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An Optimized Hybrid Model for Perishable Product Quality Inference in the Food Supply Chain

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Abstract

The supply chain for perishable products faces significant challenges in monitoring and maintaining product quality. These products are particularly vulnerable to environmental dynamic conditions and variations in distribution and transportation. To address these challenges, leveraging the Internet of Things (IoT) and quality inference techniques during transportation can provide valuable insights for both consumers and producers. The objective of the research is to develop a model for inferring the quality of perishable products using an IoT sensor dataset to monitor perishable product quality continuously. This research applied a hybrid approach combining a Fuzzy Inference System (FIS), clustering models, and genetic algorithms to infer the product quality during supply chain distribution with IoT sensors. The result shows that the hybrid FIS model, which employs Gaussian membership functions and fuzzy c-means clustering for rule generation, achieves a high accuracy with an R^2: 0.873. This research contributes to improving the model by employing genetic algorithms in optimizing the inference model by activating only five out of seven rules. The model optimization achieves optimal computation time while aiming to preserve model accuracy. However, test results indicate that the combination of rules has not yet significantly enhanced the model's accuracy, though it holds potential for future development.

Keywords:

Supply Chain Management;
Optimization;
Quality Control;
Fuzzy Inference;
Genetic Algorithms.

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1- Introduction

Quality is a key attribute that consumers consider when evaluating a product, especially food. Food has a low tolerance for quality deviations and must meet all consumer requirements to justify its value; therefore, it is called perishable products. Quality management for all products, including food and other perishable products, must focus on consumer satisfaction [1] with guarantees in the highest safety and quality. Meanwhile, perishable product distribution is often overlooked, despite its complexity, uncertainty, and high risk of loss [2], although it has a significant impact on food quality and safety. With advancements in technology and science, issues related to product quality and safety losses should be minimized.

Perishable products face more complex challenges in maintaining quality. Perishable products such as vegetables, milk, and meat tend to deteriorate over time before reaching consumers [3, 4]. Poor quality management and control of perishable products lead to consumer disappointment, loss of trust in producers, and potential health risks. Producers, on the other hand, are the first to be affected by the quality, reliability, and safety of food products. They need to ensure

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that products are transported to consumers under various uncertain environmental conditions. Ultimately, if quality is not well maintained, it launches non-conformance costs of quality, impacting producers due to the loss of consumer trust. Moreover, maintaining the quality of perishable products is highly challenging and cannot be considered fixed and linear, as the quality is significantly influenced by storage conditions, handling time, and transportation facilities [2, 5].

Perishable products experience the most significant quality degradation during retail storage (15%) and transportation (35%) [6, 7]. Previous studies have estimated perishable product quality based on degradation models [2]. While theoretical predictions of quality degradation are accurate, moreover, practical implementation requires a system that can monitor product quality throughout transportation and provide this information to all stakeholders. Furthermore, earlier research has proposed solutions for monitoring perishable product quality through RFID-based traceability during transportation and distribution [8-10]. However, these solutions have not fully addressed the problem, as they only provide location information without detailing the product's quality level. Producers have made efforts to minimize and monitor this degradation using traceability systems, but this information has typically been available only to producers [11]. The key issue of asymmetric information in the supply chain remains unresolved because such systems only offer information to producers, not to other supply chain stakeholders.

Previous research has explored the design of tracing and tracking systems for products using various Internet of Things (IoT) devices. Li et al. [12] and Srinivas et al. [13] agree on the potential for more extensive use of IoT combined with machine learning in supply chain management. Several prior studies have also confirmed the use of IoT in supply chains, both with prescriptive and predictive approaches. Wang [14] utilizes IoT and ANFIS-based machine learning for demand volume prediction in e-commerce supply chains. Upon review, IoT has already been widely applied in various supply chains and holds significant potential for further implementation. However, challenges arise with perishable products, as their quality is highly dependent on environmental conditions during transportation and distribution to customers.

The monitoring of perishable product quality through IoT has also been explored in various previous studies. The use of IoT and machine learning for the supply chain of perishable products was employed by Jauhar et al. [15], where machine learning was used to predict consumer demand based on inventory levels and customer characteristics. Pal & Kant [16] introduced the term "Internet of Perishable Logistics" (IoPL), but still focused on prescriptive approaches and optimization. In addition to these two studies that emphasized prescriptive approaches, other research related to IoT use in the supply chain of perishable products has also been conducted. For instance, Mohammadi et al. [17] applied IoT for inventory management of perishable products using evolutionary algorithms, Sathiya et al. [18] developed an IoT system for monitoring the quality of perishable products using the ANFIS algorithm, and Selukar et al. [19] focused on using IoT for inventory management of perishable products to prevent losses due to opportunity cost for producers.

Based on the previous research, IoT has been widely utilized in the supply chain, including perishable products management. However, most studies focus on optimization or prescriptive approaches to minimize risks related to costs and quality. Predictive approaches, on the other hand, are still quite limited, even though they have the potential to detect risks earlier and monitor product quality throughout the supply chain during transportation, which can benefit both producers and consumers. The use of predictive models for perishable products is still underexplored, despite its promising potential, as demonstrated by Hu et al. [20] in vaccine quality management. Additionally, combining predictive and prescriptive approaches through hybrid methods should be considered for product quality in enhancing model reliability.

The use of IoT for monitoring perishable product quality should be a key focus, as it offers an effective means to intervene and infer the desired quality levels for perishable products according to consumer expectations. IoT is a highly effective control tool for monitoring product shelf life, given that product quality is not linear with time and is heavily dependent on storage conditions, making it challenging to monitor and predict quality [4]. Therefore, it is important to recognize that product quality is not solely a function of time or temperature but also requires accurate attention to environmental conditions and their impact on quality, such as the potential bacterial growth in the product. The use of IoT and sensors, along with environmental monitoring during transportation, can also provide recommendations for producers to maintain product quality under optimal conditions. Additionally, IoT can help minimize the quality gap in e-commerce products during short transportation times, thereby enhancing customer satisfaction [21].

Monitoring the quality of perishable products offers valuable opportunities to improve information sharing across the supply chain. IoT technology, in particular, enhances profitability, but it needs further development to infer any recommendations and valuable information [22]. IoT can provide data that helps all stakeholders understand the environmental conditions affecting perishable goods [23]. To boost supply chain efficiency, it is essential to have a model and system that can clearly interpret the quality of perishable products based on environmental conditions captured by data collection through IoT with complete prescriptive and predictive analytics. Previous research has indeed extensively utilized IoT in supply chains, but it has been limited to prescriptive analytics that merely display data, without fully leveraging predictive analytics using machine learning approaches to optimize quality.

Using IoT for product quality monitoring has been limited to temperature and humidity, which are used to infer product shelf life and quality [2, 8, 24]. The quality of perishable products cannot be assessed solely based on temperature or humidity. Various environmental factors can affect product quality during storage and transportation, including environmental conditions and gas constants [25, 26], activation energy [25], and bacterial contamination [4, 27-29]. In fact, the gas conditions within storage environments during transportation are a major factor influencing product loss, quality, and nutritional content [30]. Additionally, the shelf life of perishable products, which is linearly related to quality, is also significantly affected by microbes, storage temperature, and time [31].

Related to perishable product quality with uncertain environmental conditions prediction with machine learning, several algorithms have been developed for some models for monitoring the quality of perishable products, including fuzzy logic and neural networks [32], XGBoost algorithms for detecting and tracking the positions of perishable goods [24], and fuzzy logic for evaluating perishable product quality [25]. Advanced research has also proposed methods for quality detection using image processing techniques, such as Convolutional Neural Networks (CNNs) and their optimizations [33]. Additionally, mathematical approaches have been employed to optimize the dynamic quality of perishable products throughout the supply chain [4]. Furthermore, optimization models for vehicle routing problems and evolutionary algorithms have been used to minimize transportation costs and maximize product quality [34].

Among various optimization techniques, machine learning, and artificial intelligence, fuzzy logic has advantages in handling fuzzy and uncertain information commonly encountered in real-world applications [21]. Fuzzy logic also integrates well with other machine learning and artificial intelligence techniques to enhance model performance, as demonstrated in real-world scenarios. However, the use of fuzzy logic and data-based fuzzy inference models is still limited when it comes to integrating with advanced techniques to improve model performance. A fuzzy inference system alone cannot sufficiently enhance model accuracy. To improve accuracy, optimization, and faster inference processes, a hybrid model is needed to support practical and targeted decision-making. A quantitative approach to monitoring and predicting quality is essential for perishable products [22]. Data collected from IoT can provide a basis for developing precise algorithms to quantitatively predict the quality of perishable products, but it is crucial that this process should be carried out efficiently.

This research contributes by designing an efficient algorithm for predicting the quality of perishable products based on environmental conditions collected through sensors/IoT. A quantitative prediction approach combined with transparent and easily understandable information can enhance the accuracy and efficiency of the supply chain system. Therefore, this study proposes a hybrid model to improve the accuracy and efficiency of processing data obtained from sensors. The fuzzy inference model that was firstly proposed by Zadeh [35] is combined with clustering models to design inference models and rules curated through IoT. Furthermore, the developed hybrid model is optimized to enhance its efficiency and accuracy with the use of evolutionary algorithms and genetic algorithms.

The objective of this research is to design a hybrid inference model for determining the quality of perishable products. The developed hybrid model combines clustering techniques with a data-driven fuzzy inference system. Additionally, the model is optimized using evolutionary algorithms to enhance both accuracy and efficiency in inferring the quality of perishable goods. This study seeks to address research gaps by advancing models and algorithms for controlling and inferring the quality levels of perishable products, aiming for high performance and accuracy with efficient operations.

This paper is organized as follows: Section 2 details the research method used for model development, including data collection, preprocessing, and model evaluation and optimization. Section 3 presents the experimental result of the model development in any scenarios and employs the model performance with relevant metrics. Section 4 concludes the paper, summarizes the key findings, and provides potential further research.

2- Material and Methods

2-1- Research Stage

The research process is illustrated in Figure 1. This study consists of three main parts: data pre-processing and clustering, inference modelling, and model optimization. Data pre-processing is a crucial step to ensure that the acquired data is clean and ready for further processing. Data clustering is employed to determine data clusters, which will later be used to design the number of fuzzy rules for inference system design. The second part involves fuzzy inference modeling for developing a system to predict perishable product quality. The combination of clustering approaches with a fuzzy inference system is adopted to predict product quality. This modeling also develops two types of membership functions: triangular and gaussian. The final part focuses on model optimization to enhance the performance of predictions. Genetic algorithms are used in model optimization to define which fuzzy rules should be retained within an optimal number of rules. The following sections will describe the details of each process and stage in this research.

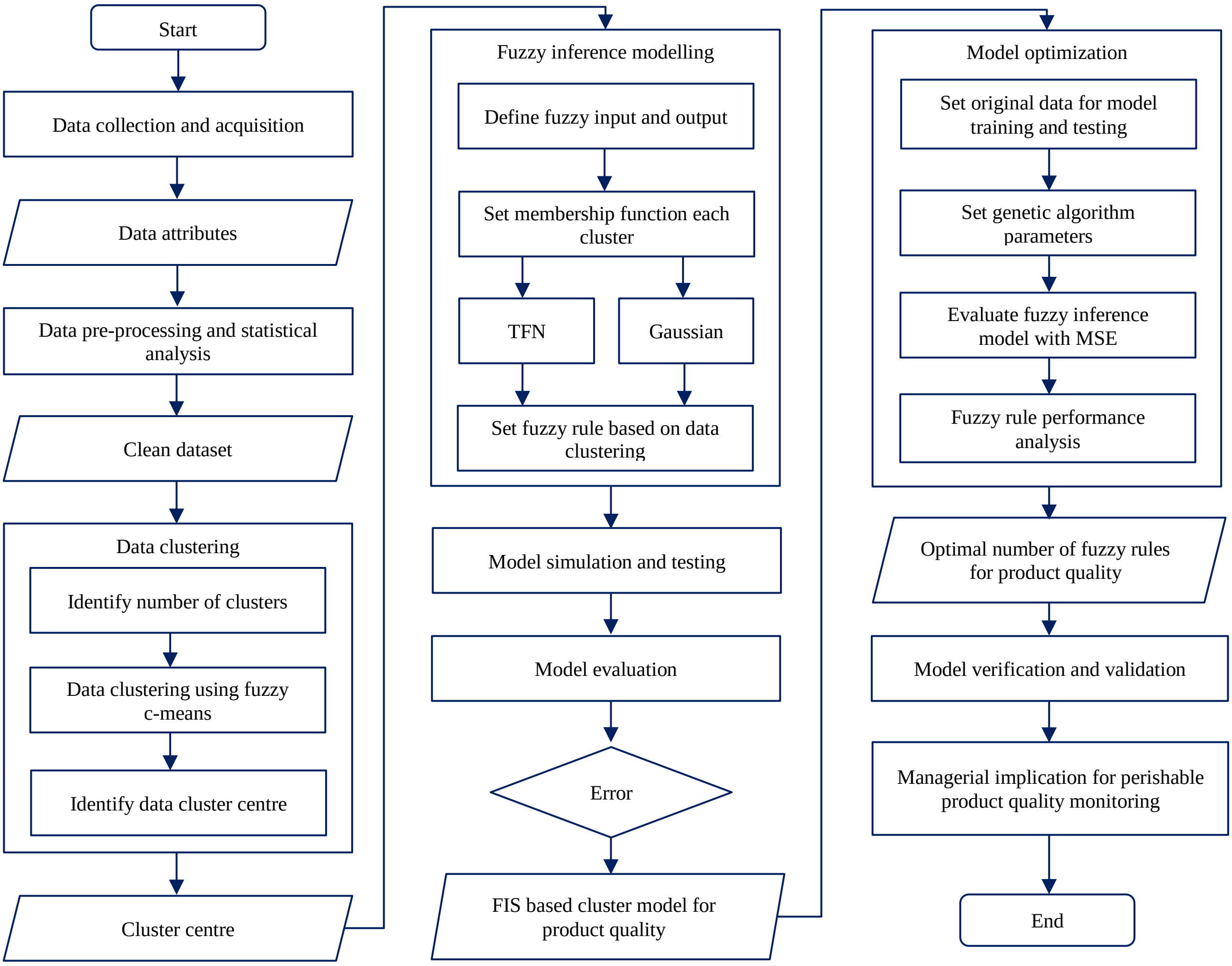


Figure 1. Research stage

2-2- Data Acquisition and Preprocessing

The challenges in implementing IoT in the e-commerce supply chain industry include data acquisition and the high potential for errors. In line with the research objective of developing a product quality prediction model for e-commerce, the data acquired in this study consists of meat quality and environmental condition data collected using various types of sensors. This data is sourced from previous research [27, 36] and has been publicly published here: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/XNFVTS.

The data set consists of twelve types of beef cuts, with environmental conditions monitored using relevant sensors. There are eleven types of gas sensors used to measure the storage environment of the meat every second over a period of 2,220 seconds. Each observation also includes the meat quality level, measured using the total viable count (TVC). This data represents the storage conditions of perishable products during transportation and distribution. The data can be used to develop algorithms that could later be implemented in the real world. As a prototype, the tenderloin beef cut is proposed as an experiment for the development and evaluation of the hybrid fuzzy quality monitoring model.

Given the large number of dimensions in the data, with eleven attributes and 2,220 samples, significant effort is required to minimize the curse of dimensionality. A correlation-based approach is proposed to evaluate the attributes against the TVC data as the target variable. A simple correlation approach is suggested to ensure that minimal information is lost from the original data while still having an impact on the target data. Suppose x represents an attribute and y represents the target data; $\hat{x}$ and $\hat{y}$ as the average of attribute and target data respectively, then the Pearson correlation is described by Equation 1.

$$r = \frac{\sum(x_i - \hat{x})(y_i - \hat{y})}{\sqrt{\sum(x_i - \hat{x})^2 \sum(y_i - \hat{y})^2}} \tag{1}$$

2-3- Hybrid Inference System Development

Fuzzy modelling was first proposed by Zadeh [35] and has since evolved into various models to support decision-making in the real world. One of the fuzzy models that applied research is the fuzzy inference system (FIS) with the Mamdani model [37, 38]. The development of an FIS model consists of several stages: crisp input, fuzzification, rule generation, defuzzification, and crisp output. One of the challenges in designing an FIS model is the difficulty in creating fuzzy rules. The number of rules that need to be formulated grows exponentially with the number of input variables [39-41], making the decision-making system less agile and less reliable for real-world applications.

This research adopts a clustering approach to design the FIS model. The hybrid FIS and clustering model aims to create a more computationally efficient model while maintaining high accuracy. Two clustering models are adopted for rule design: the fuzzy c-means clustering model and the k-means clustering model.

2.3.1. Data Clustering Model

Data input is used to design fuzzy rules through clustering. Clustering is a supervised algorithm that needs to determine the number of clusters. The silhouette method is used for analysing the number of clusters. The optimal number of clusters is determined by the maximum silhouette score. Let $S(x_i)$ be the silhouette score for data x_i, $a(x_i)$ be the average distance of x_i to the data within its own cluster, and $b(x_i)$ be the average distance of x_i to the data in the nearest neighbouring cluster. According to Shutaywi & Kachouie [42], the silhouette score can be seen in Equation 2.

$$s(x_i) = \frac{b(x_i) - a(x_i)}{\max\{b(x_i), a(x_i)\}} \tag{2}$$

The k-means clustering method aims to maximize similarity within clusters and maximize variability between clusters. The number of clusters in k-means are determined using the silhouette method. In line with its goal of minimizing variability within clusters, the k-means clustering model can be described according to Sinaga and Yang [43] as shown in Equation 3. The variable j represents the distance of data x to the cluster centre, x_j is the data point j, μ_i is the centre of cluster I, k is the number of clusters determined through the silhouette method, and C_i is the cluster i.

$$\min J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \left\| x_j - \mu_i \right\|^2 \tag{3}$$

The Fuzzy c-means (FCM) clustering is an improvement over the k-means clustering method which was first introduced by Bezdek et al. [44]. This fuzzy approach uses membership function parameters to determine the degree of belonging of a data point within a cluster. Fuzzy c-means has algorithmic characteristics with k-means but uses a fuzzy approach to primarily reduce errors in the placement of data points within clusters. Similar to k-means, fuzzy c-means aims to minimize the distance of data points to the cluster center (j). According to Izakian & Abraham [45], the process of determining the cluster center (z_j) in c-means is iterative and depends on the membership function value ($\mu_{i,j}^m$) and vector data i (x_i) for all N number dataset, also m fuzziness level, as shown in Equation 4 dan 5.

$$z_j = \frac{\sum_{i=1}^{N} \mu_{i,j}^m x_i}{\sum_{i=1}^{N} \mu_{i,j}^m} \tag{4}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - \mu_i \right\|}{\left\| x_j - \mu_k \right\|} \right)^{\frac{2}{m-1}}} \tag{5}$$

2.3.2. Fuzzy Inference System Modelling

The most complex part of developing an inference system is defining fuzzy rules. The number of fuzzy rules depends on the number of input variables and linguistic levels, which makes the computational process very complex [46]. Using a clustering model to determine rules in an FIS makes the model simpler, more accurate, and speeds up the computational process.

Fuzzy rules consist of antecedent and consequent parts. In setting rules within a hybrid clustering and FIS model, the antecedent and consequent parts are extracted from the cluster centres obtained using Equations 2-5. The cluster centres are transformed into membership functions for further processing with fuzzification. There are two types of membership functions used in this inference model: Gaussian and Triangular membership functions. Let c_j be the cluster centre obtained from the k-means or FCM algorithm, and x be the input variable. For gaussian membership function, it needs cluster centre (c) from FCM and standard deviation of each cluster (σ). While for the triangular fuzzy numbers, itu define the membership function with lower (a), medium (b) and upper (c) number to represent the membership function. The membership functions for cluster j in gaussian and triangular membership function can be seen in Equations 6 and 7, respectively.

$$\mu_j(x) = exp\left(-\frac{(x - c_j)^2}{2\sigma_j^2} \right) \tag{6}$$

$$\mu_j(x) = \begin{cases} 0 & if\ x \leq a_j \\ \frac{x - a_j}{b_j - b_j} & if\ \ a_j < x \leq b_j \\ \frac{c_j - x}{c_j - b_j} & if\ \ b_j < x \leq c_j \\ 0 & if\ x > c_j \end{cases} \tag{7}$$

If x_i is the input variable, y is the single output variable of the fuzzy inference system, and c_j is the cluster centre obtained from the clustering algorithm, then the form of the fuzzy rule is as follows:

If x_1 near c_1 AND x_2 near c_1 AND x_3 near c_1 … AND x_i near c_1 then y near c_1

If x_1 near c_2 AND x_2 near c_2 AND x_3 near c_2 … AND x_i near c_2 then y near c_1

If x_1 near c_i AND x_2 near c_i AND x_3 near c_i … AND x_i near c_j then y near c_i

The specifications of the model applied for the development of the FIS-based data model for predicting meat quality in this study can be seen in Table 1.

Table 1. Specification for the FIS based data model.

No.	Parameter	Specification
1	Membership function	Triangular fuzzy number Gaussian fuzzy number
2	Inference model	Mamdani
3	Rules operator	AND
4	Aggregation function	Max
5	Implication function	Min
6	Defuzzification model	Centroid
7	Evaluation	RMSE; MSE; MAE; R^2

2.3.3. Model Optimization

Perishable products supply chains require an efficient and accurate model to predict the quality level of products during transportation and distribution in real time. Model optimization is necessary to enhance model efficiency. The fuzzy inference system model which has high rule complexity based on the number of input variables and linguistic labels must be optimized. A model is proposed to optimize the number of fuzzy rules that have the highest fitness for quality output inference, thereby enabling the model to operate efficiently in all stages of supply chains operations.

Previously, the development of data-driven FIS models involved creating rules based on clustering models. To improve the efficiency and accuracy of the model, this research proposes optimizing the FIS model using an evolutionary algorithm: the genetic algorithm (GA). The underlying logic in this model optimization is to use the most optimal number of rules to process input data efficiently for producing an accurate inference output for perishable product quality prediction. Previous research has also utilized GA for optimizing fuzzy models, such as Savrun & İnci [47], who optimized training data for the development of ANFIS models, and [48-50], who optimized membership functions within FIS using GA. Genetic algorithm (GA) is an optimization algorithm inspired by the principles of human evolution and fitness. GA employs a probabilistic approach to optimize models and find global optimal solutions. However, genetic algorithms are most efficient in vast and complex solution spaces, rather than in problems with narrow and simple solution spaces. Optimizing fuzzy rules while considering various factors of uncertainty with levels of linguistic labels face a complex issue, thus making it essential for optimizing the system to operate efficiently. In this context, optimizing the FIS model with GA is highly necessary.

In FIS, there are three approaches to generating rules: (1) building rules based on expert opinion, (2) building rules based on data and providing data to adjust membership functions, and (3) building rules using linear and structured approaches. In this research, the Genetic Algorithm is applied to determine the most effective and efficient combination of rules which have been applied in FIS model to produce an accurate output prediction.

In this research, the optimization of FIS using GA begins with chromosome representation. Chromosomes are represented by the rules *(r)* of the FIS that have been previously developed, and the length of the chromosome *(M)* corresponds to the number of rules specified in the FIS model. Chromosomes are illustrated in Equation 8. Each gene in the chromosome (r_M) is represented by a binary number for rule testing.

$$chromosome = \{r_1, r_2, \dots, r_M\} \tag{8}$$

According to the GA framework, chromosomes can be altered to improve model accuracy. Several parameters are set in the randomly generated chromosome representation model as shown in Table 2. The model's output can be evaluated using the model fitness function. In this optimization model, the fitness function is the model with the lowest error rate compared to actual data. Therefore, in this case, the fitness function adopts the mean square error (see Equation 9).

Table 2. Model parameters for model optimization using GA

No.	Parameter	Specification
1	Number of populations	50
2	Crossover probability	50%
3	Individual mutation probability	20%
4	Genetic mutation probability	5%
5	Fitness model	Mean Square Error

2-4- Model Evaluation

To ensure the model accurately predicts product quality, four evaluation metrics are proposed to assess the model. The models being evaluated are inference models with Gaussian and triangular fuzzy number membership functions. Evaluating the FIS models with triangular and gaussian membership functions is necessary to determine the most accurate model for optimization with the genetic algorithm. Furthermore, the performance of the optimization model with the genetic algorithm is also compared with that of the FIS models using gaussian and triangular membership functions.

Let $\widehat{y_i}$ be the actual target data value, y_i represents the value predicted by the gaussian or triangular inference engine model, and $\overline{y_i}$ represents the average of the actual values. Thus, the metrics for evaluating the model with mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and R^2 can be seen in Equations 9 to12, respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}| \tag{10}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{11}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} \tag{12}$$

3- Results and Discussion

3-1- Data Description and Preprocessing

The data used in this study comes from previous research that has been publicly shared [27, 36]. The advantage of using public data is the transparency in model development, allowing for validation with subsequent research. The data set consists of eleven attributes with one target variable and includes a total of 2,220 samples. Each sample represents an observation taken every minute based on information captured by IoT-based sensors installed in the environment of perishable products, specifically tenderloin beef cuts in this case. This research assumes that IoT tools enable reading, collecting, and delivering data efficiently and accurately. The data collected from the sensor then analyses and predicts the perishable product quality based on the model development that is proposed in this research. A general statistical description of the collected data from public sources for this case is described in Table 3.

Based on the data description, each attribute has its own uniqueness, as observed from its data distribution. Most of the data follows an almost normal distribution with skewness values close to zero. Generally, the data skewness is positive, except for MQ137, MQ5, and TVC. Negative skewness indicates that over time, the values collected by the sensors for each attribute are high, with outliers occurring at lower values. From the kurtosis description, it is interpreted that most of the data is negative, except for sensors MQ136, MQ138, MQ4, and MQ6. Negative kurtosis indicates few outliers, which is advantageous for further processing to produce accurate decisions.

The data description above is also very useful in the subsequent process for data preprocessing. Given that the data received is already clean, the next step in preprocessing is feature selection. At this stage, a simple Pearson correlation analysis is proposed to examine the correlation between the attribute data and the target data, which is TVC. The results of the correlation analysis can be seen in Figure 2.

Table 3. Data description

No.	Type	Code	Data	Min	Max	Std	Skewness	Kurtosis
1	Attribute	MQ135	Ammonia, carbon dioxide, alcohol, benzene	9.86	20.69	3.073	0.395	-1.161
2	Attribute	MQ136	Hydrogen sulfide	3.73	14.36	2.299	1.186	1.178
3	Attribute	MQ137	Ammonia	7.11	22.5	4.302	-0.736	-0.590
4	Attribute	MQ138	Aldehydes, alcohols ketones	10.08	21.64	3.044	1.829	1.914
5	Attribute	MQ2	Methane, alcohol, LPG, hydrogen, smoke, propane, i-butane	3.79	8.95	1.223	0.684	-0.427
6	Attribute	MQ3	Alcohol, benzine, methane, hexane, LPG, carbon monoxide	10.83	21.63	2.944	0.692	-0.383
7	Attribute	MQ4	Methane	2.84	15.2	2.558	1.366	1.574
8	Attribute	MQ5	Hydrogen, LPG, methane, carbon monoxide, alcohol	6.68	21.67	3.240	-0.350	-0.683
9	Attribute	MQ6	Propane, LPG, iso-butane	9.2	34.25	2.855	0.256	2.615
10	Attribute	MQ8	Hydrogen	22.8	50.6	7.055	0.218	-1.356
11	Attribute	MQ9	Methane, carbon monoxide, and propane	8.16	13.5	1.694	0.361	-1.458
12	Target	TVC	Total viable count	1.875	5.758	1.137	-0.975	-0.281

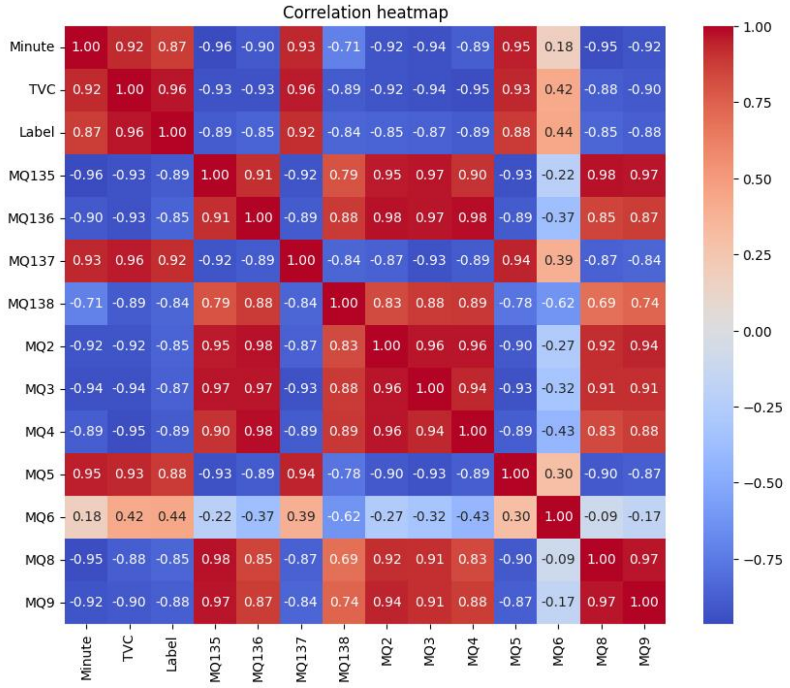


Figure 2. Attribute correlation

The threshold set for feature selection using Pearson correlation is ±0.5. It can be observed that most attributes and the target data, TVC, have correlations greater than 0.88, except for the data from sensor MQ6, indicating a strong correlation between the attributes and the target data. This will also strengthen accurate conclusions in the development of the inference system. As for the MQ6 attribute, it may be excluded from further analysis due to its correlation not meeting the threshold. Additionally, the data description shows that it has the highest positive skewness, indicating a high number of outliers. Excluding sensor MQ6 will also improve model accuracy as data noise is removed from the dataset. Ultimately, the dataset to be included in the analysis and subsequent model development consists of ten attributes and one target variable. An example of the data can be seen in Table 4.

Table 4. Data head for model development

No.	TVC	MQ135	MQ136	MQ137	MQ138	MQ2	MQ3	MQ4	MQ5	MQ8	MQ9
1	1.876	17.11	11.63	7.14	19.2	7.58	19.18	12.7	7.99	37.22	11.71
2	1.876	17.4	11.72	7.11	19.37	7.65	19.34	13.12	6.92	36.78	11.62
3	1.876	18.55	13.46	7.64	21.04	8.88	21.14	15.07	7.06	41.05	12.92
4	1.876	18.47	13.3	7.73	21.14	8.95	21.24	15.2	7.06	41.58	13.03
…	…	…	…	…	…	…	…	…	…	…	…
2219	5.758	10.49	4.11	21.89	11.9	4.42	11.44	3.05	19.1	26.2	9.15
2220	5.758	10.45	4.07	21.79	11.81	4.42	11.35	3.04	19.02	27.41	9.01

3-2- Hybrid Model Development

The hybrid model is a combination of data clustering models using k-means and fuzzy c-means (FCM) to generate rules within a fuzzy inference system. K-means and FCM clustering models have different approaches to forming data clusters, so the accuracy of the output inference between these two clustering models will be evaluated. Managing FIS rule modeling with clustering has been proposed by previous research. Leonori et al. [51] proposed k-means for rule and membership function generation of FIS, which performs close to optimal solutions, while Barrios et al. [52] and İsen & Boran [53] provide FCM for rule generation of FIS and ANFIS models, which show satisfactory performance. The hybrid FIS model incorporating k-means and FCM represents an effort to optimize conventional FIS models, which have limitations and complexities in developing rule combinations. Complex rule combinations have been proposed by Phillis et al. [54] and Grigoroudis et al. [55], but the number of rules generated is exponential and reduces computational and inferential performance [56].

The conceptual framework for developing a hybrid FIS with clustering involves using the results of data clustering to design rules and infer the output. It is important to ensure that the available data is sufficient and then the hybrid FIS and clustering model have the potential to be applied.

Determining the number of clusters in the development of this hybrid model is crucial, as it directly influences the number of rules that will be formed within the FIS. The number of data clusters is determined using the Silhouette Technique, following Equation 2. Based on the analysis, the Silhouette score for each number of clusters can be observed in Figure 3. The Silhouette analysis results indicate that the optimal number of clusters is seven, as they provide the highest silhouette score among others. This serves as the basic decision to define the number of clusters to develop a model using the k-means and FCM models. Consequently, the cluster centers for the FCM and k-means models can be found in Tables 5 and 6, respectively. The cluster center that is produced by FCM and k-means shows slightly different results for all attributes. For example, in the TVC cluster center, for each cluster in FCM and k-means, there are different values for each cluster and different distances between clusters. FCM and K-means approaches in developing cluster centers have confirmed that both models will produce different membership functions of FIS rule generation.

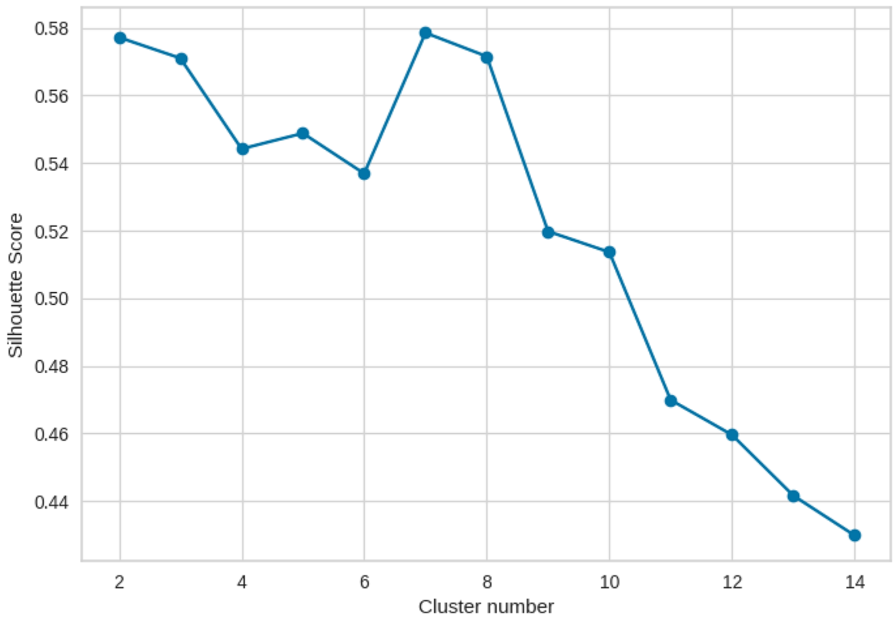


Figure 3. Silhouette score

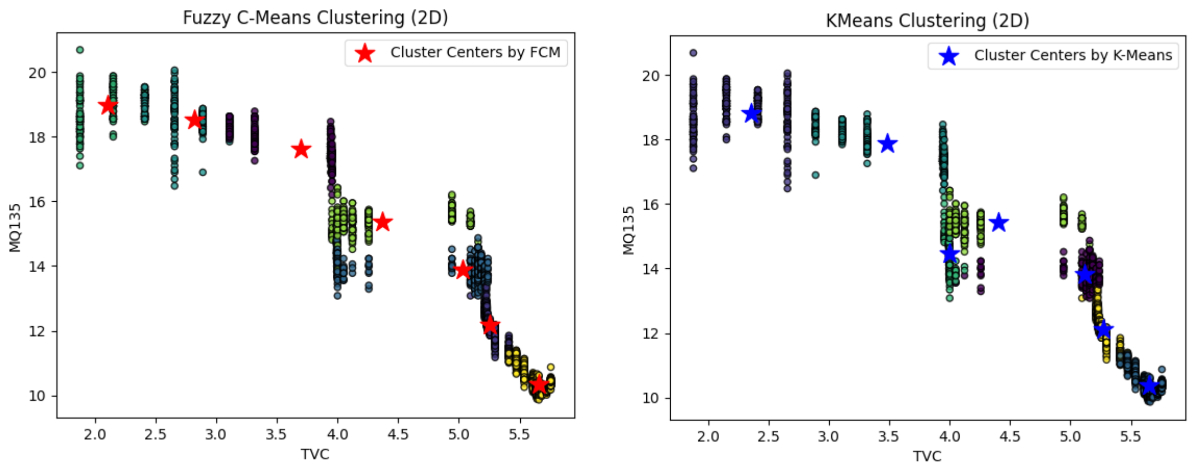
Table 5. Cluster center from FCM model

Cluster	TVC	MQ135	MQ136	MQ137	MQ138	MQ2	MQ3	MQ4	MQ5	MQ8	MQ9
1	5.428	11.275	4.339	19.763	11.177	4.355	12.616	3.135	16.390	27.159	8.806
2	2.252	18.941	11.410	8.865	20.529	7.829	20.766	11.037	8.647	42.402	12.931
3	5.680	10.276	3.932	21.970	11.128	4.166	11.380	2.958	17.968	25.055	8.785
4	3.355	17.991	7.632	12.156	15.115	6.532	17.707	7.000	10.308	43.825	12.841
5	4.344	15.417	7.316	18.037	12.013	6.381	15.773	6.385	13.336	38.576	11.840
6	5.001	13.953	6.400	17.643	11.325	5.519	14.895	4.804	14.339	34.052	10.405
7	5.220	12.422	5.235	17.953	11.192	4.705	13.794	3.561	14.618	30.214	9.183

Table 6. **Cluster center for K-Means model**

Cluster	TVC	MQ135	MQ136	MQ137	MQ138	MQ2	MQ3	MQ4	MQ5	MQ8	MQ9
1	3.996	14.477	6.286	13.965	11.009	5.462	14.409	5.760	12.077	36.460	10.862
2	5.654	10.380	3.964	21.746	11.101	4.182	11.507	2.972	17.860	25.283	8.781
3	2.349	18.818	10.986	9.046	20.120	7.633	20.515	10.479	8.838	42.505	12.899
4	4.404	15.444	7.396	18.405	12.045	6.445	15.860	6.416	13.480	38.620	11.883
5	5.274	12.112	4.982	18.369	11.238	4.600	13.557	3.398	15.031	29.387	9.023
6	3.477	17.868	7.423	12.577	14.637	6.479	17.397	6.795	10.558	43.815	12.831
7	5.113	13.817	6.345	17.960	11.310	5.480	14.880	4.702	14.760	33.657	10.317

For further interpretation, the differences of cluster centers with FCM and K-Means models are illustrated in Figure 4. It can be observed that while both clustering models have the same number of cluster centers, their locations differ slightly between the two models. The cluster center defined by FCM and k-means will further determine the FIS membership function model and rule generation. For the prediction model, training and testing datasets are employed to test the FIS model with FCM and k-means model accuracy in predicting meat quality, as adopted as a model deployment case study.



(a) (b)

Figure 4. **Cluster center illustrations for (a) FCM and (b) K-Means**

The FIS model is developed by crisp input, fuzzification, rule generation with related membership function, defuzzification, and crisp output. Normally, the rule generation with the related membership function stage of the FIS model is developed by the numbers of input attributes of the FIS. An exponential number of rules is generated by the number of attributes and linguistic labels of the attribute. Moreover, with the hybrid FIS-clustering model, the number of rules is generated using the cluster center of the FCM and k-means results. The cluster center results from FCM and K-Means with all attributes designed to support quality inference in the FIS. Unlike conventional FIS models developed based on expert opinions, the number of rules formed in the hybrid FIS-Clustering model is much more optimal. As a result, the system can achieve maximum performance and an efficient process in providing inferences based on input variables. According to the result of the number of clusters generated by the FCM or k-means model, the fuzzy rules generated by FIS and clustering models in this case are as follows:

1. IF MQ135[cluster_1] AND MQ136[cluster_1] AND MQ137[cluster_1] AND MQ138[cluster_1] AND MQ2[cluster_1] AND MQ3[cluster_1] AND MQ4[cluster_1] AND MQ5[cluster_1] AND MQ8[cluster_1] AND MQ9[cluster_1] THEN TVC[cluster_1]
2. IF MQ135[cluster_2] AND MQ136[cluster_2] AND MQ137[cluster_2] AND MQ138[cluster_2] AND MQ2[cluster_2] AND MQ3[cluster_2] AND MQ4[cluster_2] AND MQ5[cluster_2] AND MQ8[cluster_2] AND MQ9[cluster_2] THEN TVC[cluster_2]
3. IF MQ135[cluster_3] AND MQ136[cluster_3] AND MQ137[cluster_3] AND MQ138[cluster_3] AND MQ2[cluster_3] AND MQ3[cluster_3] AND MQ4[cluster_3] AND MQ5[cluster_3] AND MQ8[cluster_3] AND MQ9[cluster_3] THEN TVC[cluster_3]
4. IF MQ135[cluster_4] AND MQ136[cluster_4] AND MQ137[cluster_4] AND MQ138[cluster_4] AND MQ2[cluster_4] AND MQ3[cluster_4] AND MQ4[cluster_4] AND MQ5[cluster_4] AND MQ8[cluster_4] AND MQ9[cluster_4] THEN TVC[cluster_4]
5. IF MQ135[cluster_5] AND MQ136[cluster_5] AND MQ137[cluster_5] AND MQ138[cluster_5] AND MQ2[cluster_5] AND MQ3[cluster_5] AND MQ4[cluster_5] AND MQ5[cluster_5] AND MQ8[cluster_5] AND MQ9[cluster_5] THEN TVC[cluster_5]
6. IF MQ135[cluster_6] AND MQ136[cluster_6] AND MQ137[cluster_6] AND MQ138[cluster_6] AND MQ2[cluster_6] AND MQ3[cluster_6] AND MQ4[cluster_6] AND MQ5[cluster_6] AND MQ8[cluster_6] AND MQ9[cluster_6] THEN TVC[cluster_6]
7. IF MQ135[cluster_7] AND MQ136[cluster_7] AND MQ137[cluster_7] AND MQ138[cluster_7] AND MQ2[cluster_7] AND MQ3[cluster_7] AND MQ4[cluster_7] AND MQ5[cluster_7] AND MQ8[cluster_7] AND MQ9[cluster_7] THEN TVC[cluster_7]

The rules in the hybrid FIS model with FCM and K-Means have the same structure, but the values at the cluster centers differ. The value of cluster_1 to cluster 7 of the aforementioned FIS rules is substituted by the cluster center of each attribute that is found by FCM and k-means in Tables 5 and 6, respectively. Consequently, using the cluster center of FCM and k-means for FIS rules, the output inferences will vary between the two models. For validation, the model will evaluate using related performance metrics.

A conventional FIS model development employs three approaches to designing fuzzy rules: data-driven adjustment of membership functions, expert-based approaches and validation [57], and combinations of input variables [55]. Each of these approaches has its advantages and disadvantages. For instance, expert-based rule development is highly subjective to the knowledge of the experts, while the approach based on combinations of input variables requires generating rules exponentially, which can reduce model performance. Therefore, this study adopts a data-driven approach that is deepened with clustering. The clustering approach can extract specific information from the data, ensuring the system and rules are aligned with the data conditions, thereby improving the accuracy of model inference. Additionally, the clustering approach in FIS model development is highly efficient in rule formation while maintaining a prominent level of accuracy.

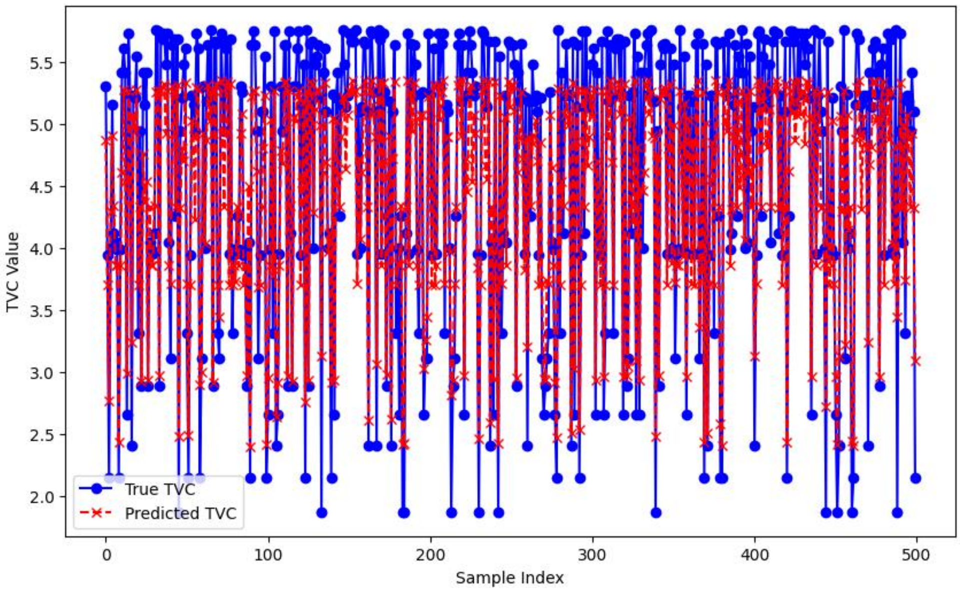
3-3- Hybrid FIS Model Evaluation

A hybrid FIS and clustering model for predicting meat quality was evaluated using four main metrics: MAE, MSE, RMSE, and R^2. The model was evaluated with 500 datasets (>20%) taken from actual data to predict the consequent values (TVC). The FIS model for predicting the meat quality developed in a hybrid FIS-clustering model that combines membership functions type and clustering models: FCM and K-Means.

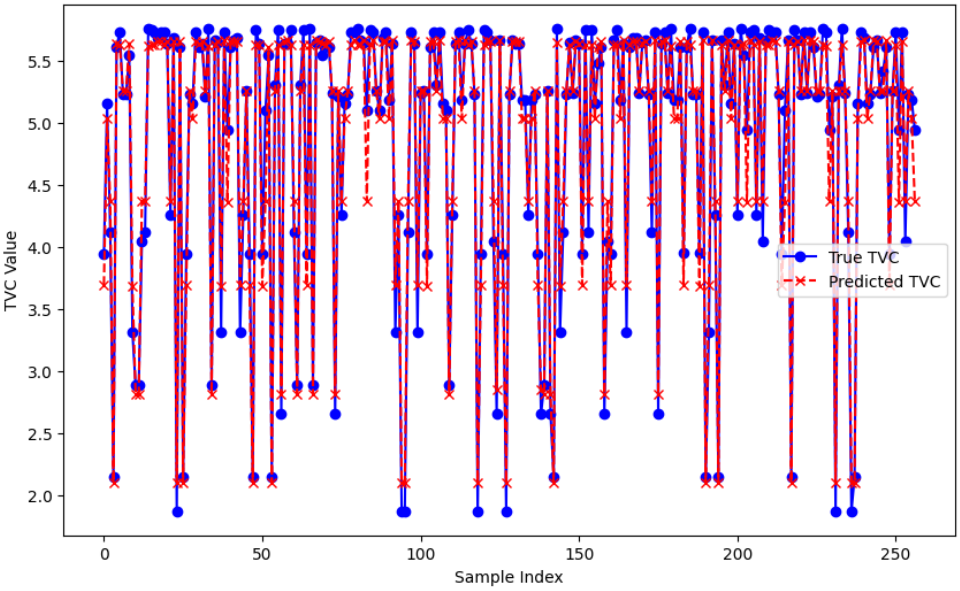
The evaluation results suggest that the FIS-TFN model demonstrates superior R^2 values, whether using K-Means or FCM for rule development. A complete overview of the model evaluation results can be found in Table 7. For illustration, the comparison between actual data and the hybrid FCM-FIS model with the TFN model is presented in Figure 5.

Table 7. Model evaluation results

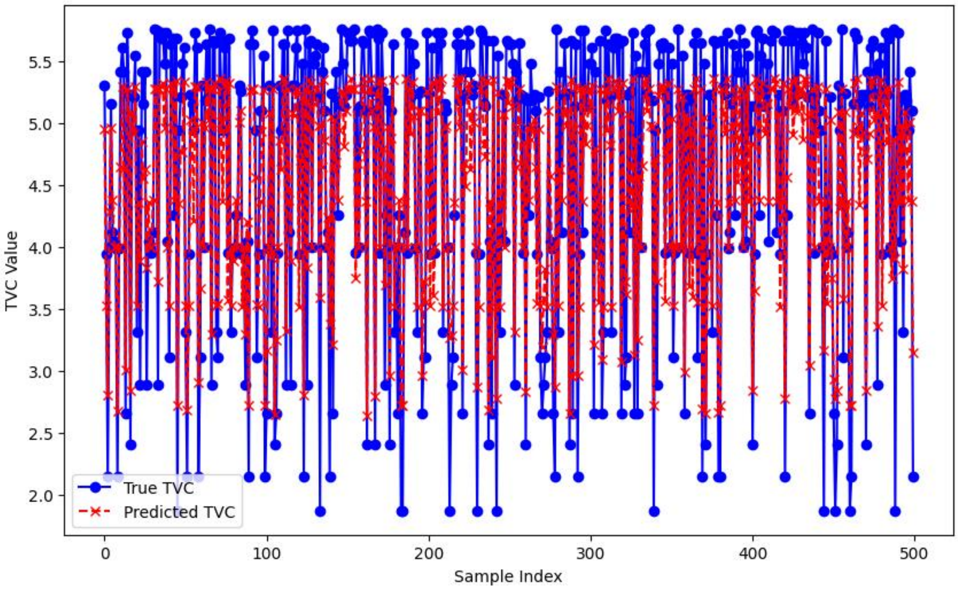
Metric	FCM clustering model		K-Means clustering model	
	Gaussian inference model	TFN inference model	Gaussian inference model	TFN inference model
MAE	0.360	0.119	0.375	0.114
MSE	0.173	0.316	0.199	0.035
RMSE	0.416	0.178	0.446	0.446
R2	0.873	0.974	0.853	0.961



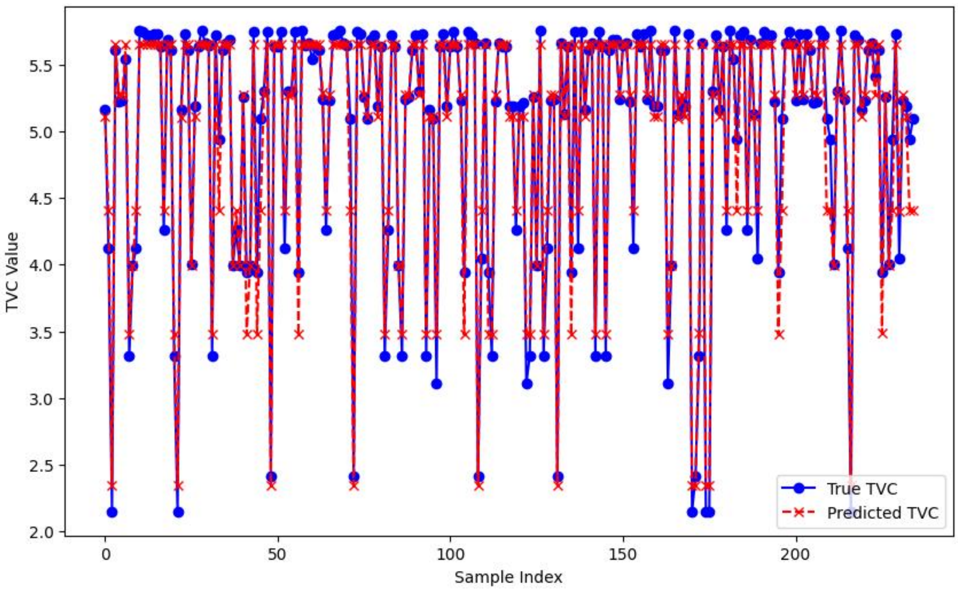
(a) Model FCM-FIS with gaussian



(b) Model FCM-FIS with triangular



(c) Model KMeans-FIS with gaussian



(d) Model KMeans-FIS with triangular

Figure 5. FIS model evaluation using predicted vs actual data

Model evaluation indicates that the FIS model with TFN using either FCM or K-Means clustering demonstrates good performance. However, from Figure 5, it is evident that the FIS model with TFN has limitations in accommodating various data conditions that reflect dynamic real-world situations. Figure 5 shows that x-axis as the number of samples while y-axis as TVC as the output of meat quality prediction model using FIS. All four models employ five hundred data samples to evaluate the model's accuracy and reliability. However, the TFN model with FCM or k-means model is only accurate to predict half of data samples. It is indicated that the TFN model is unable to process input variables to be an output consequence due to models' limitations. TFN failures to process input variables to be an output consequence impacted the prediction model reliability and accuracy.

Figure 5 shows that the FIS model with gaussian fuzzy numbers exhibits better reliability compared to the triangular model. The TFN model is unable to interpret all input variables for transformation into output variables. This system's inadequacy can significantly impact decision-makers by failing to provide recommendations to enhance the quality of perishable products. Therefore, choosing the gaussian model over the TFN model can minimize system failures in predicting the quality of perishable products like meat due to environmental uncertainties. This has also been confirmed in previous research, which found that the gaussian model performs better than the triangular fuzzy number model [58, 59].

3-4- Model Optimization and Comparison to Previous Model

Despite the limitations of the TFN model to produce output consequences and the result of model evaluation as mentioned in Table 7, it is found that meat quality prediction may predict with the Gaussian FIS model with the FCM clustering model. However, the model has an opportunity to improve the performance in accuracy and also avoid overfitting and underfitting problems. Therefore, in this phase, the FIS model is optimized using Genetic Algorithms (GA) to determine the most optimal number of rules for predicting meat quality. The number of rules in the FIS model determines the process and output accuracy. Using GA, the number of rules is optimized using a mathematical model with the chromosome representation for FIS rules combination and optimization. According to the GA model, the length of the chromosome in this optimization model is seven, which reflects the seven FIS rules. In line with the GA approach, which evaluates the accuracy of the inference model through a fitness function, in this model the fitness function is defined by the combination of rules that perform the best performance will be identified.

The fitness function in this optimization is the FIS rules combination that reflects the smallest Mean Square Error (MSE). The model being optimized reflects the rule combinations that were developed by the Hybrid Fuzzy Inference System and Clustering model. Therefore, the potential rule combinations will come from the seven rules, each of which can be either active or inactive (binary), resulting in 27=128 rule combinations to be evaluated.

Genetic algorithms are effective at finding the best solutions for complex and combinatorial problems, as also found in this case. In this model, GA finds the best model with numbers of rules and combinations that have the best model performance. The genetic algorithm has been utilized to assess each possible combination of FIS-based clustering rules for model accuracy and computation time. Based on the GA parameters for model evaluation, ten types of rules combinations from 128 models with the smallest error tested on the raw data are presented in Table 8.

Table 8. **Rule combinations, error, and computation time**

Rules combination NUMBER	Status of seven rules (0=NON-ACTIVE; 1 = ACTIVE)							number of active rules	MSE	Computation time
	1	2	3	4	5	6	7			
127	1	1	1	1	1	1	1	7	0.204	82.238
119	1	1	1	0	1	1	1	6	0.205	69.193
126	1	1	1	1	1	1	0	6	0.218	69.488
118	1	1	1	0	1	1	0	5	0.219	57.780
111	1	1	0	1	1	1	1	6	0.227	69.297
103	1	1	0	0	1	1	1	5	0.228	59.145
110	1	1	0	1	1	1	0	5	0.240	59.993
102	1	1	0	0	1	1	0	4	0.243	49.335
115	1	1	1	0	0	1	1	4	0.349	61.429
123	1	1	1	1	0	1	1	5	0.350	71.599

The mapping of the rules number, model error, and computation time for all models using Genetic Algorithms is illustrated in Figure 6. The figure clearly shows the relationships between these three parameters in model evaluation, which indicate that as the number of rules increases, the model error decreases, while computation time increases. Using seven rules of the prediction model may improve the computation time; moreover, it will increase the model error (MSE).

This condition led to model prediction error that affects the wrong conclusion of perishable product quality. In other conditions, using only one rule, it may improve computation time, but the model error is still increasing. This research proposes to adopt a moderate approach by using five rules. Figure 6 illustrates that the model with five active rules decreases the model error efficiently with tolerable computation time.

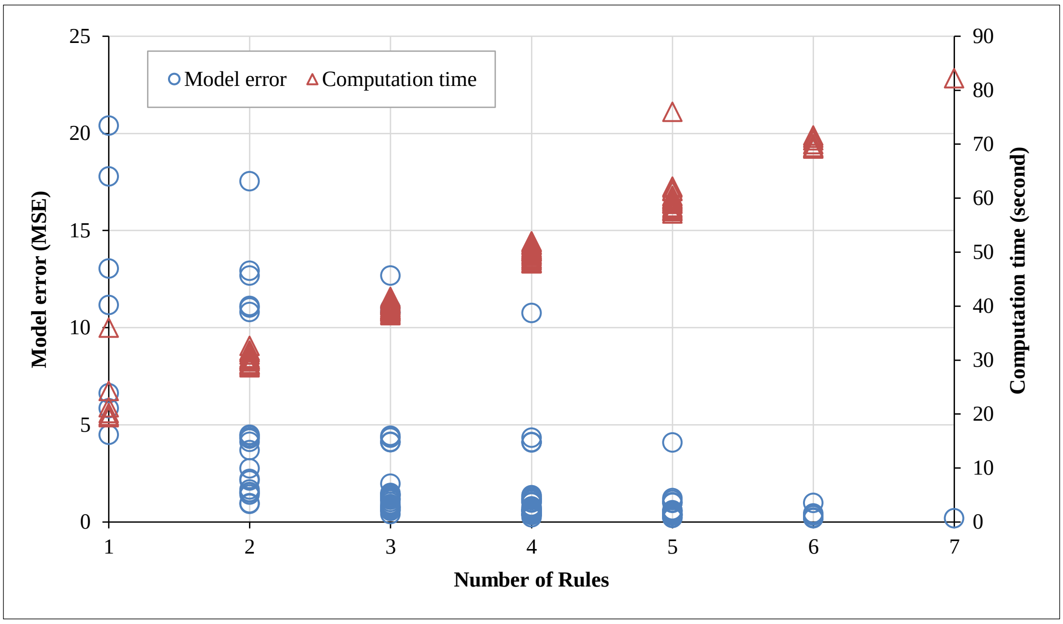


Figure 6. Model error vs. computation time in any rule combinations

A higher number of rules enhances system complexity but helps in minimizing prediction errors. The GA has effectively optimized the model, proposing configurations with both optimal accuracy and efficient computation time. Based on these results, the number of active rules can be utilized for predicting the quality of perishable products. Specifically, five FIS rules with a Gaussian membership function and fuzzy c-means (FCM) clustering have proven suitable for further testing.

The optimized model is then evaluated using model evaluation metrics, including MAE, MSE, RMSE, and R^2, as shown in Table 9. For this test, rule combination number 118 is applied, with five active rules, deactivating rules number 4 and 6, according to previous evaluation results. The evaluation results indicate that the optimized model does not show significant improvements, particularly in the R^2 metric. Nevertheless, the model can optimize the number of rules to achieve an acceptable level of error and R^2 with computation time suitable for real-world application.

Table 9. Model evaluation and comparison

Model	Number of rules	MAE	MSE	RMSE	R^2
FCM-FIS Gaussian	7	0.360	0.173	0.416	0.873
K-Means-FIS Gaussian	7	0.375	0.199	0.446	0.853
Optimized rule FCM-FIS Gaussian	5	0.383	0.209	0.45	0.845

In previous research, IoT systems for predicting meat quality have been utilized by various researchers for prediction and system development, such as Kaya et al. [26], and Deepa & Jayalakshmi [60] for sensor error mitigation, Wijaya & Afianti [61] for predicting meat quality using a classification approach, and Pulluri & Kumar [62] for using e-nose sensors to develop a meat quality monitoring system with classification. However, most of the studies mentioned above rely on classification machine learning models to assess product quality.

To compare and evaluate the performance of the proposed model in this study, it is necessary to compare it with previous models that are relevant, specifically regression-based models. Previous research that predicts the quality of perishable products such as meat using regression models is still limited, despite the high accuracy required and the need for implementation in the industry. Two studies that serve as benchmarks for the performance of the proposed model in this research can be found in Wijaya et al. [27], and Wijaya et al. [63], which predict the total viable count (TVC) as a representation of meat quality using regression-based models. The performance comparison of previous models with the proposed model in this study can be seen in Table 10.

Table 10. Model performance comparison with RMSE and R^2

No	Prediction model	Sources	RMSE	R^2
1	NNR-non framework	Wijaya et al. [27]	2.556	0.771
2	NNR-framework	Wijaya et al. [27]	0.519	0.953
3	k-nearest neighbor	Wijaya et al. [63]	0.4648	0.814
4	Linear discriminant analysis	Wijaya et al. [63]	0.6818	0.829
5	Support vector regression	Wijaya et al. [63]	0.6465	0.909
6	Multi-linear programming	Wijaya et al. [63]	0.6072	0.414
7	Long short-term memory (LSTM)	Wijaya et al. [63]	3.2622	0.958
8	Discrete wavelets transform LSTM	Wijaya et al. [63]	0.3835	0.971
9	Optimized rule FCM-FIS Gaussian	This research	0.450	0.845

It can be observed that, based on Table 10, the proposed model in this study has a good R^2 value with a low error rate, except for the LSTM and DWTLSTM models. In the model comparison above, it is shown that LSTM and DWTLSTM perform well, but the challenge is that these models are complex and result in longer computation times [63]. In contrast, the model proposed in this study, namely the FCM-FIS Gaussian model optimized with GA proposed an efficient and fast computation times, as elaborated in the previous section. Therefore, the proposed model in this study can be implemented more widely and efficiently in the industry.

4- Conclusions and Recommendations

Monitoring the quality of perishable products involves both challenges and advantages in maintaining a responsive and efficient supply chain. Although many quality monitoring models have been proposed, IoT technology offers promising opportunities for real-time information delivery. The challenges in monitoring perishable products are not only in implementing IoT technology during transportation but also in how to accurately process data and information to ensure decisions are well-informed and precise for both customers and producers.

This research has successfully developed a hybrid model for evaluating the quality of perishable products such as meat. Public data has been utilized for model evaluation, making it useful for industries to provide quality information about perishable products to both producers and consumers during distribution and transportation processes. The hybrid model combining the Fuzzy Inference System (FIS) and clustering has accurately extracted information from data collected via IoT. Specifically, the FIS model with a Gaussian membership function and the Fuzzy C-Means (FCM) clustering model have proven capable of producing accurate and reliable predictions. Reliable in this context means that the model effectively identifies each input data and infers outputs with high accuracy.

This research also proposes a hybrid optimization model to enhance the efficiency and accuracy of the model using genetic algorithms. The results show that optimizing seven rules in the hybrid FCM-FIS model to five rules using genetic algorithms did not significantly improve model accuracy, particularly in the R^2 metric. However, the use of the GA optimization model was successful in mapping and reducing model computation time while maintaining model accuracy. Therefore, the study concludes that for datasets on product quality and storage conditions for perishable goods collected via IoT, the hybrid FCM-FIS model can be used for real-time quality prediction. The hybrid FIS-Gaussian model with FCM achieved the best accuracy with an R^2 value of 0.875. Additionally, the research found that genetic algorithm optimization holds significant potential for improving model efficiency, especially in terms of computation time, system responsiveness, and maintaining model accuracy.

Although this research utilizes public data, there are many further opportunities that can be explored. The model developed in this study is highly applicable to the supply chain of perishable product industries. The test results have shown that the algorithm can quickly and accurately predict the quality of perishable products based on the total viable count. For model implementation in industry, several aspects need to be considered: (1) the preparation of an IoT-based sensor system in accordance with the attributes demonstrated by the model, (2) the provision of a server for data storage and supporting real-time data processing, and (3) the implementation of the model to predict the quality of perishable products. Based on the research framework and supporting data from public sources, this model can certainly be utilized specifically for meat products. If applied to other types of products, the results of this study have also confirmed that the FIS-Clustering model framework, optimized with a genetic algorithm, can be further utilized.

It can be observed that the algorithms in this research have been proposed and have identified the model with the best accuracy. Given the urgent need for IoT in perishable products to meet customer satisfaction, future research should focus on implementing the model for real-time quality monitoring of perishable products throughout the entire supply chain until the product reaches the consumer. More practical implementation is needed, particularly regarding how the model can be presented on a dashboard and how product quality can be tracked and traced in real time.

5- Declarations

5-1- Author Contributions

Conceptualization, M.A. and S.; methodology, M.A.; software, M.A.; validation, M.A., S., and R.J.; formal analysis, M.A., S., and R.J.; investigation, M.A., S., and R.J.; resources, M.A., S., and R.J.; data curation, M.A.; writing—original draft preparation, M.A.; writing—review and editing, S. and R.J.; visualization, M.A.; project administration, M.A.; funding acquisition, M.A. All authors have read and agreed to the published version of the manuscript.

5-2- Data Availability Statement

Publicly available datasets were analyzed in this study from Ref. [27], [36]. This data can be found here: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/XNFVTS.

5-3- Funding

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5-5- Institutional Review Board Statement

Not applicable.

5-6- Informed Consent Statement

Not applicable.

5-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

6- References

[1] Bruhn, M. (2023). Quality Management for Services. Springer, Berlin, Germany. doi:10.1007/978-3-662-67032-3.

[2] Rong, A., Akkerman, R., & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. International Journal of Production Economics, 131(1), 421–429. doi:10.1016/j.ijpe.2009.11.026.

[3] Shukla, M., & Jharkharia, S. (2013). Agri- fresh produce supply chain management: a state- of- the- art literature review. International Journal of Operations & Production Management, 33(2), 114–158. doi:10.1108/01443571311295608.

[4] Lejarza, F., & Baldea, M. (2022). An efficient optimization framework for tracking multiple quality attributes in supply chains of perishable products. European Journal of Operational Research, 297(3), 890–903. doi:10.1016/j.ejor.2021.04.057.

[5] LaBuza, T.P. (1982). Shelf-Life Dating of Foods. Food & Nutrition Press, Inc., Westport, Ireland.

[6] Ferguson, M., & Ketzenberg, M. E. (2006). Information Sharing to Improve Retail Product Freshness of Perishables. Production and Operations Management, 15(1), 57–73. doi:10.1111/j.1937-5956.2006.tb00003.x.

[7] Göbel, C., Langen, N., Blumenthal, A., Teitscheid, P., & Ritter, G. (2015). Cutting food waste through cooperation along the food supply chain. Sustainability (Switzerland), 7(2), 1429–1445. doi:10.3390/su7021429.

[8] Alfian, G., Syafrudin, M., Fitriyani, N. L., Rhee, J., Ma'arif, M. R., & Riadi, I. (2020). Traceability system using IoT and forecasting model for food supply chain. 2020 International Conference on Decision Aid Sciences and Application, DASA 2020, November, 903–907. doi:10.1109/DASA51403.2020.9317011.

[9] Zhu, L. (2017). Economic analysis of a traceability system for a two-level perishable food supply chain. Sustainability (Switzerland), 9(5), 682. doi:10.3390/su9050682.

[10] Abad, E., Palacio, F., Nuin, M., Zárate, A. G. de, Juarros, A., Gómez, J. M., & Marco, S. (2009). RFID smart tag for traceability and cold chain monitoring of foods: Demonstration in an intercontinental fresh fish logistic chain. Journal of Food Engineering, 93(4), 394–399. doi:10.1016/j.jfoodeng.2009.02.004.

[11] Gallo, A., Accorsi, R., Manzini, R., Santi, D., & Tufano, A. (2018). Improving integration in supply chain traceability systems for perishable products. Proceedings of the 4th International Food Operations and Processing Simulation Workshop (FoodOPS 2018), 28–36. doi:10.46354/i3m.2018.foodops.004.

[12] Li, J., Zhang, R., Jin, Y., & Zhang, H. (2022). Optimal Path of Internet of Things Service in Supply Chain Management Based on Machine Learning Algorithms. Computational Intelligence and Neuroscience, 4844993. doi:10.1155/2022/4844993.

[13] Srinivas, D., Kirthiga, N., Vani, V. D., Raj, V. H., Nijhawan, G., & Dhanraj, J. A. (2024). Enhancing Supply Chain Management Efficiency with IoT and Machine Learning Integration. Proceedings of 2024 International Conference on Science, Technology, Engineering and Management, ICSTEM 2024. doi:10.1109/ICSTEM61137.2024.10561126.

[14] Wang, W. (2024). A IoT-Based Framework for Cross-Border E-Commerce Supply Chain Using Machine Learning and Optimization. IEEE Access, 12, 1852–1864. doi:10.1109/ACCESS.2023.3347452.

[15] Jauhar, S. K., Harinath, S., Krishnaswamy, V., & Paul, S. K. (2024). Explainable artificial intelligence to improve the resilience of perishable product supply chains by leveraging customer characteristics. Annals of Operations Research. Springer, United States. doi:10.1007/s10479-024-06348-z.

[16] Pal, A., & Kant, K. (2019). Internet of Perishable Logistics: Building Smart Fresh Food Supply Chain Networks. IEEE Access, 7, 17675–17695. doi:10.1109/ACCESS.2019.2894126.

[17] Mohammadi, T., Sajadi, S. M., Najafi, S. E., & Taghizadeh-Yazdi, M. (2024). Multi Objective and Multi-Product Perishable Supply Chain with Vendor-Managed Inventory and IoT-Related Technologies. Mathematics, 12(5), 679. doi:10.3390/math12050679.

[18] Sathiya, V., Nagalakshmi, K., Raju, K., & Lavanya, R. (2024). Tracking perishable foods in the supply chain using chain of things technology. Scientific Reports, 14(1), 21621. doi:10.1038/s41598-024-72617-3.

[19] Selukar, M., Jain, P., & Kumar, T. (2022). Inventory control of multiple perishable goods using deep reinforcement learning for sustainable environment. Sustainable Energy Technologies and Assessments, 52, 102038. doi:10.1016/j.seta.2022.102038.

[20] Hu, H., Xu, J., Liu, M., & Lim, M. K. (2023). Vaccine supply chain management: An intelligent system utilizing blockchain, IoT and machine learning. Journal of Business Research, 156, 113480. doi:10.1016/j.jbusres.2022.113480.

[21] Tsang, Y. P., Choy, K. L., Wu, C. H., Ho, G. T. S., & Lam, H. Y. (2019). An internet of things (IoT)-Based shelf life management system in perishable food e-commerce businesses. PICMET 2019 - Portland International Conference on Management of Engineering and Technology: Technology Management in the World of Intelligent Systems, Proceedings, 8893684. doi:10.23919/PICMET.2019.8893684.

[22] Yan, R. (2017). Optimization approach for increasing revenue of perishable product supply chain with the Internet of Things. Industrial Management and Data Systems, 117(4), 729–741. doi:10.1108/IMDS-07-2016-0297.

[23] Heising, J. K. (2014). Intelligent packaging for monitoring food quality: a case study on fresh fish. Ph.D. Thesis, Wageningen University and Research, Wageningen, Netherlands.

[24] Alfian, G., Syafrudin, M., Farooq, U., Ma'arif, M. R., Syaekhoni, M. A., Fitriyani, N. L., Lee, J., & Rhee, J. (2020). Improving efficiency of RFID-based traceability system for perishable food by utilizing IoT sensors and machine learning model. Food Control, 110(October 2019), 107016. doi:10.1016/j.foodcont.2019.107016.

[25] Shahbazi, Z., & Byun, Y. C. (2021). A procedure for tracing supply chains for perishable food based on blockchain, machine learning and fuzzy logic. Electronics (Switzerland), 10(1), 1–21. doi:10.3390/electronics10010041.

[26] Kaya, A., Keçeli, A. S., Catal, C., & Tekinerdogan, B. (2020). Sensor failure tolerable machine learning-based food quality prediction model. Sensors (Switzerland), 20(11), 1–18. doi:10.3390/s20113173.

[27] Wijaya, D. R., Sarno, R., & Zulaika, E. (2019). Noise filtering framework for electronic nose signals: An application for beef quality monitoring. Computers and Electronics in Agriculture, 157, 305–321. doi:10.1016/j.compag.2019.01.001.

[28] Wang, X., & Li, D. (2012). A dynamic product quality evaluation-based pricing model for perishable food supply chains. Omega, 40(6), 906–917. doi:10.1016/j.omega.2012.02.001.

[29] Sherlock, M., & Labuza, T. P. (1992). Consumer Perceptions of Consumer Time-Temperature Indicators for Use on Refrigerated Dairy Foods. Journal of Dairy Science, 75(11), 3167–3176. doi:10.3168/jds.S0022-0302(92)78081-3.

[30] Thompson, A. K., Prange, R. K., Bancroft, R. D., & Puttongsiri, T. (Eds.). (2018). Controlled atmosphere storage of fruit and vegetables. CABI, Wallingford, United Kingdom. doi:10.1079/9781786393739.0000.

[31] Aung, M. M., & Chang, Y. S. (2014). Temperature management for the quality assurance of a perishable food supply chain. Food Control, 40(1), 198–207. doi:10.1016/j.foodcont.2013.11.016.

[32] Wang, J., Yue, H., & Zhou, Z. (2017). An improved traceability system for food quality assurance and evaluation based on fuzzy classification and neural network. Food Control, 79, 363–370. doi:10.1016/j.foodcont.2017.04.013.

[33] Kumar, A., & Agrawal, S. (2024). A quality-based sustainable supply chain architecture for perishable products using image processing in the era of industry 4.0. Journal of Cleaner Production, 450(April), 141910. doi:10.1016/j.jclepro.2024.141910.

[34] Gharehyakheh, A., Krejci, C. C., Cantu, J., & Rogers, K. J. (2020). A multi-objective model for sustainable perishable food distribution considering the impact of temperature on vehicle emissions and product shelf life. Sustainability (Switzerland), 12(16), 30–40. doi:10.3390/su12166668.

[35] Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338–353. doi:10.1016/S0019-9958(65)90241-X.

[36] Wijaya, D. R., Sarno, R., & Zulaika, E. (2018). Electronic nose dataset for beef quality monitoring in uncontrolled ambient conditions. Data in Brief, 21, 2414–2420. doi:10.1016/j.dib.2018.11.091.

[37] Mamdani, E. H., & Assilian, S. (1999). Experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Human Computer Studies, 51(2), 135–147. doi:10.1006/ijhc.1973.0303.

[38] Mamdani, E. H. (1974). Application of Fuzzy Algorithms for Control of Simple Dynamic Plant. Proceedings of the Institution of Electrical Engineers, 121(12), 1585–1588. doi:10.1049/piee.1974.0328.

[39] Phillis, Y. A., Grigoroudis, E., & Kouikoglou, V. S. (2011). Sustainability ranking and improvement of countries. Ecological Economics, 70(3), 542–553. doi:10.1016/j.ecolecon.2010.09.037.

[40] Phillis, Y. A., Kouikoglou, V. S., & Verdugo, C. (2017). Urban sustainability assessment and ranking of cities. Computers, Environment and Urban Systems, 64, 254–265. doi:10.1016/j.compenvurbsys.2017.03.002.

[41] Jayarathna, L., Kent, G., O'Hara, I., & Hobson, P. (2022). Geographical information system based fuzzy multi criteria analysis for sustainability assessment of biomass energy plant siting: A case study in Queensland, Australia. Land Use Policy, 114, 105986. doi:10.1016/j.landusepol.2022.105986.

[42] Shutaywi, M., & Kachouie, N. N. (2021). Silhouette analysis for performance evaluation in machine learning with applications to clustering. Entropy, 23(6), 1–17. doi:10.3390/e23060759.

[43] Sinaga, K. P., & Yang, M. S. (2020). Unsupervised K-means clustering algorithm. IEEE Access, 8, 80716–80727. doi:10.1109/ACCESS.2020.2988796.

[44] Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. Computers & Geosciences, 10(2–3), 191–203. doi:10.1016/0098-3004(84)90020-7.

[45] Izakian, H., & Abraham, A. (2011). Fuzzy C-means and fuzzy swarm for fuzzy clustering problem. Expert Systems with Applications, 38(3), 1835–1838. doi:10.1016/j.eswa.2010.07.112.

[46] Askari, S. (2017). A novel and fast MIMO fuzzy inference system based on a class of fuzzy clustering algorithms with interpretability and complexity analysis. Expert Systems with Applications, 84, 301–322. doi:10.1016/j.eswa.2017.04.045.

[47] Savrun, M. M., & İnci, M. (2021). Adaptive neuro-fuzzy inference system combined with genetic algorithm to improve power extraction capability in fuel cell applications. Journal of Cleaner Production, 299. doi:10.1016/j.jclepro.2021.126944.

[48] Wang, L. X., & Mendel, J. M. (1992). Generating Fuzzy Rules by Learning from Examples. IEEE Transactions on Systems, Man and Cybernetics, 22(6), 1414–1427. doi:10.1109/21.199466.

[49] Jang, J. S. R. (1992). Self-Learning Fuzzy Controllers Based on Temporal Back Propagation. IEEE Transactions on Neural Networks, 3(5), 714–723. doi:10.1109/72.159060.

[50] Berenji, H. R., & Khedkar, P. (1992). Learning and Tuning Fuzzy Logic Controllers Through Reinforcements. IEEE Transactions on Neural Networks, 3(5), 724–740. doi:10.1109/72.159061.

[51] Leonori, S., Paschero, M., Rizzi, A., & Mascioli, F. M. F. (2019). FIS synthesis by clustering for microgrid energy management systems. Smart Innovation, Systems and Technologies, 102, 61–71. doi:10.1007/978-3-319-95098-3_6.

[52] Barrios, J. A., Villanueva, C., Cavazos, A., & Colas, R. (2016). Fuzzy C-means Rule Generation for Fuzzy Entry Temperature Prediction in a Hot Strip Mill. Journal of Iron and Steel Research International, 23(2), 116–123. doi:10.1016/S1006-706X(16)30022-X.

[53] İsen, E., & Boran, S. (2018). A Novel Approach Based on Combining ANFIS, Genetic Algorithm and Fuzzy c-Means Methods for Multiple Criteria Inventory Classification. Arabian Journal for Science and Engineering, 43(6), 3229–3239. doi:10.1007/s13369-017-2987-z.

[54] Phillis, Y. A., Kouikoglou, V. S., & Andriantiatsaholiniaina, L. A. (2003). Sustainable development: A definition and assessment. Environmental Engineering and Management Journal, 2(4), 345–355. doi:10.30638/eemj.2003.030.

[55] Grigoroudis, E., Kouikoglou, V. S., & Phillis, Y. A. (2014). SAFE 2013: Sustainability of countries updated. Ecological Indicators, 38, 61–66. doi:10.1016/j.ecolind.2013.10.022.

[56] Yani, M., MacHfud, Asrol, M., Hambali, E., Papilo, P., Mursidah, S., & Marimin, M. (2022). An Adaptive Fuzzy Multi-Criteria Model for Sustainability Assessment of Sugarcane Agroindustry Supply Chain. IEEE Access, 10, 5497–5517. doi:10.1109/ACCESS.2022.3140519.

[57] Thaseen Ikram, S., Mohanraj, V., Ramachandran, S., & Balakrishnan, A. (2023). An Intelligent Waste Management Application Using IoT and a Genetic Algorithm–Fuzzy Inference System. Applied Sciences (Switzerland), 13(6), 3943. doi:10.3390/app13063943.

[58] Olunloyo, V. O. S., Ajofoyinbo, A. M., & Ibidapo-Obe, O. (2011). On Development of Fuzzy Controller: The Case of Gaussian and Triangular Membership Functions. Journal of Signal and Information Processing, 2(4), 257–265. doi:10.4236/jsip.2011.24036.

[59] Adil, O., Ali, A., Ali, M., Ali, A. Y., & Sumait, B. S. (2015). Comparison between the Effects of Different Types of Membership Functions on Fuzzy Logic Controller Performance. International Journal of Emerging Engineering Research and Technology, 3, 76.

[60] Deepa, S. N., & Jayalakshmi, N. Y. (2022). An Intelligent Neural Network Algorithm for Uncertainty Handling in Sensor Failure Scenario of Food Quality Assurance Model. Computer Assisted Methods in Engineering and Science, 29(1–2), 105–123. doi:10.24423/cames.409.

[61] Wijaya, D. R., & Afianti, F. (2021). Information-Theoretic Ensemble Feature Selection with Multi-Stage Aggregation for Sensor Array Optimization. IEEE Sensors Journal, 21(1), 476–489. doi:10.1109/JSEN.2020.3000756.

[62] Pulluri, K. K., & Kumar, V. N. (2022). Development of an Integrated Soft E-Nose for Food Quality Assessment. IEEE Sensors Journal, 22(15), 15111–15122. doi:10.1109/JSEN.2022.3182480.

[63] Wijaya, D. R., Sarno, R., & Zulaika, E. (2021). DWTLSTM for electronic nose signal processing in beef quality monitoring. Sensors and Actuators, B: Chemical, 326, 128931. doi:10.1016/j.snb.2020.128931.