Proceedings of the 6th Asia Pacific Conference on Industrial Engineering and Operations Management
Bali, Indonesia, August 5-7, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AP06.20250194
Published: August 5, 2025

Classification of Beef Freshness Based on Ammonia and CO_2 Concentrations Using Support Vector Machine

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Abstract

This research developed an automatic classification system to determine the freshness level of beef using the MQ-135 gas sensor, which detects the concentration of ammonia and carbon dioxide as the primary indicators of spoilage. Additional sensors, MQ-3 and MQ-2, were used to detect ethanol and butane, ensuring that no external gas contamination occurred during the data collection process. Data were collected over thirty-five days and manually classified into three categories of freshness: fresh, less fresh, and not fresh. Due to an imbalance in the number of data points across categories, the RandomOverSampler method was applied to balance the class distribution. The Support Vector Machine algorithm was used as the classification model, and optimisation was carried out using GridSearchCV. The final model demonstrated an accuracy of 95.24%, with excellent performance in distinguishing between fresh and non-fresh classes, and improved recognition for the less fresh category. Six experts conducted validation through assessments of the colour, odour, and texture of the meat. The validation results indicated a high level of consistency between the system output and expert assessments. In addition, visualisation of gas concentration trends during the storage period reinforced the relationship between increasing gas levels and decreasing freshness. The integration of multi-gas sensors with machine learning algorithms resulted in an objective, non-invasive, and real-time monitoring system. This approach can be implemented in the food industry distribution chain to enhance safety, reduce spoilage, and support sustainable quality control.

Keywords
Ammonia, Butane, Carbon dioxide, Freshness, SVM.

1. Introduction
Meat freshness is a primary concern in the food industry as it directly affects product safety, shelf life, and consumer health (Kuleshova et al., 2024). Spoiling meat undergoes biochemical changes and microbial activity that produce volatile gases such as ammonia and carbon dioxide. These gases serve as reliable indicators of spoilage and can be detected using the MQ-135 gas sensor (Hadi et al., 2022). However, environmental factors, such as temperature, humidity, and airborne contaminants, can also impact meat quality. To achieve a more comprehensive assessment, additional sensors such as MQ-3 (Tazi et al., 2024) and MQ-2 (O. A. et al., 2024) are used to detect ethanol and butane. These gases may originate from external contamination or improper storage conditions, which can accelerate

spoilage (Haniza et al., 2025). Real-time detection of these compounds is essential to prevent the consumption of unsafe meat.

The main challenge lies in accurately processing and classifying sensor data, especially when the dataset used is imbalanced. This research applies the Support Vector Machine algorithm due to its capability in handling non-linear classification problems (Bridgelall, 2022; Piccialli & Sciandrone, 2022; Roy & Chakraborty, 2023; Wang, 2022). The RandomOverSampler method is employed to address class imbalance (Kamalov et al., 2023; Nhita et al., 2023; Zhang et al., 2023), while GridSearchCV is applied to optimise the model's performance (Ahmad et al., 2022; Oluchi Anyanwu et al., 2023; Zhao et al., 2024).

1.1 Objectives

The objective of this research is to design and develop an automatic classification system to determine the level of beef freshness based on gas concentration data obtained from multiple sensors. The system is designed to combine ammonia and carbon dioxide readings from the MQ-135 sensor with supporting data from the MQ-3 and MQ-2 sensors, which detect ethanol and butane. These gases are considered indicators of spoilage and external contamination. The classification process will be carried out using the Support Vector Machine algorithm, which is deemed suitable for handling complex and non-linear data. To address the issue of class imbalance in the dataset, the RandomOverSampler method will be employed, while GridSearchCV will be used to optimise the model's performance. The ultimate goal of this system is to be integrated into an Internet of Things (IoT) platform in real-time, enabling continuous monitoring and supporting informed decision-making in quality control across the food supply chain.

2. Literature Review

Beef is considered a primary source of nutrition due to its high-quality protein content and complete profile of essential amino acids. These amino acids are crucial for human growth and development, but cannot be naturally synthesised by the body. In addition to protein, beef also contains fat, which enhances flavour, thereby contributing to palatability and consumer preference. According to previous research (Farmer et al., 2022), bone-in tenderloin and bone-in ribeye demonstrate a stronger flavour compared to boneless cuts from the same muscle, with tenderloin also rated as the most tender by a sensory panel. Each cut possesses different characteristics in terms of tenderness, fat content, and culinary applications.

Beef freshness is closely related to physical attributes such as odour, colour, texture, and taste. Volatile organic compounds (VOCs), particularly ammonia and carbon dioxide, are metabolic by-products formed during spoilage (Epping & Koch, 2023; Khatib & Haick, 2022). The presence and concentration of these gases are strong indicators of microbial activity and declining meat quality (Sequino et al., 2024). Ammonia, a colourless gas with a pungent smell, is released during the bacterial breakdown of proteins. Elevated ammonia levels usually indicate that the meat is no longer safe for consumption (Karimi Alavijeh et al., 2024; Kim et al., 2024). Meanwhile, carbon dioxide is produced during microbial respiration and fermentation, signifying active spoilage. Prior research (Sai-Ut et al., 2025) has demonstrated that elevated CO_2 levels in high-oxygen modified atmosphere packaging can inhibit the growth of Pseudomonas fragi, a common spoilage microorganism in beef.

Ethanol and butane are two additional gases that are important for monitoring the freshness of meat. Ethanol, a polar compound often released during microbial fermentation, can be detected using infrared spectroscopy (Herdiana, 2025). Butane, a hydrocarbon found in industrial environments or contaminated storage conditions, is colourless and highly flammable. The presence of butane may also indicate external contamination that accelerates spoilage (Goyal et al., 2023; Park et al., 2025).

The development of automatic systems for detecting meat freshness requires a combination of chemical sensors and intelligent classification methods. The MQ-135 sensor is commonly used to measure ammonia and carbon dioxide levels, while MQ-3 and MQ-2 sensors are employed to detect ethanol and butane, respectively. MQ-3 provides an analogue output proportional to ethanol concentration and is frequently used in alcohol detection devices. The MQ-2 sensor detects flammable gases and particles such as butane, LPG, and smoke, through changes in conductivity influenced by interactions between gas molecules and the SnO_2 surface. These three sensors provide real-time data that is essential for assessing meat freshness.

To utilise sensor data effectively, machine learning algorithms such as Support Vector Machine (SVM) are required. SVM, introduced by Vapnik in 1992, is a classification algorithm that separates classes using an optimal hyperplane and is suitable for both binary and multi-class classification problems. It performs well on small datasets and offers strong generalisation capabilities with minimal tuning. In meat freshness classification, SVM can categorise data into classes such as fresh, less fresh, and not fresh, based on sensor input. Its robustness against overfitting makes it a reliable tool in food quality control applications.

To enhance functionality, these sensors and algorithms are generally integrated with Internet of Things (IoT) platforms. IoT allows for wireless and real-time data transmission from devices to cloud servers, supporting automation without direct human intervention. According to previous research (Denih et al., 2023, 2025; Denih & Kurnia, 2022), an IoT system consists of hardware (sensors), network connectivity, and cloud infrastructure. Microcontroller boards, such as the Arduino Uno and NodeMCU ESP8266, serve as interfaces between sensor inputs and the IoT platform. Arduino IDE is used for programming and data management, while LCD and I2C modules facilitate user-friendly data display and control.

This combination of technologies enables the development of real-time meat freshness monitoring systems, which have significant potential to reduce food waste and enhance food safety throughout the distribution chain.

3. Methods

This research employed an experimental quantitative approach to design a beef freshness classification system based on gas sensors and machine learning algorithms. The system was constructed using several components, including an MQ-135 sensor to detect ammonia and carbon dioxide gases, an MQ-3 sensor to detect ethanol, and an MQ-2 sensor to detect butane. These gases serve as indicators of meat spoilage and the possible presence of external contamination. The sensors are connected to a microcontroller that processes the data and transmits it to a NodeMCU ESP8266 module for real-time monitoring via the Internet of Things (IoT) platform.

Beef samples were placed in a sealed gas chamber for the data collection process. The sensors measured gas concentrations at regular intervals. The analogue data obtained from the sensors was converted into digital values measured in parts per million (ppm). This data was then transmitted to a server and visualised through a web interface. Before the classification process began, the system ensured that there were no contaminant gases in the testing chamber to guarantee the validity of the collected data.

Once the data was validated, it was stored using PHPMyAdmin and processed using the Support Vector Machine (SVM) algorithm. This model classified the samples into three categories: fresh, less fresh, and not fresh. The classification results were displayed on an LCD screen and a web interface for user reference. The diagram below illustrates the overall process flow of the developed system.

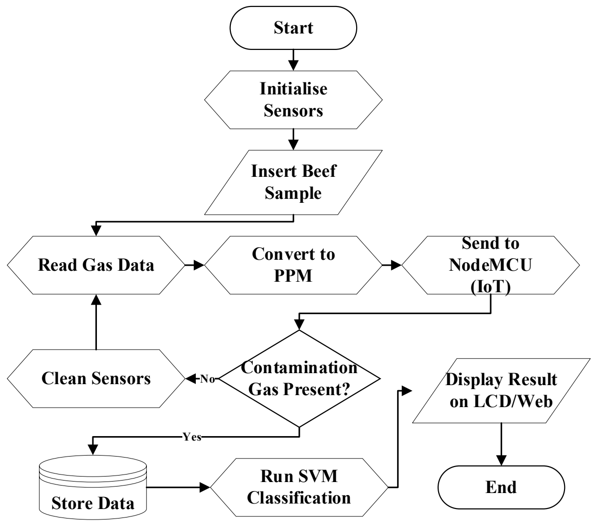

Figure 1. Flowchart of the Beef Freshness Classification System

Figure 1 illustrates that the system begins with the initialisation of the microcontroller and gas sensors. Once the sensors are active, the beef sample is placed inside the sensor chamber. The sensors then detect the concentrations of ammonia, carbon dioxide, ethanol, and butane gases. The analogue data produced by the sensors is converted into digital values in parts per million (ppm).

After conversion, the information is sent to the NodeMCU ESP8266 module and forwarded to a web server. The system then performs a check for the presence of contaminant gases such as ethanol or butane. If contamination is detected, the sensors are cleaned and the data reading process is repeated. If no contamination is found, the data is considered valid.

The validated sensor data is then stored in a database. Subsequently, the data is classified using the Support Vector Machine (SVM) algorithm to determine the level of meat freshness. The final result, which includes sensor values and classification output, is displayed on an LCD screen and a web dashboard. This stage marks the completion of one data collection cycle.

4. Data Collection

Before the data collection process began, an initial validation was carried out to ensure that the sensor chamber was free from gas contamination. This step aimed to ensure that the readings of ammonia and carbon dioxide were not affected by the presence of other gases such as ethanol and butane. Validation was conducted by spraying test gases into the measurement chamber, followed by readings using the MQ-3 and MQ-2 sensors in three stages: before exposure, after exposure, and after the cleaning process. Each stage was measured fifteen times (Table 1).

Table 1. Ethanol and Butane Gas Measurements Before and After Cleaning

MQ-3 (Ethanol) (*PPM)*															
Description	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8	Data 9	Data 10	Data 11	Data 12	Data 13	Data 14	Data 15
Before exposure	4,05	4,08	4,10	4,11	4,13	4,15	4,17	4,18	4,19	4,21	4,22	4,23	4,25	4,25	4,26
After exposure	7,75	7,70	7,74	7,39	7,34	7,08	6,04	6,79	6,78	6,76	6,75	6,74	6,74	6,75	6,76

After cleaning	4,90	4,90	4,85	4,80	4,76	4,73	4,70	4,67	4,64	4,61	4,50	4,56	4,21	4,10	4,05
MQ-2 (Butane) (*PPM)*															
Description	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8	Data 9	Data 10	Data 11	Data 12	Data 13	Data 14	Data 15
Before exposure	0,79	0,79	0,79	0,79	0,79	0,79	0,79	0,79	0,79	0,79	0,79	0,79	0,79	0,80	0,80
After exposure	1,53	1,20	1,32	1,33	1,35	1,70	1,69	1,46	1,42	1,40	1,39	1,38	1,37	1,36	1,35
After cleaning	0,83	0,83	0,83	0,83	0,83	0,83	0,82	0,82	0,82	0,82	0,82	0,82	0,82	0,81	0,79

The validation results showed that the MQ-3 sensor values returned to 4.05 ppm after cleaning, and the MQ-2 sensor returned to 0.79 ppm. These values were set as the lower thresholds, indicating that the sensor chamber was ready for the primary data collection process to begin.
Data collection was carried out by placing beef samples in a closed chamber at room temperature. The MQ-135 sensor was used to measure ammonia and carbon dioxide levels as indicators of spoilage. Measurements were taken once daily over a 35-day storage period.

A freshness assessment was conducted manually by a panel of experts based on visual and sensory observations of the meat. The evaluation included colour, smell, and texture. Based on these observations, each sample was classified into one of three categories of freshness: fresh, less fresh, and not fresh (Table 2).

Table 2. Visual and Sensory Criteria for Beef Freshness Classification

Freshness Level	Characteristic Description
Fresh	Meat recently removed from cold storage, marked by a bright red colour and the natural aroma of fresh beef.
Less Fresh	The meat is still stored in the refrigerator, but is showing signs of fading colour and the emergence of a mild sour smell that is not yet pungent.
Not Fresh	The meat remains refrigerated but has turned brownish and emits an unpleasant odour.

To support objective labelling, a mapping was conducted between gas sensor readings and freshness categories. The gas concentration values were grouped according to observations made throughout the storage process. The ranges of ammonia and carbon dioxide concentrations for each category are presented in Table 3.

Table 3. Gas Sensor Value Ranges for Beef Freshness Classification

NO	Freshness Level	MQ-135 (Ammonia)	MQ-135 (CO_2)
1	Fresh	1,90	2,00
2	Less Fresh	2,00 – 3,81	2,10 – 2,96
3	Not Fresh	3,90 – 6,10	3,00 – 4,23

Sensor values were converted into parts per million (ppm). Each sensor reading was matched with a freshness label based on manual expert evaluation. This dataset was used for both training and testing the classification model based on the Support Vector Machine algorithm. A sample of sensor readings, along with their actual labels and classification results, is shown in Table 4.

Table 4. Ammonia and CO_2 Sensor Readings with Freshness Labels

Data	**MQ-135 (Ammonia)**	**MQ-135 (CO_2)**	**Label**	**Predicted Label**
Data 1	1,90	2,00	Fresh	Fresh
Data 2	2,00	2,10	Less Fresh	Less Fresh
Data 3	2,08	2,13	Less Fresh	Less Fresh
Data 4	2,16	2,17	Less Fresh	Less Fresh
Data 5	2,24	2,21	Less Fresh	Less Fresh
Data 6	2,33	2,25	Less Fresh	Less Fresh
Data 7	2,41	2,29	Less Fresh	Less Fresh
Data 8	2,49	2,33	Less Fresh	Less Fresh
Data 9	2,57	2,37	Less Fresh	Less Fresh
Data 10	2,66	2,41	Less Fresh	Less Fresh
Data 11	2,74	2,45	Less Fresh	Less Fresh
Data 12	2,82	2,49	Less Fresh	Less Fresh
Data 13	2,90	2,53	Less Fresh	Less Fresh
Data 14	2,99	2,56	Less Fresh	Less Fresh
Data 15	3,07	2,60	Less Fresh	Less Fresh
Data 16	3,15	2,64	Less Fresh	Less Fresh
Data 17	3,23	2,68	Less Fresh	Less Fresh
Data 18	3,32	2,72	Less Fresh	Less Fresh
Data 19	3,40	2,76	Less Fresh	Less Fresh
Data 20	3,48	2,80	Less Fresh	Less Fresh
Data 21	3,56	2,84	Less Fresh	Less Fresh
Data 22	3,65	2,88	Less Fresh	Less Fresh
Data 23	3,73	2,92	Less Fresh	Less Fresh
Data 24	3,81	2,96	Less Fresh	Not Fresh
Data 25	3,90	3,00	Not Fresh	Not Fresh
Data 26	4,20	3,20	Not Fresh	Not Fresh
Data 27	4,30	3,30	Not Fresh	Not Fresh
Data 28	4,40	3,40	Not Fresh	Not Fresh
Data 29	4,40	3,52	Not Fresh	Not Fresh
Data 30	4,92	3,93	Not Fresh	Not Fresh
Data 31	5,50	4,80	Not Fresh	Not Fresh
Data 32	5,50	3,76	Not Fresh	Not Fresh
Data 33	5,70	4,50	Not Fresh	Not Fresh
Data 34	5,24	4,20	Not Fresh	Not Fresh
Data 35	6,10	4,23	Not Fresh	Not Fresh

Table 4 illustrates a pattern of increasing gas concentration corresponding to the declining freshness of the beef. Samples from days one to five are categorised as fresh. Samples from days six to twenty-three fall under the less fresh category. Meanwhile, samples from days twenty-four to thirty-five are classified as not fresh. This pattern demonstrates that gas sensor data can serve as a reliable basis for freshness classification using a machine learning approach.

5. Results and Discussion

5.1 Numerical Results

The performance of the classification model was evaluated using a confusion matrix and standard evaluation metrics. The dataset consisted of thirty-five entries representing various levels of beef freshness. The classification process was carried out using the Support Vector Machine algorithm, with hyperparameters optimised using GridSearchCV. To address class imbalance, the RandomOverSampler method was applied before model training.

Table 5. Confusion Matrix of the SVM Model

	Predicted Fresh	**Predicted Less Fresh**	**Predicted Not Fresh**
Actual Fresh	7	0	0
Actual Less Fresh	1	6	0
Actual Not Fresh	0	0	7

Based on the results in Table 5, the model achieved complete accuracy in classifying the Fresh and Not Fresh classes. The Less Fresh class exhibited a minor error, indicated by one sample being misclassified as Fresh.

Table 6. Performance Metrics of the SVM Model

Class	**Precision**	**Recall**	**F1-score**	**Support**
Fresh	1,00	1,00	1,00	7
Less Fresh	1,00	0,86	0,92	7
Not Fresh	0,88	1,00	0,93	7
Accuracy			0,95	21
Macro Avg	0,96	0,95	0,95	
Weighted Avg	0,96	0,95	0,95	

Table 6 shows that the model achieved high precision and recall values across all classes, with an overall accuracy of ninety-five percent. The best performance was observed in the "Fresh" and "Not Fresh" classes. Meanwhile, a slight decrease in recall for the Less Fresh class indicates that some data in this category were more difficult for the model to identify accurately.

5.2 Graphical Results

This section presents a visualisation of the trends in ammonia and carbon dioxide gas concentrations obtained from MQ-135 sensor readings over a thirty-five-day observation period. The graphs show a steady increase in gas values over time, representing the decreasing freshness of the beef. This upward trend aligns with the classification results from the Support Vector Machine model, reinforcing the use of gas concentration data as an indicator of spoilage level.

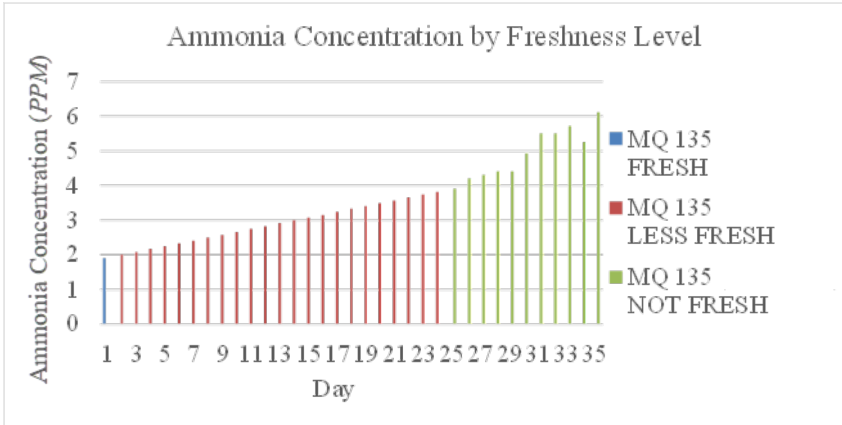

Figure 2. Ammonia Concentration Graph Based on Observation Days

Figure 2 shows that the ammonia concentration increases consistently from day one to day thirty-five. The lowest concentrations were recorded in fresh samples at the beginning of the observation period, while the highest concentrations were noted in the final days when the meat was no longer fresh. This increase reflects the protein degradation process caused by microbial activity, which produces ammonia as a by-product.

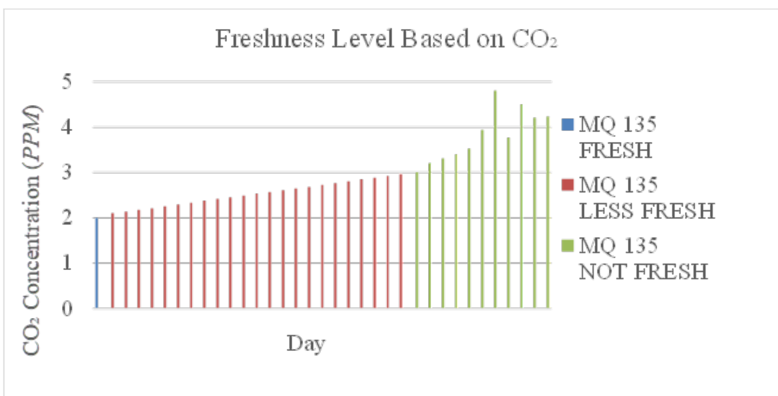

Figure 3. Carbon Dioxide Concentration Graph Based on Observation Days

Figure 3 shows a similar upward trend in carbon dioxide concentration. The increase in CO_2 levels begins on the first day and reaches its peak towards the end of the storage period. This gas is produced as a result of microbial respiration that intensifies during spoilage. The pattern suggests that CO_2, in conjunction with ammonia, can serve as a relevant additional parameter in a sensor-based system for classifying meat freshness.

5.3 Proposed Improvements

Although the classification model demonstrated a high level of accuracy, several aspects could still be improved. The dataset used in this research consists of thirty-five samples, which may limit the model's ability to generalise to broader conditions. Increasing the number and diversity of samples, including different types of meat or varying storage conditions, is recommended to strengthen the model's robustness in real-world scenarios.

Furthermore, the current classification system only uses ammonia and carbon dioxide as input parameters. The integration of additional sensors, such as MQ3 for ethanol and MQ2 for butane, during the classification phase may provide more comprehensive information regarding the decomposition profile, especially in less controlled environments.

Subsequent developments may also consider the use of deep learning algorithms such as Convolutional Neural Networks, which are capable of automatically recognising gas signal patterns. This approach has the potential to enhance classification accuracy, particularly in categories with overlapping characteristics, such as those with less fresh content.

Incorporating the system into a mobile or cloud-based Internet of Things platform with real-time alert features may further increase its applicability in distribution chains and meat quality monitoring.

5.4 Validation

The validation in this research aimed to evaluate the extent to which the automatic classification model could produce outputs consistent with expert assessments and demonstrate quantitatively measurable performance. The validation process was conducted through two primary approaches: technical validation and classification validation.

First, technical validation was performed on the sensor chamber to ensure that the measurement environment was free from contaminant gases before data collection commenced. Measurements from the MQ3 and MQ2 sensors showed that after the cleaning process, the concentrations of ethanol and butane gases returned to their normal thresholds of 4.05 ppm and 0.79 ppm, respectively. This indicated that the data used for training and testing were collected under controlled and valid conditions.

Second, classification validation was conducted by comparing the prediction results of the Support Vector Machine model with reference labels provided by six experts based on their visual and sensory evaluations of the meat. The classification results showed an accuracy of 95.24%, with high values for precision, recall, and F1 score across all classes, particularly for the "Fresh" and "Not Fresh" categories. This demonstrates that the model successfully identified patterns of meat degradation based on gas concentrations with strong consistency relative to expert manual observations.

To reinforce the validation, comparisons were made with two other studies using similar datasets and data sources but employing different classification approaches, namely:

1. The KNN method (Denih & Anggraeni, 2023) achieved 100% accuracy on six supermarket test samples, along with a precision, recall, and F1 score of 1.0 across the tested categories (Fresh and Not Fresh).
2. The Fuzzy Mamdani method (Denih, 2024) also achieved 100 percent accuracy with identical evaluation metrics for the same categories.

Both studies demonstrated high performance in classifying limited test data. However, the SVM-based model in this research offers several advantages:

1. A larger and more varied dataset (35 days of observation).
2. A more balanced label distribution due to the use of the RandomOverSampler technique.
3. Higher generalisation capability, as it was able to identify the Less Fresh category, which is often challenging to classify.
4. Technical validation of the measurement environment using additional sensors.

Thus, the validation indicates that the SVM-based approach is not only accurate but also more adaptable to data complexity and real-world conditions, making it well-suited for implementation in automatic and sustainable systems for classifying meat freshness.

6. Conclusion

This research successfully designed and implemented an automatic classification system to determine the freshness level of beef based on the concentrations of ammonia and carbon dioxide gases. The use of the MQ135 sensor as the primary detector, along with initial validation using MQ3 and MQ2 sensors, ensured that the collected data was accurate and free from interference from contaminant gases.

The classification system employed the Support Vector Machine algorithm, optimised through GridSearchCV, and reinforced with the RandomOverSampler method to address data imbalance. Evaluation results showed that the model achieved an accuracy of 95%, with excellent classification performance in the "Fresh" and "Not Fresh" categories, and relatively high performance in the "Less Fresh" category.

Validation by six experts indicated a high degree of alignment between the system output and manual assessments based on the colour, odour, and texture of the meat. Visualisation of gas trends over a thirty-five-day period further strengthened the observed relationship between rising gas levels and declining meat quality.

This system offers a real-time, objective, and non-invasive solution for monitoring meat freshness. The approach has strong potential for broad implementation within the food industry, supporting quality control, reducing waste, and enhancing product safety throughout the distribution chain.

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Biographies

Asep Denih, S.Kom., M.Sc., Ph.D., is the Dean of the Faculty of Mathematics and Natural Sciences at Pakuan University, Bogor, Indonesia. He earned his undergraduate degree in Informatics Engineering from Gunadarma University (1996), his master's degree in Information Technology from IPB University (2005), and his doctoral degree in Information Technology from the University of Miyazaki, Japan (2019). His professional experience includes roles as Head of Laboratory, Programme Secretary, and Research Assistant in Japan. He is currently active as a reviewer for various national and international journals.

His areas of expertise include geographic information systems, remote sensing, machine learning, and Internet of Things (IoT) technology. He has led numerous research projects related to spatial data, environmental monitoring, digital agriculture, and renewable energy. Many of his research findings have been published in reputable journals and presented at international conferences, including the IEOM Society. He has authored more than fifteen reference books and holds six registered copyrights in the fields of technology and education.

Prof. Asep Denih is also active as a plenary speaker, international competition judge, and global conference facilitator in the field of science and technology. He has received multiple awards from both national and international institutions, including overseas scholarships from the Ministry of Research and Higher Education, community service grants, and recognition for his contributions to doctoral supervision and innovation in technology-based research.

Irma Anggraeni, M.Kom., is a dedicated lecturer in the Department of Computer Science at Universitas Pakuan, Bogor, Indonesia. With a strong academic background and expertise in computer science, she actively teaches and mentors students, helping to shape the next generation of technology professionals. Her commitment to education is reflected in her engaging lectures and her involvement in guiding student research projects within the department. Beyond teaching, Irma Anggraeni is also an active researcher, particularly in the fields of machine learning and applied computing. She has contributed to various scientific journals, such as "Komputasi: Jurnal Ilmiah Ilmu Komputer dan Matematika," and her work is recognized in academic circles, as evidenced by her Google Scholar citations and SINTA score. Through her research and academic service, she continues to advance the field of computer science education and contribute to the scientific community in Indonesia. In addition to her academic roles, Irma is known for her dedication to professional development and collaboration. She frequently participates in seminars, workshops, and conferences, both as a speaker and an attendee, to stay updated with the latest advancements in technology and pedagogy. Her active involvement in these events not only enhances her own knowledge but also brings fresh insights and innovative teaching methods to her students.Irma Anggraeni's passion for computer science extends beyond the classroom. She is committed to inspiring young people, especially women, to pursue careers in technology. By fostering an inclusive and supportive learning environment, she encourages her students to explore their interests, develop critical thinking skills, and contribute meaningfully to the rapidly evolving world of information technology.