Comparison of k-NN and Naive Bayes Algorithms for Classifying Mackerel Tuna Freshness Through Gas Sensors

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***Abstract*—The high production and consumption of mackerel tuna in Indonesia and globally underscore its significance both as a staple food and as an export product that contributes to the national economy. Mackerel tuna is valued for its nutritional content and affordability, making its freshness and quality critical for consumer satisfaction and trade. This study demonstrates the effectiveness of k-Nearest Neighbors (k-NN) and Naïve Bayes algorithms in classifying fish freshness by analyzing gases emitted during spoilage, using MQ-2, MQ-9, and MQ-135 gas sensors. Both models achieved accuracy rates close to 100%. The k-NN algorithm performed with near-perfect accuracy, misclassifying only one sample out of 7,207. Although the Naïve Bayes algorithm was slightly less precise, it maintained high accuracy while offering prediction times nearly seven times faster and requiring 400 times less memory. These findings provide valuable insights for the development of real-time quality control solutions using machine learning and gas sensor technologies.**

***Keywords*—classification, machine learning, tuna, gas sensor**

I. Introduction

The fisheries sector is a significant component of Indonesia's economy, contributing substantially to both national and agricultural GDP. In 2022, the sector accounted for approximately 555 billion IDR which is 2.6% of the national GDP and 21% of the agricultural GDP [1]. It employs approximately six million individuals, underscoring its role in livelihood and economic stability [2]. Additionally, per capita fish consumption in Indonesia reached 35.26 kilograms per year [3], underscoring the pivotal role of fish in the country's food security. Indonesia's fishery sector demonstrated its global significance in 2023, with a projected export value of $7.66 billion based on government targets [4], However, the actual export figures may not have fully met these aspirations [5].

In 2021, Indonesia's fisheries sector contributed approximately 2.7% to the nation's total exports, valued at USD 5.15 billion [1]. The sector is crucial for the Indonesian economy, and maintaining high-quality fishery products is essential to avoid financial losses. Quality control for fishery products is predominantly performed manually, which is time-consuming and labor-intensive [6]. This manual process is not only time-consuming but also prone to a 5-10% risk of human error, potentially compromising product quality. Non-compliance with international quality standards can lead to significant economic losses for exporters, as evidenced by product rejections in major markets like the United States. These rejections can result in substantial financial penalties, with estimates suggesting a significant economic impact. Additionally, poor product quality can damage the reputation of producers and shrink demand in the long run from global markets [7]. Ensuring high quality and safety standards is economically beneficial, as it minimizes losses from spoilage and trade disruptions. Therefore, implementing advanced and accurate technologies for assessing fishery product quality is vital.

The fisheries sector is essential to Indonesia's economy and plays a critical role in global food security. Seafood provides a significant source of protein for millions of people worldwide. Ensuring the freshness and quality of fish products is imperative, as failure to meet international standards can lead to considerable economic losses for exporters and disrupt global supply chains. An alternative approach to assessing the quality of fishery products involves analyzing the gases emitted during spoilage. The concentration of gases released during the spoilage process can be measured using gas sensors. Electronic nose (e-nose), comprising sensors that detect odors, have been successfully employed in numerous studies to evaluate the freshness of beef and pork [8]. This technology presents a promising solution for assessing the quality of seafood products.

This research seeks to assess the quality of seafood, specifically mackerel tuna, by using a gas sensor array system to analyze gases emitted during spoilage. The study proposes training an algorithm capable of rapidly and accurately classifying the freshness of mackerel tuna. To achieve this, experiments were conducted with four different types of gas sensors. The e-nose system was integrated with machine learning (ML) algorithms, incorporating hyperparameter optimization (HPO) and noise filtering techniques to improve accuracy in evaluating seafood freshness. The k-Nearest Neighbors (k-NN) and Naïve Bayes algorithms were selected for this study based on prior research demonstrating their effectiveness in classification tasks, particularly with sensor data. k-NN is noted for its simplicity and robustness in handling multi-class problems, while Naïve Bayes provides a fast and lightweight alternative, making both algorithms well-suited for real-time applications in seafood freshness detection.

II. Related Works

The incorporation of sensors and machine learning technology for fish quality detection has become a crucial area of research toward effective and trustworthy seafood quality assessment systems. This study owes to its unique approach and more detailed progress retrieval [9] in the field concentrating on well-diversified sensors and machine learning algorithms as well as fish freshness estimation. Concerning this aspect, another review [10] shifts the gaze into the latest trends in sensing configurations to determine fish shelf-life along with the merits, downsides, and synergies of different sensors – gas, colorimetric – coupled with machine learning constructs. Another research [11] provides a detailed and high-level application of the electronic nose supported with advanced machine learning assisted by hyperparameter tuning for seafood quality detection. This study established that the most accurate algorithm was the k-NN model which recorded a classification accuracy of 1.0 and the best-performing model in regression tasks achieving an RMSE of 0.003 and an R^2 of 0.99 in the detection of microbes in seafood. This emphasizes the applicability level of the e-nose and k-NN in seafood quality evaluation.

While previous studies have explored electronic noses and machine learning for seafood quality detection [12, 13], this research distinguishes itself by employing a comprehensive gas sensor array and optimizing algorithm performance through hyperparameter tuning and noise filtering techniques.

III. Methodology

A. Dataset Acquisition

The device used in this experiment, shown in Fig. 1, consists of a gas sensor array connected to an ESP DevKit-C S3 microcontroller. The gas sensor array, the combination of which is detailed in Table I, is embedded in a semi-airtight container that serves as the sample chamber (see Fig. 2). The sample used in the experiment was procured fresh on the morning of July 22nd and immediately placed in the sample chamber. An algorithm periodically captures the data from the electronic nose and stores it in a Pandas DataFrame. The sampling process was carried out for 10 hours, recording data as the sample transitioned from fresh to spoiled at room temperature (25°C). Data was captured once every second, resulting in over 36,000 records, which were subsequently saved in CSV format.

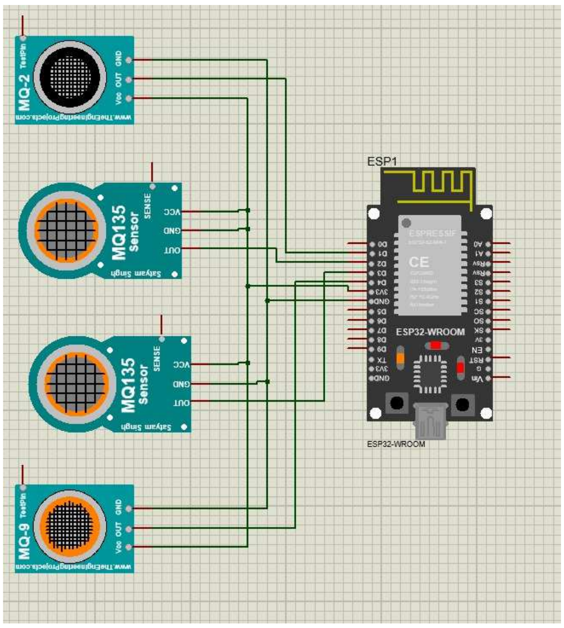

Fig. 1. E-nose device circuit diagram.

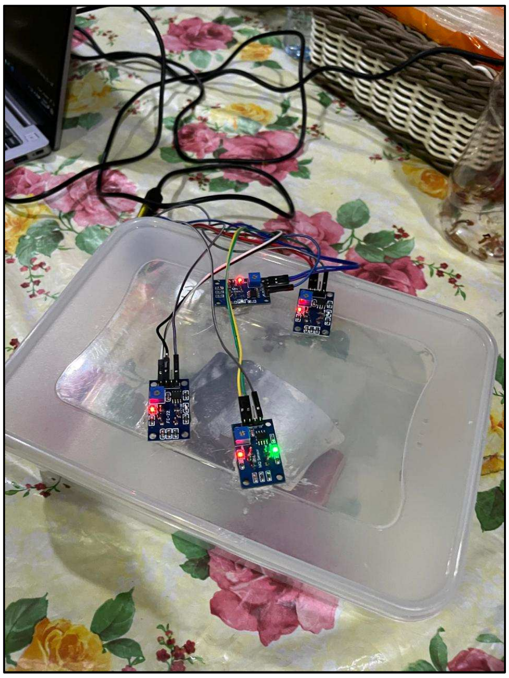

Fig. 2. Data acquisition

In this study, an experimental setup was designed to evaluate the effectiveness of the k-NN and Naive Bayes algorithms in classifying the freshness of mackerel tuna. The gas sensors used, as detailed in Table 1, include two MQ-135 sensors, one calibrated for Ammonia and the other for carbon dioxide, along with an MQ-2 sensor calibrated for Alcohol, and an MQ-9 sensor calibrated for Methane. These sensors are used to detect the compounds released during fish spoilage.

To ensure the reliability and validity of the experimental results the following measures were taken. To ensure the stability of the output data from the sensors, the sensors were pre-heated for more than 24 hours before use. In data preprocessing, raw and collected data were cleaned as per the requirement for having quality data. The data was then split into 80% to training data and 20% to testing data.

TABLE I. Gas Sensors Used.

No.	Gas Sensor	Selectivity
1.	MQ-135	Ammonia
2.	MQ-2	Alcohol
3.	MQ-9	Methane
4.	MQ-135	Carbon Dioxide

The collected data were then labeled based on the time elapsed from the beginning of the sampling process, using a Python script. The labeling criteria were based on the time the samples remained at room temperature, categorizing them into three distinct freshness levels: The samples with an exposure time of fewer than 5 hours are labeled as – "Fresh"; the samples with an exposure time of between 5 and 7 hours are labeled as "Less Fresh"; and samples with an exposure time exceeding 7 hours are labeled as "Not Fresh/Reject.". The criteria used in the labeling process were provided by an expert in fish quality control who has worked in the field for more than 19 years.

B. Proposed Method

This study compares the k-NN and Naive Bayes algorithms to determine the most suitable model for predicting the freshness of mackerel tuna. The raw data obtained from the sensors required little data cleaning. The collected sensor data is then divided into an 80% training set and a 20% test set manner. The 80% training data is utilized for the training of the k-NN and Naive Bayes models which also undergo hyperparameter tuning by using the grid search method. For the k-NN algorithm, three key parameters are optimized: the number of neighbors (k), the weights used in prediction, and the algorithm to find the nearest neighbors. The last 20% of the dataset is utilized to assess the accuracy of the models in classifying the freshness of mackerel tuna. The main purpose of this approach is to find an efficient, accurate, and lightweight algorithm for fish freshness classification using gas sensors, to be used as an effective and reliable quality control process.

Fig. 3 presents the workflow of the proposed method for the machine learning aspect of this research. It outlines key stages, including model training with hyperparameter optimization (HPO), performance testing, and evaluation. The process begins with the selection and preparation of the dataset, followed by splitting the data into training and testing sets. During model training, HPO is employed to fine-tune the algorithms for optimal performance. Once trained, the model is tested on the validation set to assess its accuracy and generalization capability. Finally, the model's performance is evaluated, ensuring a thorough assessment of its effectiveness in classifying mackerel tuna freshness.

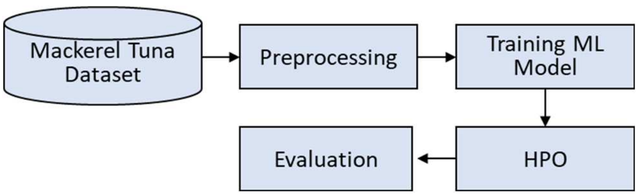

Fig. 3. Proposed method for classifying mackerel tuna freshness.

The evaluation metrics used in the evaluation are accuracy, precision, recall, F1 score, and confusion matrix. Further, 5-fold cross-validation is used to estimate model accuracy by dividing the dataset into five subsets, in which only one subset is used for validation while the other four subsets are used for training, then performance measure is averaged over all five splits, improving the reliability of the evaluation and reducing the effects of how the data is split. These steps are very useful to provide a reliable comparison between the two models.

A method was also developed to evaluate the average classification speed and memory usage of both algorithms, both algorithms were used to classify 100 random data points from the test set then the results of said test were plotted in a line graph, and lastly the average classification time and memory usage was calculated.

IV. Results and Analysis

The performance of the k-NN and Naïve Bayes models was compared to evaluate their ability to detect the freshness level of mackerel tuna using gas sensors. The performance metrics used in this analysis include 5-fold cross-validation, accuracy, precision, recall, F1 score, classification speed, and memory usage. Table II presents the parameters tested using the grid search method, along with the optimal parameters identified.

TABLE II. Grid Search Model Hyperpameters.

Algorithm	Parameters	Parameter Values	Best Parameters
k-NN	n_neighbors	5	10
		10	
		20	
		50	
		100	
		150	
	weights	uniform	uniform
		distance	
	algorithm	auto	auto
		ball_tree	
		kd_tree	
		brute	
		linear	
Naive Bayes	var_smoothing	1e -9	1e -9
		1e -8	
		1e -7	
		1e -6	
		1e -5	
		1e -4	
		1e -3	
		1e -2	
		1e -1	
		1	
		10	
		100	

The exceptional performance of the k-NN model can be seen in its confusion matrix shown in Fig. 4, with only one misclassification out of 7,207 samples which resulted in an accuracy rate of almost 100%. This was further enforced by the average cross-validation score of 0.99916, showing the strong generalization ability of the model. The Precision, recall, and F1-score performance metrics for the k-NN model were also remarkably high to attest to its strong classification capability.

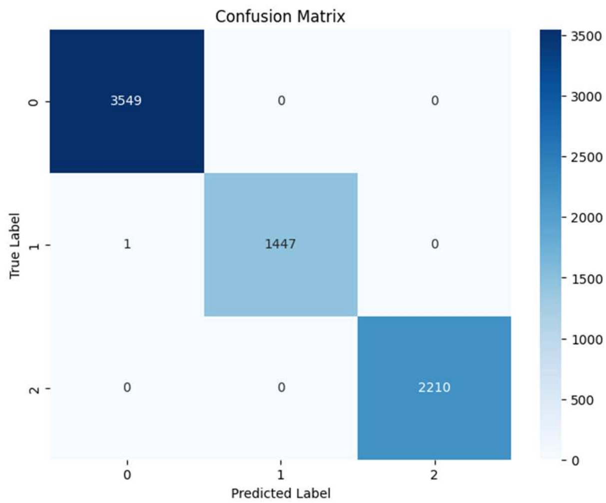

Fig. 4. k-NN model confusion matrix.

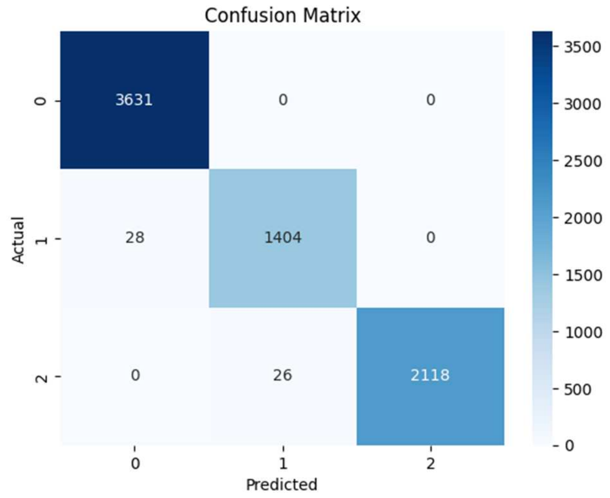

Fig. 5. Naive Bayes model confusion matrix.

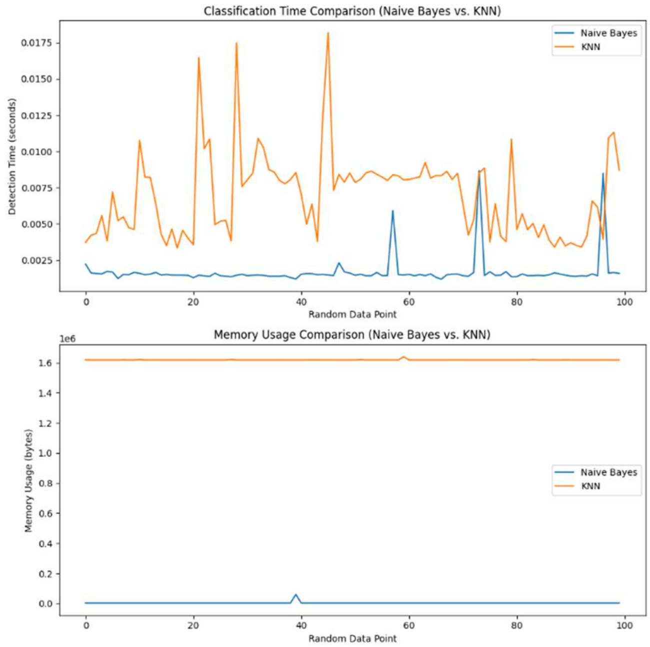

Fig. 6. Algorithm classification speed and memory usage comparison.

In comparison, the Naive Bayes model also performed reasonably well, although, with lower accuracy, it misclassified fifty-four samples out of 7,207, which can be seen in its confusion matrix in Fig 5, thus resulting in an accuracy percentage of 99.2%. The average cross-validation score was 0.982, which indicates solid generalization ability but lower in comparison with k-NN. The Precision, recall, and F1-score performance metrics for the Naive Bayes model also showed good reliability in classification tasks.

To evaluate the classification time and memory usage of both algorithms, a testing method was developed that involves classifying 100 randomly selected data points from the test set. The results, which are plotted in Fig. 6 and summarized in Table III, indicate that while the Naive Bayes algorithm exhibits slightly lower accuracy and cross-validation scores compared to the k-NN algorithm, it significantly outperforms k-NN in terms of average classification time and memory usage. This suggests that Naive Bayes, despite its marginally lower accuracy, is more efficient for applications where speed and memory efficiency are critical, whereas k-NN may be better suited for scenarios prioritizing classification accuracy.

TABLE III. ALGORITHM AVERAGE SPEED AND MEMORY USAGE COMPARISON

Algorithm	**Average Classification Speed (seconds)**	**Average Memory Usage (bytes)**
k-NN	0.007	1,618,185
Naive Bayes	0.0016	4028

The evaluation also showed the class that received most of the misclassifications was the "Less Fresh" class, likely because of its underrepresentation in the dataset. This imbalance likely caused the higher rate of errors associated with this class and affected the overall classification performance. The complete performance metrics of both algorithms are shown in Table IV.

TABLE IV. MODEL PERFORMANCE COMPARISON.

Algorithm	**Class**	**Precision**	**Recall**	**F1-score**	**Accuracy**
k-NN	Fresh	1.00	1.00	1.00	1.00
	Less fresh	1.00	1.00	1.00	
	Reject	1.00	1.00	1.00	
	Average	1.00	1.00	1.00	
Naive Bayes	Fresh	0.99	1.00	1.00	0.99
	Less fresh	0.98	0.98	0.98	
	Reject	1.00	0.99	0.99	
	Average	0.99	0.99	0.99	

Consistent with previous research findings, our study confirmed that the k-NN algorithm consistently yields the highest accuracy rates among various classification methods. This aligns with existing literature highlighting k-NN's robustness in sensor data classification tasks.

In summary, while the k-NN model is effective in real-world applications where high classification accuracy is required, the Naïve Bayes model's higher classification speed and lower memory usage might also prove to be a suitable alternative given the specific needs of the application.

V. CONCLUSION

This study evaluated the performance of the k-Nearest Neighbors (k-NN) and Naive Bayes algorithms in detecting fish freshness using gas sensor data. Both models demonstrated strong potential for real-time, automated quality control in the seafood industry. The k-NN algorithm excelled in accuracy, with nearly flawless results, misclassifying only one sample out of 7,207. Although the Naive Bayes algorithm was slightly less precise, it still performed admirably, achieving a high accuracy rate while offering prediction times almost 7× faster and 400× less memory usage. These findings underscore the potential of combining machine learning algorithms with gas sensors to assess fish quality, presenting a promising approach to improving freshness detection and enhancing quality control systems in the seafood sector. However, the study's scope was somewhat limited, as it focused on a single type of fish. Future research could expand on this by incorporating a wider variety of fish species to enhance model robustness and account for potential variations in quality.

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