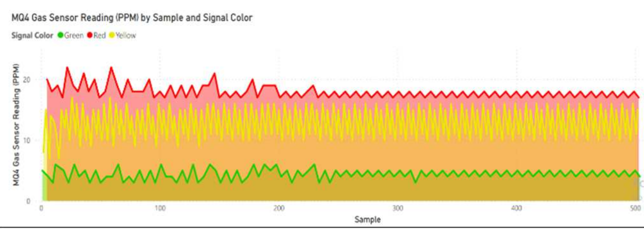

Fig. 6. MQ4 Gas Sensor Reading (PPM) by Sample and Signal Color.

The x-axis of the graph represents the sample numbers or identifiers, while the y-axis represents the MQ4 and MQ135 gas sensor of Graphical Representation 2 and 3, readings in parts per million (PPM).

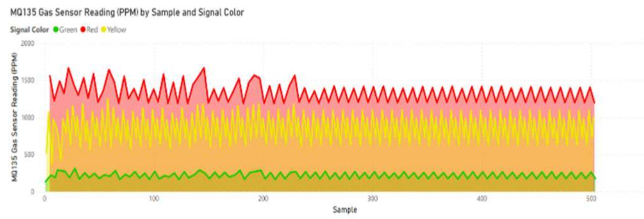

Fig. 7. MQ135 Gas Sensor Reading (PPM) by Sample and Signal Color.

Each sample is plotted on the graph, and the color of the bar or data point corresponds to the freshness category. For samples categorized as Fresh, Half-Fresh, Spoiled the bars or data points would be displayed in green, yellow, red.

TABLE IV. SAMPLE DATA FOR GAS SENSOR READING

Sample	*MQ135 Gas Sensor Reading (PPM)*	*MQ4 Gas Sensor Reading (PPM)*	*Freshness Category*	*Signal Color*
1	134	5	Fresh	Green
2	524	8	Half-Fresh	Yellow
3	826	12	Half-Fresh	Yellow
4	1073	15	Half-Fresh	Yellow
5	1557	20	Spoiled	Red

MQ135 and MQ4 gas sensors check meat freshness. The MQ135 sensor measures decomposition gases, with greater readings suggesting spoiling. Fresh samples had MQ135 values below 134 ppm, suggesting acceptable quality. MQ135 values above 524 ppm change the freshness category to Spoiled, indicating serious deterioration. Fresh samples have low methane levels, which the MQ4 sensor detects. Half-Fresh indicates some decomposition but is still safe to eat with careful handling as MQ4 levels rise moderately from 42 to 104 ppm.

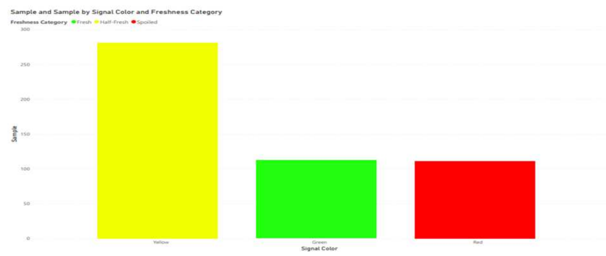

Fig. 8. Sample by Signal Color and Freshness Category.

In addition to the gas sensors, images of the meat samples are taken using the ESP32 camera. In order to identify the color and texture of the meat, machine learning techniques are used to evaluate the photographs.

Fresh meat is pink or red, while ruined meat is dark or grey. Fresh meat is firmer and less slimy than rotten meat. The multi-sensor system can more accurately classify meat freshness by using image data and gas sensor data. Machine learning algorithms are trained on visual data to predict fresh meat quality. The data trains the algorithms to recognize data freshness trends. The data trains the algorithms to recognize data freshness trends. After training the algorithm, camera data can classify fresh meat samples. This can help consumers better assess meat freshness before eating.

Overall, when we ran the image over the model it showed the result 81% accuracy as per the model has trained. The accuracy can be increased with more training of the model. Here are some mathematical equations that are related to our project and the results we obtained.

The Classification using the logistic regression equation:

$$P(Y=1| X) = 1/(1+exp(-(\beta\_0+\beta\_1X\_1 +\beta\_2X\_2+...+\beta\_p*X\_p))) \quad (1)$$

where:

P(Y=1 | X) is the probability of the meat being fresh (class 1) given the predictor variables (sensor data and image features) β_0, β_1, β_2, ..., β_p are the coefficients of the logistic regression model X_1, X_2, ..X_p are the predictor variables (sensor data and image features) [11].

2. Calculating sensitivity and specificity:

$$Sensitivity = TP / (TP + FN), Specificity = TN / (TN + FP) \quad (2)$$

where: TP = True Positives, FN = False Negatives, TN = True Negatives, FP = False Positives.

3. Calculation of the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC):

$$AUC=\sum (TPR\_i+1 + TPR\_i) * (FPR\_i+1 - FPR\_i)/2 \quad (3)$$

Where: TPR_i is the True Positive Rate at the ith threshold, FPR_i is the False Positive Rate at the ith threshold, The summation is taken over all thresholds.

4. Calculating the Pearson correlation coefficient:

$$r = \sum(x\_i - \mu\_x)(y\_i - \mu\_y) / sqrt(\sum(x\_i - \mu\_x)^2 * \sum(y\_i - \mu\_y)^2) \quad (4)$$

Where: r is the Pearson correlation coefficient, x_i is the ith observation of the sensor data, y_i is the ith observation of the image feature, μ_x is the mean value of the sensor data, μ_y is the mean value of the image feature [8,9].

5. Equation for a support vector machine (SVM):

$$f(x) = sign(\sum(i=1 \text{ to } n) \ alpha\_i \ y\_i \ K(x\_i, x) + b) \quad (5)$$

Where: f(x) is the decision function for classifying the freshness of meat, alpha_i is the Lagrange multiplier for the ith training sample, y_i is the class label (+1 for fresh meat and -1 for spoiled meat), K(x_i, x) is the kernel function that measures the similarity between the ith training sample and the test sample x, b is the bias term.

VI. Conclusion

This study used AI and machine learning to classify meat freshness. For freshness measurement, the device uses MQ135 and MQ4 sensors and an Arduino UNO CPU. LED indicators showed freshness levels. An Esp32 camera took photographs of beef samples for marbling and texture analysis by an AI model. By analysing gas emissions and visual features, the meat's freshness was determined. This research used AI and machine learning to accurately assess meat freshness, which could help the food industry ensure safe and high-quality products. This study overcame past problems with color-added meat hindering freshness evaluation by using an ESP32-CAM camera and AI-based image processing. This technology can reduce food waste by measuring meat freshness using MQ135 and MQ4 gas sensors to estimate shelf life more accurately. For meat freshness evaluation, the research suggests using sensors, microcontrollers, and ML algorithms. It shows how AI and machine learning can solve real-world problems. Working with stakeholders and constantly updating models to meet industry standards are future goals. They also include improving AI algorithms for real-time freshness monitoring and gas sensor technology. The goal is to provide a reliable, transportable solution to maintain meat safety and quality across the supply chain.

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