

# Web-Based Smart Aquaculture: Comparative Analysis of Mamdani, Sugeno, and Tsukamoto Fuzzy Inference Systems for Shrimp Pond Water Quality Assessment

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**ABSTRACT** Indonesia has a lot of potential for marine aquaculture development but stable water quality is a major problem in shrimp pond management. The constant changes and unclear limits of environmental parameters in aquaculture environments require intelligent water quality assessment systems to support sustainable pond management. This study selected four core parameters—water temperature, pH, salinity, and dissolved oxygen—to compare and evaluate the shrimp pond water quality classification performance of three fuzzy inference systems (FIS): Mamdani, Sugeno, and Tsukamoto. The study adopted trapezoidal membership functions, and combined expert-defined reference labels aligned with aquaculture water quality standards to divide water quality into four categories: excellent, medium, poor, and extremely poor. The dataset used consists of 994 water quality records collected from shrimp ponds in Surabaya, Indonesia, between December 2024 and April 2025. Experimental results show that the Mamdani method has the highest consistency with expert rules, with an accuracy of 0.800, precision of 0.825, recall of 0.800, and F1-score of 0.797. The Sugeno and Tsukamoto models recorded an accuracy of 0.700 and an F1-score of 0.728, with only their precision reaching 0.880. These findings prove that Mamdani inference is more stably suited to the rule framework for shrimp pond water quality assessment. The web-based monitoring system built for this study also verified that fuzzy logic can support the sustainable management of smart aquaculture.

**KEYWORDS:** Fuzzy Logic; Mamdani; Sugeno; Tsukamoto; Water Quality Classification

## 1. INTRODUCTION

Indonesia boasts exceptional natural endowments of fishery resources. The country is home to more than 17,000 islands, 81,000 kilometers of coastline, and approximately 5.8 million square kilometers of maritime territory, making it one of the world's leading producers of fishery products [1]. Within the aquaculture sector, shrimp farming is a core niche segment with enormous development potential. Maintaining stable water quality remains one of the major challenges in shrimp aquaculture because environmental conditions continuously fluctuate and directly affect shrimp health and pond sustainability. Poor water quality is a key threat to shrimp health, with several parameters exerting

particularly significant impacts, including pH, salinity, and dissolved oxygen (DO). Only through regular monitoring and regulation of water quality can sustainable shrimp farming be supported.

Water quality classification is a core support for aquaculture management, as it can guide decision-making to optimize pond aquaculture conditions [2]. Water quality in shrimp ponds exhibits the characteristics of uncertainty and gradual category transition; core parameters such as pH may fall across multiple classification categories, and the linguistic classification of fuzzy inference systems can be well adapted.

The main aim of this study is to compare three fuzzy logic methods: Mamdani, Sugeno and Tsukamoto and check their applicability for water

quality classification based on four core parameters namely: temperature, pH, salinity and dissolved oxygen (DO). The three methods were chosen because they represent different inference mechanisms and different output characteristics, which allow for their comparative evaluation within the same aquaculture rule framework. Mamdani produces interpretable linguistic outputs for human-centered decision support [3]. Sugeno generates computationally efficient numerical outputs for control systems [4]. Tsukamoto produces monotonic rule-based outputs supporting gradual decision transitions [5]. The purpose of this comparison is to identify the most consistent inference approach for shrimp pond water quality assessment.

Fuzzy logic can model linguistic reasoning and simulate human decision-making processes, making it suitable for decision systems operating in uncertain environments [4]. The three most commonly used fuzzy inference systems each have distinct advantages: Mamdani systems gain interpretability through their reliance on linguistic rules; Sugeno systems achieve high computational efficiency by adopting mathematical output functions; Tsukamoto systems' smooth, monotonic inference mechanism is well-adapted for scenarios that require gradual transitions. All three systems have been applied in prior research to fields including environmental monitoring, aquaculture, and prediction-related domains.

Existing studies note that fuzzy logic can be effectively applied to water quality monitoring for shrimp aquaculture, with the adopted monitoring parameters including temperature, pH, salinity, and dissolved oxygen (DO) [6], [7]. Previous studies have also evaluated Mamdani, Sugeno, and Tsukamoto methods in prediction and decision support scenarios. Although these studies demonstrate the feasibility of fuzzy logic for aquaculture applications, their findings remain difficult to compare because different studies often use different datasets, rule structures, evaluation approaches, and implementation environments. However, two key research gaps remain in the current field: first, most studies only focus on prediction outcomes or isolated accuracy metrics and fail to analyze the inference consistency of different methods under identical aquaculture rule conditions; second, comparative studies integrating multiple fuzzy inference systems within a unified real-time web-based shrimp pond monitoring environment remain limited.

Previous studies have demonstrated the effectiveness of fuzzy logic for aquaculture water quality assessment. Amaliah et al. (2018) used a fuzzy classification system to assess the water quality of shrimp ponds based on environmental parameters including temperature, pH, salinity, and dissolved oxygen [6]. Other research has compared Mamdani, Sugeno and Tsukamoto inference systems in decision-support and prediction domains [8]. However, these studies were generally performed with different datasets and experimental settings, which makes it difficult to directly compare inference behavior.

Therefore, this study evaluates the Mamdani, Sugeno and Tsukamoto inference systems using the same datasets, rule structures and evaluation procedures to examine inference consistency within the same shrimp aquaculture framework. Unlike previous studies that evaluated fuzzy inference methods under different experimental settings, this study provides a unified comparison framework and implements the selected method in a real-time web-based shrimp pond monitoring system.

## II.METHOD

The web-based system for shrimp pond water quality classification introduced in this paper, paired with its complete set of supporting diagrams, fully illustrates its full-chain operation logic and core architecture, which runs from the initiation of user interactions to the final presentation of visualized results. The system's user layer is divided into two categories: administrators and shrimp farmers, who access the platform through a Frontend Web Client with Next.js to build application programming interfaces (API), and adopts a MongoDB database as the central hub to uniformly manage all water quality data uploaded by external monitoring tools. The system carries out analysis based on four core environmental indicators: temperature, salinity, pH, and dissolved oxygen. All collected data first enter a preprocessing stage, where attribute selection and interpolation-based cleaning are completed, and a standardized dataset is generated by combining reference labels defined by experts. The dataset then goes through a fuzzy processing workflow that includes fuzzification, rule evaluation, and defuzzification. The final results are returned to the front end and presented in visualized forms including analytical charts and water quality classification labels.

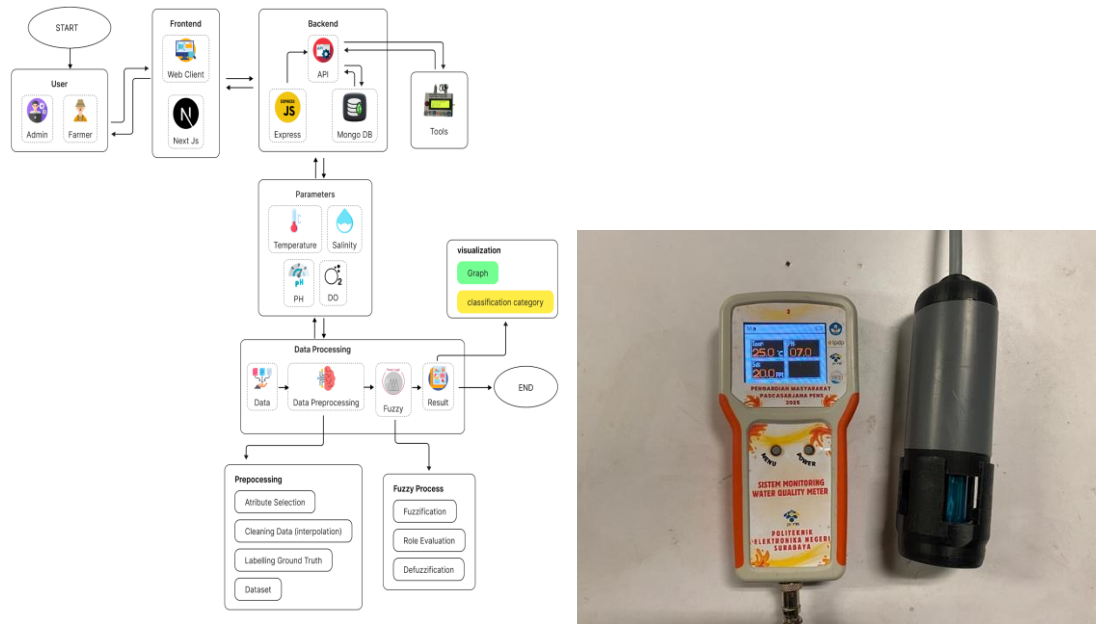


FIGURE 1. Data Process System Design and Tool

Figure 1 shows the overall architecture of the proposed web-based smart aquaculture system. The system consists of data acquisition, preprocessing, fuzzy inference and visualization modules to aid in water quality assessment. Our independently developed intelligent water quality monitoring system, tailored for sustainable shrimp farming scenarios, feeds preprocessed data into a fuzzy logic module. This module can leverage three methods Mamdani, Sugeno, and Tsukamoto backed by references [9], [10]. Following standard workflows, the system outputs water quality classifications, visualizes results, and supports real-time assessment.

The system it is equipped with four types of sensors to monitor four core parameters: water temperature, pH, salinity, and dissolved oxygen, and forms the foundation of an intelligent decision support system. Temperature was measured using a DS18B20 sensor with an accuracy of 98.15% after calibration using a reference thermometer. The pH parameter was monitored using a DFRobot pH sensor with 97.96% accuracy calibrated using pH buffer solutions. Salinity measurements were obtained from an EC sensor with 93.97% accuracy using a standard conductivity solution, while dissolved oxygen was measured using a galvanic DO sensor with 96.88% accuracy calibrated using zero-oxygen and saturated-water conditions.

### 2.1. Data Collection

The author conducted experiments and testing for the final project in the campus laboratory, using reference data taken from the 2025 community service program at the Keputih shrimp ponds in Sukolilo, Surabaya, East Java, Indonesia. The data set used in this study was obtained from the pond water. Currently, the author is collaborating with a

team responsible for developing equipment to collect real-time data from shrimp farmers. The cooperating farmers are pond owners who participated in the 2025 community service program.

### 2.2. Data Preprocessing

To provide a clean and organised dataset, numerous necessary pretreatment steps were carried out before conducting fuzzy method comparisons [11]. To begin, we performed attribute selection, which involved keeping only the qualities that were directly related to our research goals and discarding any features that were deemed superfluous or irrelevant. In order to simplify and ensure consistency throughout the dataset, data was integrated from multiple sources and aggregated when needed.

After that, the dataset was cleaned up using interpolation techniques to deal with missing values [12]. To guarantee data completeness, interpolation is essential; this is particularly true for fuzzy logic approaches that demand well-structured input. One popular approach is linear interpolation, which finds averages of nearby data points to fill in missing values [13]. Here is the formula for linear interpolation:

$$x_{before} = \frac{(x_{after} - x_{before})}{(t_{after} - t_{before})} \cdot (t - t_{after})$$

The next step was to execute an expert-defined reference labelling procedure using domain references and pertinent literature to develop aquaculture water quality standards [14]. By comparing various fuzzy approaches within the same aquaculture rule framework, these labels allow us to see how they stack up in terms of consistency and inference.

### 2.3. Expert-defined Reference Labelling

Optimal circumstances for aquatic species can only be achieved by keeping particular water parameters within specific limits, which are important in aquaculture and environmental monitoring. Temperature, salinity, pH, and dissolved oxygen (DO) are some of these factors [15]. The metabolic processes, development, and continued existence of aquatic organisms rely on each of these factors. The parameter ranges selected are shown in Table 1 and represent the optimal environmental conditions for shrimp cultivation and are used as the basis for expert defined reference labeling.

TABLE 1. Water Quality Parameters

Parameter	Ideal Range
Temperature	28 - 32
DO	$\geq 4$
Salinity	15 - 30
pH	7.5 - 8.5

To classify water quality circumstances, a rule-based approach is designed using Table 1 [16], [17]. The real monitoring data is then tagged with these expert-defined labels for additional analysis, such training and assessing inference systems, based on this classification.

**a. Very Bad**

Water conditions are hazardous and unsuitable for aquatic life. Triggered when:  $DO < 2.5$  ppm,  $Temp < 24^\circ C$  or  $> 35^\circ C$ ,  $pH < 7.0$  or  $> 10$ , Salinity  $< 5$  ppt or  $> 40$  ppt.

**b. Bad**

Parameters still support life but may induce severe stress. Occurs if:  $2.5 \leq DO < 4$ ,  $24 \leq Temp < 26$  or  $33 < Temp \leq 35$ ,  $7.0 \leq pH < 7.5$  or  $8.5 < pH \leq 9.5$ , Salinity  $< 10$  or  $> 35$  ppt.

**c. Medium**

Conditions are near-ideal, with minor potential stress. Defined as:  $4 \leq DO < 5$ ,  $26 \leq Temp < 28$  or  $32 < Temp \leq 33$ ,  $7.0 \leq pH < 7.5$  or  $8.5 < pH \leq 8.8$ ,  $10 \leq Salinity < 15$  or  $30 < Salinity \leq 35$  ppt.

**d. Good**

Good All parameters fall within the ideal range (DO 5–8 ppm, Temp 28–32°C, Salinity 15–30 ppt, pH 7.5–8.5).

**2.4. Fuzzy Inference Systems**

To deal with the non-linearity and intrinsic uncertainty of water quality data, this work primarily uses Fuzzy Inference Systems (FIS) as its computational method. To obtain accurate classification decisions, FIS allows the mapping of continuous input factors namely, temperature, salinity, dissolved oxygen (DO), and pH into

linguistic variables, as opposed to the usual binary logic. In order to ascertain the state of water quality using the rule sets specified earlier, this part describes the inner workings of three separate fuzzy inference methodologies: Mamdani, Sugeno, and Tsukamoto.

**a. Mamdani Fuzzy Inference System**

Many control systems use Mamdani because of its easy-to-understand rule representation. Fuzzy sets are used for both the input and the output, making the rules more comprehensible to humans [18].

The final output is a fuzzy set that is defuzzified using the centroid method, defined by:

$$z = \frac{\int \mu(z) z dz}{\int \mu(z) dz}$$

where  $\mu(z)$ , which is the output's aggregated membership function. System requirements for interpretability and transparency are met by Mamdani.

**b. Sugeno Fuzzy Inference System**

In contrast to Mamdani, Sugeno incorporates a mathematical function typically linear or constant in the rules' consequent element [19]. A typical Sugeno rule takes the form: If x is A and y is B then  $z = ax + by + c$ . The final output is computed as a weighted average:

$$z = \frac{\sum_{i=1}^n w_i z_i}{\sum_{i=1}^n w_i}$$

where  $w_i$  is the firing strength of the i-th rule and  $z_i$  is the output of the rule. Sugeno is known for its computational efficiency and suitability for optimization and adaptive techniques.

**c. Tsukamoto Fuzzy Inference System**

A monotonic membership function yields a sharp number as the result of each rule in this approach [20]. The final output is determined by taking the weighted average of the individual crisp outputs are generated by each rule:

$$z = \frac{\sum_{i=1}^n w_i \alpha_i}{\sum_{i=1}^n \alpha_i}$$

where  $\alpha_i$  where is the firing strength of the i rule and  $z_i$  is the crisp output of the rule. Tsukamoto is known for its smooth output characteristics and suitability for systems requiring gradual decision transitions.

**2.5. Data Processing**

Gathering pertinent data sets necessary for this study was the first step in the research process. This information was gathered from water samples taken from shrimp ponds in Keputih, Sukolilo, Surabaya. Essential water quality characteristics like

temperature, salinity, pH, and dissolved oxygen (DO) levels are included in the dataset. The salinity parameter in particular started off with a value of zero in a few dataset entries since the pond's natural circumstances were distinct from the usual parameters for shrimp cultivation. Preprocessing made use of interpolation techniques to fill in missing or zero values with estimated ones based on surrounding patterns, ensuring comprehensive and reliable data [21]. Now that the dataset with 994 entries is ready, we can use fuzzy logic classification algorithms to analyse and compare it further.

## 2.6. Membership Functions

Fuzzy logic systems rely significantly on clearly specified membership functions for their accuracy and interpretability [22]. Fuzzy sets, which reflect linguistic phrases that characterise the quality level, are created by converting the numerical values of the water quality metrics into them using these functions [23]. The four fuzzy sets, "Very Bad," "Bad," "Medium," and "Good," are defined for each parameter and are distinguished by their distinct trapezoidal or triangular shapes.

### a. Dissolved Oxygen (DO) Membership

Dissolved Oxygen (DO) is a critical indicator of water health, directly impacting aquatic life [24].

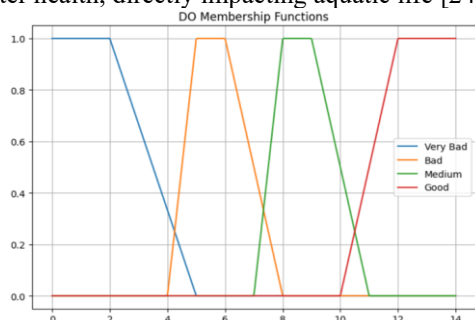


FIGURE 2. DO Membership Functions

Figure 2 illustrates the membership functions used for dissolved oxygen (DO). The figure shows that extremely low DO values (below 2 mg/L, for example) are classified as "Very Bad" and indicate extreme hypoxic conditions, as seen in Figure 2. On the other hand, water is generally considered "Good" when its DO content is more than 10 mg/L, meaning it is well-oxygenated. A constant evaluation of DO quality is provided by the "Bad" and "Medium" categories, which cover the transitional ranges.

### b. PH Membership Functions

One of the most basic markers of water quality is its pH, which indicates how acidic or alkaline the water is. Ecosystems in water might suffer from extremely acidic or basic pH levels [25].

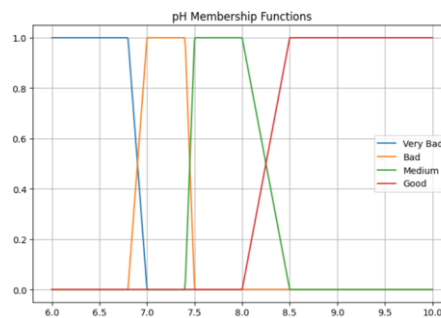


FIGURE 3. PH Membership Functions

Figure 3 demonstrates that there is a significant degree of membership in the "Good" category for a near-neutral pH range (about 7.0 to 7.5). Most aquatic organisms do not thrive in environments that are much different from this ideal range, which means that more people will fall into the "Bad" or "Very Bad" fuzzy sets when the pH drops below 6.5 or rises beyond 8.5.

### c. Temperature Membership Functions

The temperature of water has a major impact on the chemical, biological, and physical activities that take place in water [26].

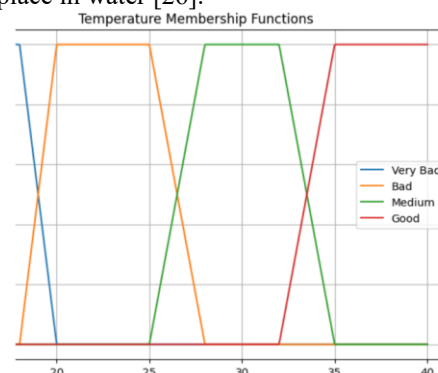


FIGURE 4. Temperature Membership Functions

Figure 4 presents the temperature membership functions adopted in this study. Most aquatic life is thought to thrive in moderate temperatures, which range from 25°C to 30°C. The aquatic biota may be threatened by temperatures that drop below 15°C or rise above 35°C, which are categorised as "Very Bad" or "Bad" respectively.

### d. Salinity Membership Functions

A critical metric, especially in coastal and estuarine environments, is salinity, which is the concentration of dissolved salts [27].

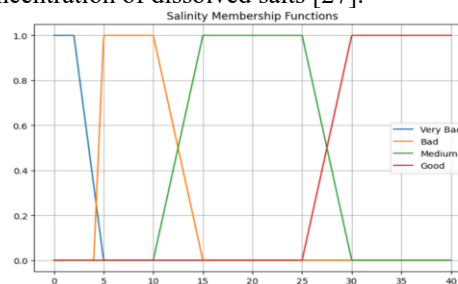


FIGURE 5. Salinity Membership Functions

Figure 5 shows the salinity membership functions and their corresponding fuzzy categories. Extremely low salinity (below 5 ppt), is typically associated with a "Good" rating for freshwater ecosystems or a "Very Bad" rating for marine-adapted species. For ecosystems that rely on freshwater, the salinity scale goes from "Good" to "Bad" or "Very Bad" as the values rise. Estuarine ecosystems rely on brackish conditions, which the "Medium" category frequently depicts.

TABLE 2. Rule Based

DO	pH	Temp	Salinity	Classification
Good	Good	Good	Good	Good
Good	Good	Good	Medium	Good
Good	Good	Medium	Good	Good
Good	Good	Medium	Medium	Medium
Good	Good	Bad	Good	Medium
Good	Good	Bad	Medium	Medium
Good	Good	Very Bad	Medium	Bad
Good	Medium	Good	Good	Good
Good	Medium	Good	Medium	Good
Good	Medium	Medium	Good	Medium
Good	Medium	Medium	Medium	Medium
Good	Medium	Bad	Good	Bad
Good	Medium	Bad	Medium	Medium
Good	Bad	Medium	Good	Bad
Good	Bad	Medium	Medium	Bad
Good	Bad	Very Bad	Good	Bad
Good	Bad	Very Bad	Medium	Very Bad
Good	Bad	Very Bad	Good	Very Bad
Good	Very Bad	Very Bad	Medium	Very Bad
Medium	Good	Good	Good	Good
Medium	Good	Good	Medium	Medium
Medium	Good	Medium	Good	Medium
Medium	Good	Medium	Medium	Medium
Medium	Good	Bad	Good	Bad
Medium	Good	Bad	Medium	Medium
Medium	Medium	Good	Good	Medium
Medium	Medium	Good	Medium	Medium
Medium	Medium	Medium	Good	Medium
Medium	Medium	Medium	Medium	Medium
Medium	Medium	Bad	Good	Medium
Medium	Medium	Bad	Medium	Bad
Medium	Bad	Good	Good	Medium
Medium	Bad	Good	Medium	Bad
Medium	Bad	Medium	Good	Bad
Medium	Bad	Medium	Good	Bad
Medium	Bad	Medium	Medium	Bad
Medium	Bad	Bad	Good	Bad
Medium	Bad	Bad	Medium	Bad
Medium	Very Bad	Very Bad	Good	Very Bad
Medium	Very Bad	Very Bad	Medium	Very Bad
Bad	Good	Medium	Medium	Bad
Bad	Medium	Good	Good	Medium
Bad	Medium	Good	Medium	Bad
Bad	Medium	Medium	Good	Bad
Bad	Medium	Medium	Good	Bad
Bad	Medium	Medium	Medium	Bad
Bad	Medium	Bad	Medium	Bad
Bad	Medium	Very Bad	Good	Very Bad
Bad	Medium	Very Bad	Medium	Very Bad
Bad	Bad	Good	Good	Bad
Bad	Bad	Good	Medium	Bad
Bad	Bad	Medium	Medium	Bad
Bad	Bad	Bad	Good	Bad
Bad	Bad	Bad	Medium	Bad
Bad	Very Bad	Very Bad	Good	Very Bad
Bad	Very Bad	Very Bad	Medium	Very Bad
Very Bad	Medium	Medium	Medium	Very Bad
Very Bad	Medium	Medium	Medium	Very Bad
Bad	Bad	Good	Good	Bad

Very Bad	Bad	Good	Medium	Very Bad
Very Bad	Bad	Medium	Good	Very Bad
Very Bad	Bad	Bad	Good	Very Bad
Very Bad	Bad	Bad	Medium	Very Bad
Very Bad	Very Bad	Good	Good	Very Bad
Very Bad	Very Bad	Good	Medium	Very Bad
Very Bad	Very Bad	Medium	Good	Very Bad
Very Bad	Very Bad	Medium	Medium	Very Bad
Very Bad	Very Bad	Bad	Good	Very Bad
Very Bad	Very Bad	Bad	Medium	Very Bad
Very Bad	Very Bad	Very Bad	Good	Very Bad
Very Bad	Very Bad	Very Bad	Medium	Very Bad

Table 2 presents the rule base used by the fuzzy inference systems. The rules were constructed from expert knowledge and aquaculture standards to map combinations of input conditions into water quality categories.

### III. RESULT AND DISCUSSION

This section gives a thorough synopsis of the comparison study that was carried out on the three algorithms used in the fuzzy inference system: Tsukamoto, Mamdani, and Sugeno. There is a systematic technique that takes into account two main aspects while evaluating the performance of the model. To start, the examination delves into the visual interpretation of defuzzification graphs and inference methods to show how each method handles data uncertainty and how classification judgements are made. As a second step, we conduct a comparative consistency analysis by comparing the model's prediction outputs to real data on water quality labels provided by experts. This data is supplied in a tabular style for easy reference. In order to compare the evaluated fuzzy techniques' inference consistency and decision behaviour, this comprehensive evaluation compares the models' correctness, consistency, and reliability in diagnosing shrimp pond environmental conditions.

#### 3.1. Fuzzy Output Comparison

This sub section gives a detailed tabular analysis of the water quality dataset. It includes important physical and chemical metrics including Dissolved Oxygen (DO), pH, Salinity and Temperature. For a rigors performance assessment, these input variables are directly compared with their respective 'expert-defined labels' labels, used as the validated baseline of reference circumstances based on aquaculture standards. The table also presents the relative outputs obtained from the Mamdani, Sugeno, and Tsukamoto fuzzy inference

systems, with the numerical predicted scores and the respective categorical classifications explicitly displayed to illustrate the level of agreement or disagreement between the computational models and the actual data.

Table 4 provides a glimpse of 15 data points from the test dataset to give insight into the model inference performance. The table shows for each sample the input parameters (DO, pH, Temperature and Salinity) and the Reference Quality category. The output of the model is a numerical Predicted Score and a final Predicted Category. If the Prediction Status column says “Match”, it means the model prediction agrees with the true category; if it says “Mismatch”, it means there’s a misclassification. This sample shows the comparative agreement patterns between the fuzzy inference outputs and the reference labels defined by the experts and highlights some specific examples where the predictions of the fuzzy inference deviated from the real conditions that might be useful for analysing inference inconsistencies and differences in the decision boundaries of the methods evaluated.

As shown in Table 4, However, there were several mismatches, especially in samples 3, 5 and 11, suggesting that extreme environmental conditions may lead to different inference outcomes from the expert-defined labels. The mismatches can

explain the decrease of overall accuracy and the sensitivity of fuzzy boundaries around critical thresholds.

### 3.2. Evaluation Result

Between December 2024 and April 2025, a total of 994 data samples were gathered for this study. Using agreement-based assessment criteria to quantify consistency with the expert-defined reference labels, the dataset is used to analyse and compare several fuzzy inference algorithms.

TABLE 3. Evaluation result of fuzzy inference methods

Method	Accuracy	Precision	Recall	F1-Score
Mamdani	0.8	0.825	0.8	0.797
Sugeno	0.7	0.880	0.7	0.728
Tsukamoto	0.7	0.880	0.7	0.728

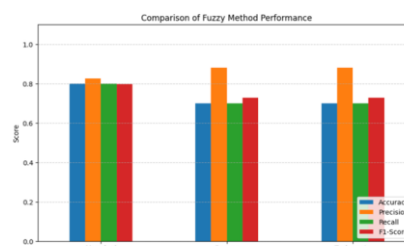


FIGURE 6. Graph Comparison of Fuzzy Method Performance

TABLE 4. SAMPLE PREDICTION RESULTS OF FUZZY INFERENCE SYSTEMS

No	DO	pH	Salinity	Temperature	Reference Label	Predicted Score	Predicted Category	Prediction Status
1	1	6.2	16	2	very bad	6.67	very bad	Match
2	0.5	8	28	25	very bad	6.67	very bad	Match
3	7	6	25	15	very bad	25.64	bad	Mismatch
4	3	7.5	17	10	very bad	23.74	very bad	Match
5	6	7.8	27	0.5	very bad	36.85	bad	Mismatch
6	2	6.3	18	1	very bad	6.67	very bad	Match
7	8	2.8	20	20	very bad	6.67	very bad	Match
8	4	7	22	10	bad	30.46	bad	Match
9	5	7.8	30	20	bad	49.15	bad	Match
10	8	7.2	28	20	bad	35	bad	Match
11	7	7.5	20	25	bad	7	very bad	Mismatch
12	8.5	8	29	7	bad	39.86	bad	Match
13	6	6.9	25	12	bad	35	bad	Match
14	3.8	7.1	24	11	bad	35	bad	Match
15	7.5	7.8	29	20	medium	51.53	medium	Match

Among the tested fuzzy inference methods, Mamdani showed the highest level of agreement with the expert-defined reference rules, according to the comparison results shown in Table 3 and visualised in Figure 6. The best F1-Score of 0.797 was attained by Mamdani, who also had the best Accuracy and Recall. With its optimal precision-to-recall ratio, the Mamdani inference system appears to have more consistent inference behaviour according to the specified rule structure for this particular water quality dataset. But with lower Accuracy and Recall scores of 0.7 and an F1-Score of 0.728, the performance metrics produced by the Tsukamoto and Sugeno approaches were similar. On

the other hand, it's worth mentioning that Sugeno and Tsukamoto showed a little better Precision (0.880) than Mamdani (0.825). Given the same output mapping structure and specified fuzzy rule configuration, the fact that Sugeno and Tsukamoto both achieved identical performance points to comparable decision boundary behaviour. Sugeno and Tsukamoto may be more careful with their predictions, reducing the number of false positives, but they can't match the breadth of positive examples covered by the Mamdani method.

### 3.3. Web-Base Smart Aquaculture System

The suggested Fuzzy Inference System was implemented within the PENS Aqua programme to provide effective decision-making and real-time monitoring through a complete web-based user interface. The front-end visualisation layer of this platform is crucial, as it is designed to continuously process raw sensor data streams for vital parameters such as pH, temperature, salinity, and dissolved oxygen. The solution allows aquaculture operators to do more than just watch changing numerical trends by integrating the fuzzy logic algorithm into the computational backend of the dashboard. Rather, it converts complicated multi-variable data into straightforward status categories, so users can get an instantaneous interpretation of the aquatic environment's overall condition. This user-friendly interface seamlessly connects raw data collecting with practical farming insights, greatly improving operational responsiveness.

The web-based monitoring platform will use the Mamdani fuzzy inference system instead of the Sugeno and Tsukamoto methods since it is more consistent, according to the comparative evaluation results. Furthermore, the system gives shrimp growers actionable advice based on the discovered water quality category. For instance, if the condition is "Medium," further monitoring is needed; if it's "Bad," improvements to water exchange and aeration are suggested; and if it's "Very Bad,"

intervention and stabilisation of parameters are required immediately.

Figure 7 shows the implementation of the proposed web-based monitoring platform. The dashboard visualizes sensor measurements, fuzzy inference results, and water quality classifications in real time. Each quadrant has a line graph of the historical and forecasted data points, showing the water conditions as a visual trajectory. The system is very important to classify the total water quality into four different language categories Good, Medium, Bad and Very Bad. The interface also displays a comprehensive inference result for each graph showing the final categorisation status and the various membership degrees (e.g., degree of 'good' vs. 'medium'). This fine-grain visualisation validates the system's ability of capturing uncertainty, providing a more granular evaluation of the system than classical binary logic, by indicating the degree to which a given parameter belongs to a certain category.

It should be noted that the fuzzy inference systems and the reference labels used in this work had comparable aquaculture rule underpinnings. Therefore, the given evaluation metrics must be interpreted not as an absolute measure of predictive accuracy in relation to independent ground truth observations, but as comparative measures of inference consistency, rule interpretation behaviour and decision stability of the evaluated fuzzy approaches.

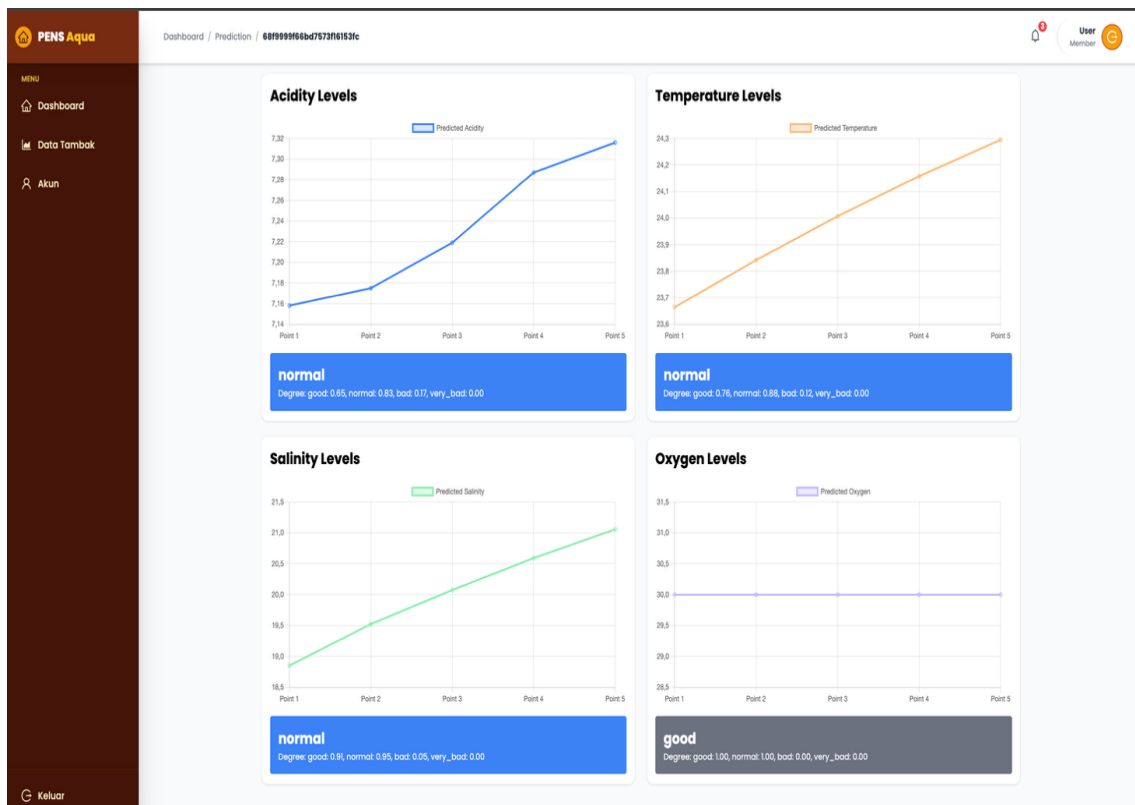


FIGURE 7. Web-Base Smart Aquaculture System

#### IV. CONCLUSION

This study aimed to compare three fuzzy inference systems, namely Mamdani, Sugeno, and Tsukamoto, for shrimp pond water quality classification based on four key parameters: temperature, pH, salinity, and dissolved oxygen, and to identify the most consistent method under a unified aquaculture rule framework. The experimental results using 994 real water quality records show that the Mamdani method achieved the highest performance and consistency with expert-defined reference labels, obtaining an accuracy of 0.800, precision of 0.825, recall of 0.800, and F1-score of 0.797, outperforming both Sugeno and Tsukamoto, which each achieved an accuracy of 0.700 and an F1-score of 0.728. Although Sugeno and Tsukamoto showed slightly higher precision, their lower recall indicates reduced capability in capturing the full range of water quality conditions. Based on these findings, Mamdani provides the most balanced and stable inference behavior for aquaculture decision-making in this study. In addition, the proposed web-based smart aquaculture system demonstrates the practical implementation of fuzzy logic for real-time monitoring and decision support, enabling interpretable water quality classification to support sustainable shrimp farming management.

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