Crab Quality Detection with Gas Sensors Using a Machine Learning

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***Abstract*— Crab is a widely recognized and favored seafood product globally. Crab's delicious taste and high nutritional value, particularly its protein content, make it a desirable food choice. Given the global popularity of seafood, including crabs, maintaining its quality is essential for both economic and consumption purposes. However, seafood products are prone to rapid spoilage due to their high-water content, with spoilage rates varying among different types of seafood. It is crucial for industries to monitor and ensure the quality of their products before they reach the market. Given the high demand for crabs, there is a pressing need for an effective method to assess their quality. This research seeks to establish a method for assessing the freshness and quality of crabs using an electronic nose (e-nose) system, employing machine learning algorithms for classification analyses. Three algorithms will be utilized, along with hyperparameter optimization, to achieve optimal accuracy in evaluating crab quality. These algorithms are K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), and Naïve Bayes. The highest result is achieved by K-NN methods with 98% accuracy percentage. The proposed method of this research has acquired targets that can contribute to advancing seafoods production for industries.**

Keywords—crabs, detection, e-nose, machine learning, quality

I. Introduction

Crab is a highly esteemed seafood product among the Indonesian population and holds substantial economic importance in the global market. According to a report by the Ministry of Maritime Affairs and Fisheries of the Republic of Indonesia, crab's export value in 2023 reached USD 305 million, underscoring the robust international demand for Indonesian crab [1]. Crab is also renowned for its nutritional value. Crab offers low-calorie, high-protein seafood that provides essential nutrients such as omega-3 fatty acids, high-quality protein, vitamin B12, and minerals including zinc, selenium, and copper, supporting muscle growth, heart health, immune function, and overall well-being [2]. This makes crab not only a flavorful food choice but also one that offers significant health benefits.

However, like many seafood products, crab is highly perishable due to its high-water content. Without proper storage and handling, its quality rapidly deteriorates. The freshness of seafood products can decline within 8 to 20 hours when stored at ambient temperatures of 25-30°C [3]. This reduction in quality not only diminishes the nutritional value but also poses potential health risks. To ensure public health and safety, food intended for consumption must meet high standards of quality and condition to prevent the spread of diseases. The Food and Agriculture Organization (FAO), an international body dedicated to achieving global food security, ensures that individuals have consistent access to sufficient, high-quality food for a healthy and active life [4]. FAO sets regulations, quality standards, and other guidelines, particularly for seafood products. These regulations include supervision and quality parameters that seafood products must meet to be suitable for both national and international markets. Producers are required to adhere to FAO's established codes and regulations to guarantee that consumers receive safe and high-quality seafood, thereby preventing foodborne illnesses. These regulations are also crucial from an economic perspective. A decline in seafood quality can lead to significant financial losses, as exemplified by the European Union, where such declines have resulted in an estimated loss of USD 100 million [5].

Despite the availability of these regulations, many industries still rely on manual methods to assess the freshness and quality of crab products, primarily through human sensory evaluation [6]. This reliance on human judgment introduces the potential for error, as sensory perceptions, mental acuity, and capacities vary across individuals. Such inconsistencies pose a challenge to ensuring uniform compliance with FAO standards. There have been numerous innovations and research efforts aimed at improving seafood quality detection without relying on human sensory evaluation. One such example is the Torrymeter, a device that measures changes in dielectric properties to assess seafood freshness [7]. However, this device is relatively expensive, costing approximately USD 2,500. Given the high costs of these devices, there is a clear need for more affordable solutions that can still deliver reliable and accurate results, ensuring both efficiency and accessibility in quality detection.

Currently, there is not a widely adopted and efficient method within the crab processing industry that utilizes gas sensors for precise, rapid, and automated quality assessment. This underscores the need for a technological solution capable of detecting and processing crab products while ensuring they meet stringent quality standards for consumer safety and satisfaction. One promising alternative is the use of scent detection to determine the quality (fresh level) of crab. An electronic nose (E-Nose), equipped with an array of gas sensors that mimic the human sense of smell [8], offers more consistent and reliable results than traditional manual methods.

This study aims to contribute to the development of a portable device capable of accurately assessing crab quality through a simpler, more cost-effective, yet reliable threshold for quality detection. The device integrates an E-Nose with machine learning algorithms, optimized via hyperparameter tuning, to improve the accuracy of seafood freshness assessments. The algorithms used in this research include K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), and Naïve Bayes.

Furthermore, this work has the potential to enhance classification quality in the seafood industry, especially within the crab sector, by providing a practical and scalable solution for quality assurance. This research could also serve as a foundational reference for future studies, functioning as either a baseline or a source of inspiration for further advancements and innovations in the field.

The remainder of this paper is structured as follows: Section II reviews related research in the field. Section III outlines the materials and methods used to collect data for assessing crab's quality. Section IV outlines the outcomes of proposed method's implementation, while Section V provides the conclusion, summarizing the study and its key findings.

II. Related Works

Maintaining the quality of food is paramount to safeguarding its safety for consumption and ensuring the well-being of individuals. High standards of food quality not only prevent health risks associated with contamination or spoilage but also contribute to overall public health by promoting the intake of nutritious and safe products. Food decomposition alters its appearance, odor, taste, and texture due to biochemical reactions and microbiological activity [9] . Various methods are employed to assess food freshness, including sensory evaluations based on human senses such as smell, taste, and sight. Laboratory tests are also utilized to determine freshness by analyzing the chemical composition of the food.

Decomposition is the process by which organic materials break down, either in the presence of oxygen (aerobic) or in its absence (anaerobic). Anaerobic digestion produces biogas, which consists primarily of 50-70% methane (CH_4) and 30-40% carbon dioxide (CO_2), with smaller amounts of hydrogen sulfide (H_2S), hydrogen (H_2), nitrogen (N_2), oxygen (O_2), and ammonia (NH_3) [10]. The decline in food quality, also referred to as decomposition, can be assessed through sensory aspects such as sight, smell, taste, touch, and hearing [17]. These aspects should be evaluated objectively, minimizing bias and subjective influence [17]. In this study, the smell aspect is utilized, and thus, the detected components correspond to those defined as biogas.

The machine learning algorithms proposed in this research for classification and regression tasks are K-Nearest Neighbors (K-NN), Support Vector Machines (SVM), and Naive Bayes, selected to further enhance accuracy. Given the variety of biogas compositions emitted during the decomposition process, the data produced is expected to follow a linear trend. A study evaluating the application of eight machine learning algorithms demonstrated that K-NN is well-suited for its simplicity and effectiveness in both classification and regression tasks [11]. SVM was chosen for its ability to handle high-dimensional data, making it particularly effective in classification tasks where the margin of separation between classes is distinct. It is widely used in applications such as image classification and bioinformatics [11]. Meanwhile, Naive Bayes was selected for its speed and simplicity, particularly in text classification tasks, where it assumes feature independence, potentially leading to improved accuracy [11]. Thus, these algorithms were selected for their unique strengths: K-NN for its straightforward approach, SVM for its capacity to manage complex, high-dimensional data, and Naive Bayes for its computational efficiency and reliable performance in specific classification.

Due to the complex biochemical reactions involved in the decomposition of food, numerous studies have focused on enhancing gas sensing technologies, such as electronic noses, to evaluate food freshness. One study conducted sensory evaluations using a low-cost electronic nose (without machine learning) on seafood samples such as rainbow trout, sea bass, and sea bream [12]. These samples were obtained from a local fish market, delivered on ice within 8 hours of harvesting, and stored in a refrigerated box. Samples were randomly selected and analyzed in the electronic nose chamber. The samples were also evaluated using sensory methods and Total Viable Count (TVC) to establish thresholds for each sample and gas sensor. The study successfully developed a low-cost electronic nose, costing less than \$20, capable of providing rapid and stable readings.

Another study focused on detecting hydrogen sulfide, ammonia, liquefied petroleum gas (LPG), and hydrogen to assess the quality of four types of seafood: squid, cuttlefish, doublewhip threadfin bream (Nemipterus nematophorus), and octopus [13]. These samples were placed in sealed, transparent chambers, and the gases were drawn through hoses connected to a mini-PC, generating a total of 108,000 records. The collected data was labeled into two categories: accept and reject, based on quality standards and microbial counts. The study also applied various machine learning models and hyperparameter optimization to accurately classify the quality of the samples. Thresholds were defined following rejected sample's laboratory tests. The highest accuracy, 99%, was achieved using the K-Nearest Neighbors (K-NN) algorithm [14]. Additionally, other research has investigated the use of artificial neural networks (ANN) to further enhance freshness detection accuracy in seafood. A study involving tuna and mackerel used ANN models to analyze data from electronic nose sensors, achieving an accuracy rate of 98% in determining the freshness of the samples [15].

Hence, based on the related studies reviewed, it is evident that electronic nose technology, especially when combined with machine learning, provides a powerful tool for assessing food freshness. This research builds on these findings by exploring additional seafood varieties and implementing further refinements to the electronic nose setup, aiming to enhance both the accuracy and cost-effectiveness of freshness assessments.

III. Materials and Method

A. Set Data

In this study, crab samples weighing approximately 200g were sourced from a fresh fish market and transported in a container filled with ice cubes to maintain their freshness during transit to the testing facility. The use of ice was essential, as it prolonged the freshness period by slowing any decomposition processes within the crab [16]. Upon arrival at the test site, the crabs were placed in an airtight plastic container, with the E-Nose device affixed to the lid. Prior to sampling, sensory evaluations were conducted to confirm the freshness of the crab meat, determining its eligibility for inclusion in the experiment. These simple assessments include a tactile check by gently pressing the meat, a scent check to assess freshness, and a visual inspection of the meat's appearance. Eligible crab meat has characteristics such as vibrant or natural color, a pleasant, ocean-like odor, and a firm, elastic texture [9]. The crabs demonstrated fresh results and were deemed suitable for data collection.

The E-Nose was connected to a laptop for real-time operation and gas detection. The E-Nose device consisted of a sensor array with four MQ gas sensors (as outlined in Table I) connected to an ESP32 microcontroller as shown in Fig. 1, a breadboard for connectivity, a customized plastic container, and a laptop. The gas sensors detected volatile compounds emitted from the crab samples without any external air intake mechanism. to ensure the integrity of the experimental process, all measurements were conducted in a controlled environment with minimal external interference. The E-Nose system was calibrated initially to guarantee accurate detection of the gases emitted by the crab samples. This calibration was performed by preheating the gas sensors. The crab samples were monitored continuously over a period of approximately 13 hours at a room temperature of 25°C, resulting in 47,087 recorded data points.

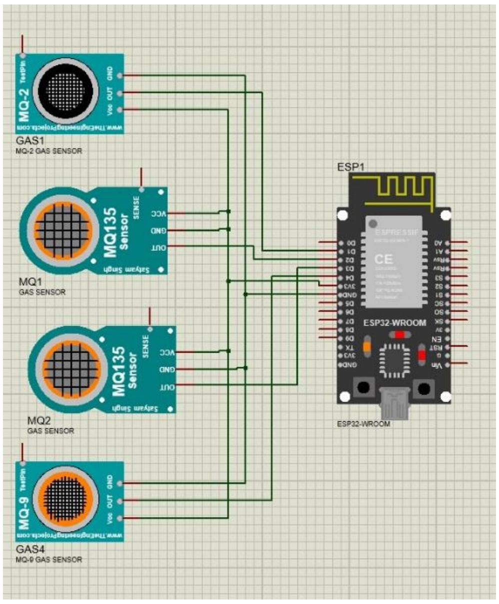

Fig. 1. E-Nose Circuit Design

TABLE I. GAS SENSOR LIST

No.	Name of the Sensor	Selectivity
I	MQ-135	NH_3
II	MQ-2	C_2H_5OH
III	MQ-9	CH_4
IV	MQ-135	CO_2

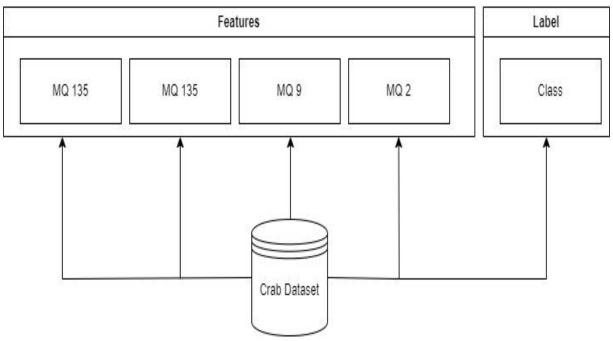

Fig. 2. Experiment Dataset's Composition

The structure of the dataset is depicted in Fig. 2. Four features, corresponding to the gas sensors, were used to detect the quality of the crab meat. The dataset featured a designed as "Class," which was categorized based on the expertise of Quality Control (QC) specialists from five different global supermarkets in Indonesia: Nanakam Fresh Market, Farmers Ranch Market, Food Daily, and Aeon Supermarket. Crab freshness was labeled into three labels: 1 (fresh), 2 (less fresh), and 3 (not fresh). The criteria for these categories were defined as follows: fresh (less than 5 hours), less fresh (5 to 7 hours), and not fresh (more than 7 hours).

Subsequently, the data gathered by e-nose device was then processed using three different machine learning models, which are: K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), and Naïve Bayes. These models were thoroughly analyzed and compared to identify the model with the highest accuracy and reliability. The best model with these criteria was then selected to use in this study contribution goal—an accurate, portable, practical, and efficient tool for assessing the freshness and quality of seafood in real-time.

B. Proposed Method

The flow of the proposed methods for classification utilized in this research are illustrated in Fig. 3. These methods comprise four key processes: Sampling, Training, Hyperparameter Optimization (HPO), and Evaluation.

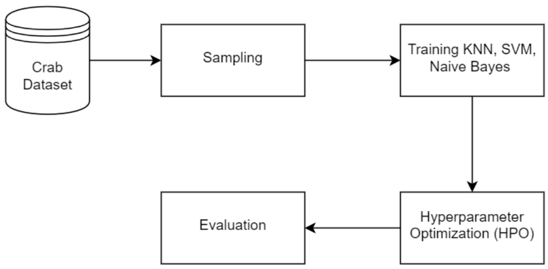

Fig. 3. Proposed Method

a) Sampling

The sampling process involved acquiring measurements from the crab samples using gas sensors, with the primary metric being the resistance values expressed in Ohms (Ω). The electronic nose (E-nose) system was calibrated through a mandatory preheating process lasting for 24 hours to stabilize the sensor array and ensure accurate and consistent readings. This pre-calibration phase was critical in minimizing sensor drift and ensuring that the sensors were fully functional before starting the actual sampling process. Once the calibration was complete, the gas sensors began capturing volatile organic compounds (VOCs) emitted by the crab samples. The collected data was stored in CSV format and subjected to a data cleaning procedure to remove any noise, outliers, or missing values. This step ensured the integrity and quality of the dataset, making it suitable for further analysis in compliance with the experimental setup. After cleaning, the dataset was split into two portions: 80% of the data was allocated for training the machine learning models, while the remaining 20% was reserved for testing and validation. This split allowed for an effective evaluation of model performance, ensuring that the models could generalize well to unseen data.

b) Training

The dataset was divided into two subsets: 80% of the data was allocated for training the machine learning models, while the remaining 20% was reserved for testing and validating the models' performance. The algorithms employed in this study include K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), and Naïve Bayes. The training process was conducted to ensure that the models developed possess the capability to generate accurate predictions when applied to new, unseen data during the testing phase.

c) Hyperparameter training and optimization (HPO)

The grid search approach was employed in this experiment to conduct HPO for both classification tasks. This method systematically explores a predefined set of hyperparameters to identify the best parameters that yield the highest accuracy for the classification task. The algorithms utilized in this experiment included K-NN, Naïve Bayes, and SVM. The optimal parameters, which produced the best classification accuracy are presented in Table II.

TABLE II. HPO OF CRABS CLASSIFIER

Algorithms	Parameters	Values
K-NN	n_neighbors	5
		10
		20
		50
		100
		150
	weights	uniform
		distance
	algorithm	auto
		ball_tree
		kd_tree
		brute
SVM	C	0.01
		0.1
		1
		10
		100
	gamma	0.1
		0.01
		0.001
		0.0001
	kernel	rbf
		linear
Naive Bayes	Var_smoothing	1e -9
		1e -8
		1e -7
		1e -6
		1e -5
		1e -4
		1e -3
		1e -2
		1e -1
		1
		10
		100

d) Evaluation

The classification models are evaluated using key metrics. Metrics used in this study: F1 score, Recall, Precision and Accuracy. To ensure the models have strong generalization ability, they must perform well not only on the training data but also on unseen test data. If a model demonstrates poor performance or overfitting, indicating weak generalization, the model will be re-trained or adjusted with different parameters to improve its accuracy and overall effectiveness. This iterative process is essential to achieving reliable and robust model performance.

IV. RESULTS AND DISCUSSION

A. *Hyperparameter Optimization Results for Classification*

The classification results, as detailed in Table III, reveal that the K-Nearest Neighbors (K-NN) algorithm achieved the topmost accuracy out of all the models tested, with an impressive accuracy rate of 98%. This exceptional performance underscores K-NN's effectiveness in classifying crab quality, significantly outperforming both the Support Vector Machine (SVM) and Naïve Bayes algorithms. The K-NN model's superior accuracy is indicative of its robust ability to discern the subtle differences in crab quality, reflecting the successful application of hyperparameter optimization (HPO) and its well-suited configuration for this dataset.

TABLE III. HPO RESULTS OF CRABS

No.	Algorithm	Best Parameter	Accuracy
1	K-NN	N_neighbors: 5 Weights: Uniform Algorithm: Auto	98%
2	SVM	C: 100 Gamma: 0.01 Kernel: rbf	87%
3	Naïve Bayes	Var_smoothing	91%

In contrast, the Support Vector Machine (SVM) model attained a lower accuracy of 87%. Although this accuracy is still commendable, it is notably less than that of K-NN, suggesting that while SVM is effective, it does not achieve the same level of precision in this context. Similarly, the Naïve Bayes model achieved an accuracy of 91%, which, while higher than SVM, still falls short compared to K-NN. These results highlight the variability in performance among different algorithms and illustrate the effectiveness of hyperparameter optimization (HPO) across all models. The optimization processes for each algorithm were carried out meticulously, aimed at enhancing their performance and adapting them to the specific characteristics of the dataset. The observed variations in accuracy among the models underscore the importance of selecting the appropriate algorithm and fine-tuning hyperparameters to achieve optimal results in classification tasks. Overall, the K-NN model's superior accuracy reaffirms its suitability and reliability for assessing crab quality in this study, validating the effectiveness of the optimization techniques employed.

Furthermore, the confusion matrix for each model offers a comprehensive analysis of both correct and incorrect classifications, providing valuable insights into the performance of each algorithm. Fig. 4 illustrates the confusion matrix for the K-Nearest Neighbors (K-NN) model, revealing that out of the total instances, 9,335 were accurately classified regarding crab quality, with only 83 instances misclassified. This low number of misclassifications underscores the K-NN model's effectiveness in distinguishing between different quality levels of crabs. In Fig. 5, the confusion matrix for the Support Vector Machine (SVM) model demonstrates a slightly better performance, with 9,342 instances correctly classified and 72 instances misclassified. The SVM's performance, while strong, indicates a marginally higher error rate compared to K-NN. Fig. 6 shows the confusion matrix for the Naïve Bayes model, where 8,638 instances were classified correctly and 780 were misclassified. The higher number of misclassifications for Naïve Bayes highlights its relative limitations in this application, especially when compared to the other two models.

Additionally, Table IV provides a detailed summary of the models' performance based on accuracy, precision, recall, and F1 score. Precision measures how well the models correctly classify instances across all categories, with a score close to 1 indicating high accuracy in minimizing false positives. The F1 score, which balances precision and recall, achieving a value of 1 signifies an ideal scenario where the number of correctly classified instances greatly exceeds the number of misclassifications. The K-NN model achieved an impressive F1 score of 0.99, reflecting its superior balance between precision and recall and its consistent ability to accurately classify various quality levels of crab. In contrast, while the SVM algorithm demonstrated competitive performance, its slightly lower F1 score indicates a marginal trade-off in accuracy. The Naïve Bayes model, although functional, showed a more pronounced decline in performance, as evidenced by its lower F1 Score, Precision, and Recall. These results reinforce the K-Nearest Neighbor model's overall superior performance in classifying crab quality compared to SVM and Naïve Bayes, making it the most reliable choice for this research.

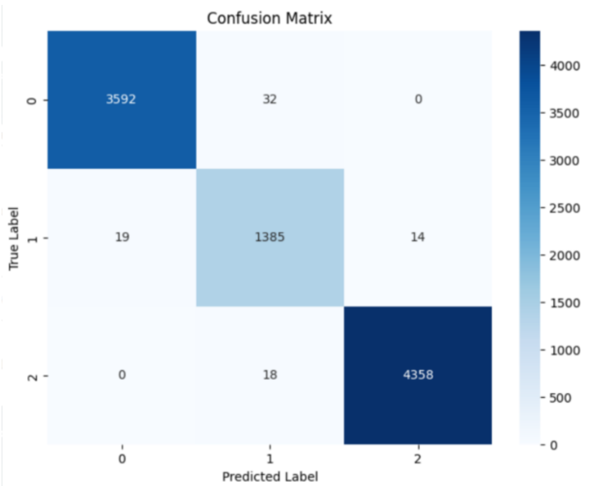

Fig. 4. K-NN Confusion Matrix

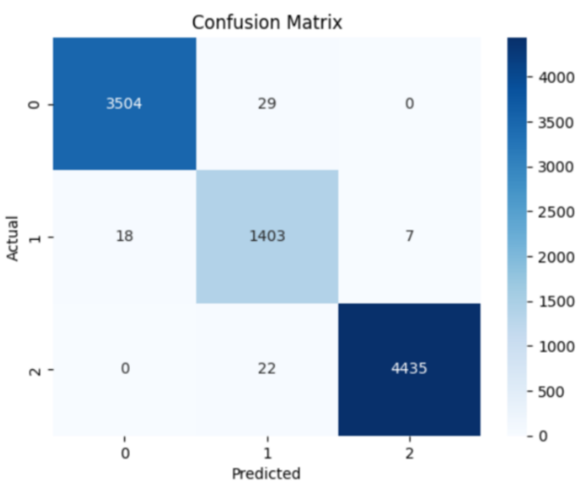

Fig. 5. SVM Confusion Matrix

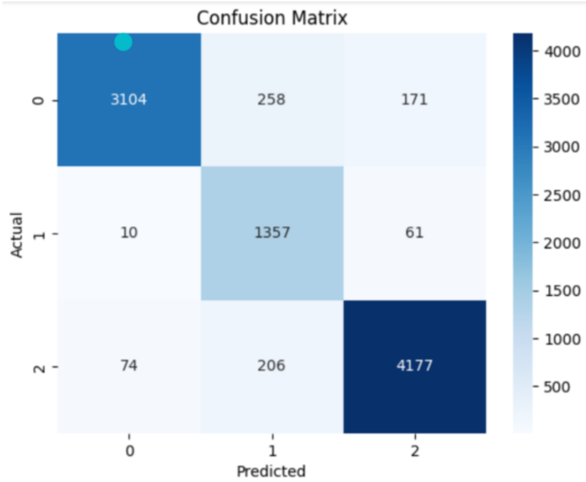

Fig. 6. Naïve Bayes Confusion Matrix

TABLE IV. COMPARISON CLASSIFICATION METHOD

Gradient	Class	Precision	Recall	F1-Score	Support
K-NN	1	0.99	0.99	0.99	3624
	2	0.97	0.98	0.97	1418
	3	1.00	1.00	1.00	4376
	Accuracy			0.99	9418
	Macro avg	0.99	0.99	0.99	9418
	Weighted avg	0.99	0.99	0.99	9418
SVM	1	0.99	0.99	0.99	3533
	2	0.96	0.98	0.97	1428
	3	1.00	1.00	1.00	4457
	Accuracy			0.99	9418
	Macro avg	0.99	0.99	0.99	9418
	Weighted avg	0.99	0.99	0.99	9418
Naive Bayes	1	0.97	0.88	0.92	3533
	2	0.75	0.95	0.84	1428
	3	0.95	0.94	0.94	4457
	Accuracy			0.92	9418
	Macro avg	0.89	0.92	0.90	9418
	Weighted avg	0.93	0.92	0.92	9418

In comparison to the approach in this study is the Portable Electronic Nose (PEN3), a sophisticated device designed to replicate human olfactory capabilities for various high-stakes applications, including medical diagnostics, food safety, and environmental monitoring [18]. PEN3 leverages advanced machine learning algorithms to interpret gas sensor data, allowing it to detect and differentiate complex odors across a wide range of substances and environments with high precision [19]. This versatility is supported by 10 different metal oxide sensors, adaptable to specific application needs, flexible sampling conditions, and stable sensor responses across varying gas concentrations and analytical settings. The system also features a rapid response time (typically under one second) and extended sensor lifespan due to its integrated dilution control, enhancing its suitability for continuous and high-frequency use in diverse environments. These advanced capabilities contribute to PEN3's high operational cost, with an initial purchase price around $26,000 and an annual maintenance expense of under $1,000. The sophisticated configuration of sensors and machine learning capabilities allow it to perform detailed analyses, but also result in complex operation requirements that may necessitate specialized handling and higher maintenance costs.

In contrast, this study utilizes machine learning with a more streamlined focus, employing only four gas sensors specifically for crab freshness detection, rather than a broad range of odor profiles as in PEN3. While this design is more limited in functionality, it offers the advantage of simplicity and ease of use, requiring less operational expertise and lowering costs significantly—coming in at under $20. This narrower focus enables a highly accessible, low-cost solution for crab quality assessment, which, while not as multifaceted as PEN3, is straightforward to operate and purpose-built for seafood freshness monitoring

V. Conclusion

This study employed a combination of gas sensors (e-nose) integrated with machine learning algorithms, including K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), and Naïve Bayes, to assess the freshness and quality of crabs. The gas sensors, placed in a plastic container, detected gases emitted during the decomposition process, providing sufficient data to accurately indicate the crabs' freshness. To minimize costs, only four gas sensors were utilized, aiming to develop a low-cost device. The data collected from these sensors were stored in CSV format and subsequently used for training the machine learning models. The goal was to enable accurate predictions regarding the crabs' quality based on the detected gases. Among the algorithms tested, K-Nearest Neighbors (K-NN) demonstrated superior performance, achieving an accuracy of 98%. This high accuracy confirms its effectiveness in evaluating crab freshness in practical applications. The results of this study contribute to the development of an automated method for detecting crab freshness, offering notable improvements in speed and accuracy over traditional manual assessment methods. This research demonstrates the potential for integrating low-cost gas sensors and machine learning models to establish an efficient and reliable system for monitoring crab quality. The design presents a portable and accurate device with applications valuable to both consumers and distributors, enhancing confidence in product quality and providing a form of quality assurance. However, limitations remain, particularly regarding the device's mobility, as it lacks the convenience of a handheld design. Additionally, the MQ series gas sensors used require a preheating period of at least 24 hours, which restricts immediate, on-demand usage. Future research should address these limitations and incorporate a broader range of food samples to enhance model robustness, enabling improved accuracy and broader applicability. As a final point, the algorithms developed in this research achieved a high accuracy rate of 98%, enhancing the reliability of the data collected and validated by the QCs. The dataset used in the study consists of 47,087 samples. Importantly, no laboratory tests were required, making the process both cost-effective in terms of tool development and experimentation.

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