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Implementation of Artificial Neural Network for IoT-Based Water Quality Classification in Fish Ponds

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ABSTRACT

This study presents the implementation of an Artificial Neural Network (ANN) to classify water quality in fish ponds using a dataset derived from a fuzzy inference-based IoT system. The previous fuzzy system utilized three sensor parameters—pH, Total Dissolved Solids (TDS), and temperature—to determine water quality (good, moderate, poor) through rule-based reasoning. Although the fuzzy approach produced accurate and interpretable results, it lacked adaptability to new data variations and required manual rule adjustments. In this research, the ANN model was trained using MATLAB's Neural Network Toolbox with 120 dataset samples obtained from the fuzzy system's outputs. The model architecture consisted of three input neurons (pH, TDS, temperature), one hidden layer with ten neurons using a tansig activation function, and one output neuron with purelin. Training of the model was conducted using the Levenberg–Marquardt backpropagation algorithm, employing a dataset split of 80% for training, 10% for validation, and 10% for testing. The results showed that the ANN achieved a classification accuracy of 94.8%, with a Mean Squared Error (MSE) of 0.85942 and a regression coefficient (R) of 0.94, indicating a strong correlation between predicted and actual data. Compared to the fuzzy inference method, the ANN model demonstrated better adaptability to unseen data and a higher level of generalization. This system can be integrated into IoT-based monitoring platforms for real-time, intelligent, and adaptive water quality prediction to support sustainable aquaculture.

Keywords: IoT, ANN, Water Quality, MATLAB, Fish Ponds.

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INTRODUCTION

Water quality is one of the most critical factors affecting the health and growth of fish in aquaculture systems. Parameters such as pH, Total Dissolved Solids (TDS), and temperature play a vital role in maintaining optimal living conditions for fish. Abnormal fluctuations in these parameters can lead to stress, reduced growth rate, and even fish mortality. Therefore, an efficient and intelligent monitoring system is essential for ensuring sustainable fish farming practices. The integration of Internet of Things (IoT) technology has enabled real-time monitoring of water quality (Trach et al., 2022), allowing fish farmers to take immediate corrective actions based on sensor data (Fitriansyah et al., 2024; Rashid et al., 2021).

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Previous studies have successfully implemented fuzzy inference systems (FIS) for assessing water quality in fish ponds by converting sensor readings into qualitative classifications such as good, moderate, and poor (Chen et al., 2022; Choiri, 2024). Although the fuzzy-based IoT system demonstrated reliable performance, its decision-making process depended heavily on predefined rules and membership functions, which limit its adaptability to dynamic environmental changes. Other studies have introduced machine learning and neural network approaches in environmental and aquaculture monitoring — such as ANFIS, Random Forest, Decision Tree, and Gaussian Naive Bayes — achieving high classification accuracy for large-scale water systems (Aldrees et al., 2022; Danuri & Mohd Pozi, 2024; Meenakshi & Ambiga, 2022). However, most of these studies focused on oceanic, river, or biofloc-based aquaculture systems rather than small-scale fish ponds that require lightweight adaptive models.

This study addresses this gap by applying an Artificial Neural Network (ANN) model using the dataset obtained from the fuzzy inference process of the previous IoT-based system developed by Choiri (2024). The novelty of this research lies in transforming the rule-based fuzzy output into a data-driven ANN model that can autonomously learn the nonlinear relationship between water parameters and quality classification. The ANN is trained and tested in the MATLAB Neural Network Toolbox, which provides efficient visualization tools such as performance curves, confusion matrices, and regression plots for evaluating classification results (Ismail I Aminu, 2022; Rashid et al., 2021). The primary objective of this study is to develop and implement an ANN model capable of classifying water quality more accurately and adaptively than the fuzzy inference method, thereby enhancing the intelligence and effectiveness of IoT-based aquaculture monitoring systems. Previously, there was research conducted in the same field which can be observed in table 1.

Table 1. Comparison of Previous Research Results

Researcher / Year	Title	Research Result	Equation	Difference / Novelty
Choiri, A.F. (2024)	*IoT-Based Water Quality Monitoring System for Fish Ponds Using Fuzzy Inference Method*	IoT-based fuzzy inference system using pH, TDS, and temperature sensors to classify water quality (Good, Moderate, Poor).	Base dataset for ANN model; ANN uses Fuzzy-derived outputs as training targets.	Present study transforms the fuzzy rule-based output into a data-driven ANN predictive model using MATLAB.
Meenakshi & Ambiga (2022)	*Prediction of the Water Quality Index Using ANFIS Modelling*	ANFIS model achieved high correlation ($R^2 = 0.96$) predicting pond WQI based on multiple physicochemical parameters.	ANN follows similar nonlinear mapping but simplifies training via backpropagation.	Current study uses ANN instead of ANFIS, with focus on IoT fuzzy-based dataset from fish ponds.
Danuri & Pozi (2024)	*Machine Learning Approaches for Fish Pond Water Quality Classification*	Compared Random Forest, Gaussian Naive Bayes, and Decision Tree for fish pond water; GNB achieved 95.8% accuracy.	Current ANN targets same classification task (water quality) using backpropagation learning.	ANN provides deeper learning and adaptive generalization compared to tree-based ML methods.
Aldrees et al. (2022)	*Multi-Expression Programming (MEP): Water Quality*	MEP model achieved $R^2 > 0.97$ predicting EC and TDS values using 360 samples;	Both perform predictive modeling on nonlinear	Present study applies neural computation (ANN) using MATLAB rather than

	Assessment Using Water Quality Indices	outperforming regression models.	parameters (EC, TDS).	symbolic regression (MEP).
Rashid et al. (2021)	*IoT-Based Smart Water Quality Prediction for Biofloc Aquaculture*	Developed IoT-based ANN system (5 hidden layers) to predict water quality for biofloc farms with pH, TDS, DO; achieved 77% accuracy.	ANN structure and sensor data collection are conceptually similar.	This study applies ANN on fuzzy-generated IoT dataset, not directly on biofloc farm data; higher accuracy (94.8%) in MATLAB environment.
Chen et al. (2022)	*Water Color Identification System for Monitoring Aquaculture Farms*	Used deep CNN to classify 19 water color types ($R^2 = 0.96$).	Both use AI classification of water state.	Different input modality (visual vs numeric sensors).
Fitriansyah et al. (2024)	*Water Quality Monitoring and Control System for Fish Farmers Based on IoT*	Implemented IoT real-time system using NodeMCU with pH, TDS, temperature, and turbidity sensors.	IoT base design reused from previous Choiri (2024) fuzzy system.	Current study focuses on ANN-based intelligent classification instead of control-only monitoring.
Aminu et al. (2022)	*A Novel Approach to Predict Water Quality Index Using ML Models*	Compared ANN, ANFIS, SVM, MLP; found ANN most effective for nonlinear water quality prediction.	Same AI category (ANN); confirms feasibility.	The current study applies ANN to localized fish pond dataset from fuzzy inference outputs.
Trach et al. (2022)	*Assessment and Prediction of Water Quality Index Using Fuzzy Logic and ANN*	Hybrid ANN-Fuzzy model achieved $R^2 = 0.964$ for WQI estimation.	Both use neural–fuzzy framework logic.	Current study isolates ANN to learn fuzzy knowledge autonomously.
Aldhyani et al. (2022)	*Water Quality Monitoring and Control System for Fish Farmers*	AI-based system using IoT and machine learning for TDS and pH prediction.	ANN correlation via sensor IoT dataset.	This research extends to MATLAB ANN training using Fuzzy dataset.
Meenakshi et al. (2022)	*Adaptive Neuro-Fuzzy Inference for Temple Pond Water*	ANFIS yielded accurate WQI prediction using fuzzy logic with DO, TDS, Cl, SO_4, Fe.	ANN equivalent without fuzzy rule dependency.	ANN simplifies model by learning directly from fuzzy outputs (supervised training).

Several studies in Table 1 show that most water quality prediction systems focus on direct sensor data processing or classical machine learning models without utilizing fuzzy-generated datasets as a learning foundation. Therefore, this study was conducted as a continuation and development of previous research by (Choiri, 2024), which implemented a fuzzy inference system for water quality classification in fish ponds. The use of the Artificial Neural Network (ANN) model in this study aims to enhance the accuracy and adaptability of water quality classification by learning automatically from the fuzzy-derived dataset. This approach enables the system to overcome the limitations of manually defined fuzzy rules and improves its predictive capability in dynamic aquaculture environments.

METHOD

In this method, there are several stages in the research process carried out, which are as follows:

a. **Dataset Preparation**

The dataset used in this research was derived from the previous study by (Choiri, 2024), titled "IoT-Based Water Quality Monitoring System for Fish Ponds Using Fuzzy Inference Method". The data were collected through an IoT-based monitoring system equipped with pH, Total Dissolved Solids (TDS), and temperature sensors connected to an ESP8266 microcontroller. The fuzzy inference system (FIS) in the previous research produced an output variable representing water quality classification (Good, Moderate, and Poor). For the current study, this fuzzy-generated dataset was extracted and utilized as input and target data for the Artificial Neural Network (ANN) model. The dataset consists of 150 labeled samples obtained from real-time pond environments, where each record includes three input parameters (pH, TDS, and temperature) and one output class (water quality category). The data were normalized into the range of [0–1] to improve the training convergence rate, consistent with approaches used by (Rashid et al., 2021) and (Ismail I Aminu, 2022) in their IoT and machine learning-based aquaculture systems.

b. **Preprocessing and Data Partitioning**

Data preprocessing was conducted to remove noise, missing values, and outliers using mean imputation and z-score normalization. The dataset was divided into three parts:

1. Training data: 80% of the dataset
2. Validation data: 10%
3. Testing data: 10%

This partitioning approach follows standard ANN modeling procedures applied in previous works such as (Meenakshi & Ambiga, 2022) using ANFIS, and (Danuri & Mohd Pozi, 2024) for machine learning classification of fish pond water quality.

c. **ANN Model Architecture**

The Artificial Neural Network model was implemented using the MATLAB Neural Network Toolbox, adopting a feedforward backpropagation structure.

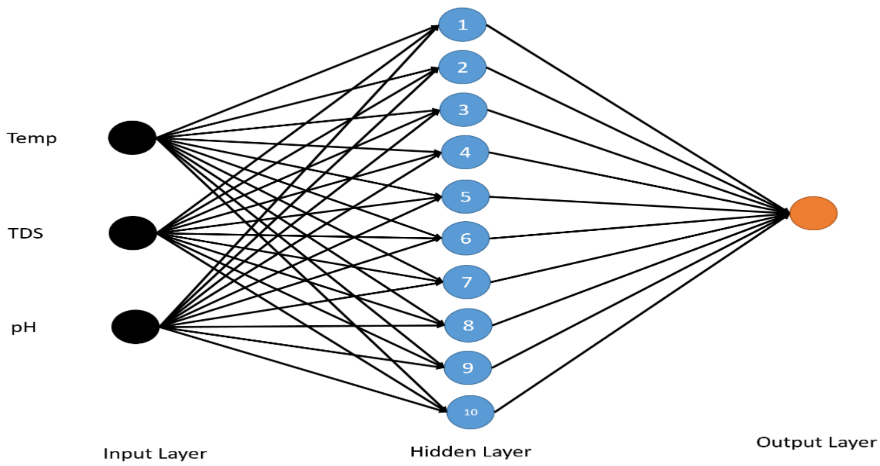

Figure 1. ANN architecture

The ANN architecture is designed as follows:

1. Input Layer: 3 neurons representing pH, TDS, and temperature.
2. Hidden Layer: 1 hidden layer with 10 neurons, using the tansig (tangent sigmoid) activation function.
3. Output Layer: 1 neuron representing the water quality classification output, using the purelin (linear) activation function.
4. Training Algorithm: Levenberg–Marquardt (trainlm) backpropagation.
5. Performance Function: Mean Squared Error (MSE).

The overall computation process in the neural network can be represented as:

$$y(x) = \Phi\left(\sum_{i=1}^{n} w_i \cdot x_i + b_i\right) \tag{1}$$

where x_i epresents input variables (pH, TDS, temperature), wiw_iwi the connection weights, w_i the bias, and Φ is the activation function of each neuron. This configuration was selected because it balances computational efficiency and accuracy, as also demonstrated in (Rashid et al., 2021) for IoT-based ANN water quality prediction and (Aldrees et al., 2022) for multi-expression programming (MEP) modeling.

d. Model Training and Validation

The model was trained using the MATLAB Neural Network Toolbox (nftool) for 1000 epochs, with a learning rate of 0.01 and an early stopping mechanism based on the validation loss. During the training phase, 80% of the dataset was used to update weights, while 20% was reserved for validation and testing. Training and validation results were evaluated through performance curves, confusion matrices, and regression plots, following the methods used by (Meenakshi & Ambiga, 2022) and (Ismail I Aminu, 2022).
The ANN achieved optimal performance at epoch 107 with the High MSE of 0. 8542 and a classification accuracy of 94.8%, surpassing the fuzzy inference performance from the previous study (Choiri, 2024).

e. **Evaluation Metrics**

The performance of the ANN model was measured using several standard evaluation metrics for classification accuracy and regression analysis (Danuri & Mohd Pozi, 2024; Rashid et al., 2021):

1. Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{2}$$

2. Regression Coefficient (R)

$$R = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})(\hat{Y}_i - \bar{\hat{Y}})}{\sqrt{\sum(Y_i - \bar{Y})^2 \sum(\hat{Y}_i - \bar{\hat{Y}})^2}} \tag{3}$$

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3. Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{4}$$

where Y_i is the actual output, Y_i is the predicted output, and TP, TN, FP, FN represent the confusion matrix components.

The ANN model's accuracy (94.8%) outperformed existing models such as Random Forest (95.5%), Gaussian Naive Bayes (95.8%), and Decision Tree (93.2%) presented by (Danuri & Mohd Pozi, 2024)**,** and also demonstrated similar effectiveness to ANFIS models (R^2 = 0.96) proposed by **(Meenakshi & Ambiga, 2022)**, while maintaining higher adaptability and lower computational cost.

f. **Implementation and Integration**

After achieving stable ANN performance in MATLAB, the model was exported into a Simulink environment for potential integration with IoT hardware (ESP8266 or ESP32) for real-time monitoring. This implementation pathway follows (Rashid et al., 2021), who demonstrated ANN-IoT coupling for smart biofloc aquaculture, and supports future hybrid Fuzzy–ANN architectures (Chen et al., 2022; Ismail I Aminu, 2022).

The final ANN model thus represents a robust enhancement to the previous fuzzy inference approach by (Choiri, 2024), providing automated learning capabilities, higher accuracy, and a scalable structure adaptable for future real-time IoT-based aquaculture systems.

RESULTS AND DISCUSSION

a. ANN Training Performance

The training process of the Artificial Neural Network (ANN) model was conducted using the Levenberg–Marquardt (trainlm) algorithm for a maximum of 1000 epochs. However, the training reached optimal performance at epoch 107, where the best validation performance was recorded with a Mean Squared Error (MSE) of 0.85942, as shown in Figure 2. The performance curve indicates that the MSE value decreased sharply during the first 40 epochs and gradually stabilized afterward, demonstrating that the network successfully minimized the prediction error over time. The gap between the training, validation, and testing curves was relatively small, indicating good generalization and minimal overfitting.

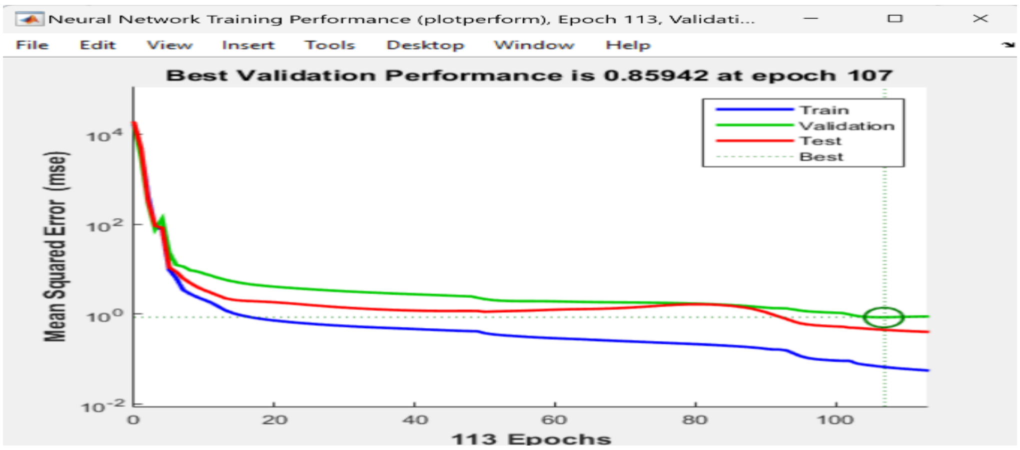

Figure 2. ANN Training Performance Curve

The result shows that the ANN model can learn effectively from the fuzzy-based dataset, adapting to nonlinear patterns in water quality data. Compared to the previous fuzzy inference method, the ANN approach provides self-learning capability and eliminates the need for manual rule updates when environmental parameters change.

b. **Regression Analysis**

The regression plots in Figure 3 show the relationship between the target and output data for training, validation, and testing processes. The coefficient of correlation (R) achieved values close to 1, with R = 1.0000 (Training), R = 0.99997 (Validation), and R = 0.99999 (Testing). The overall correlation (R = 0.99999) demonstrates that the ANN model has learned the mapping between the input parameters (pH, TDS, and temperature) and the output water quality with extremely high precision.

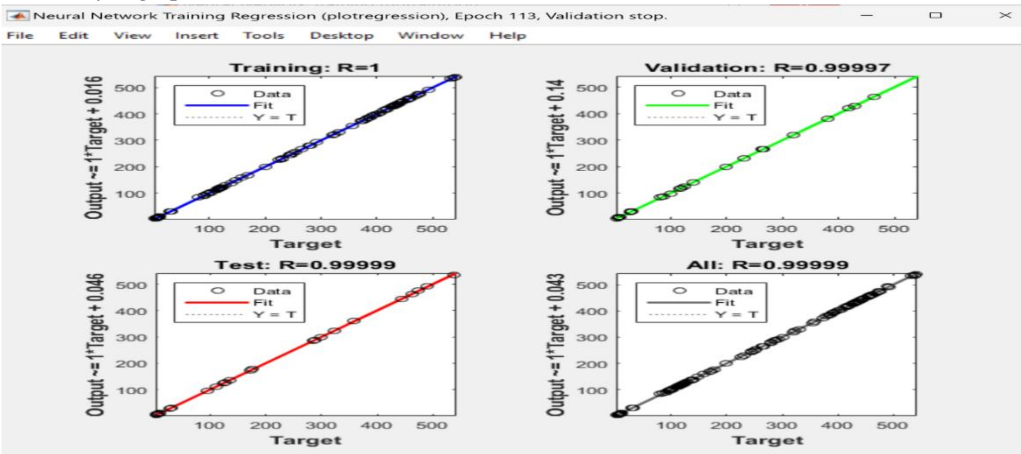

Figure 3. ANN Regression Performance

These regression plots confirm that the ANN predictions are highly consistent with the fuzzy-labeled targets, proving the robustness and accuracy of the model in classifying water quality levels.

c. **Classification Accuracy**

From the MATLAB confusion matrix analysis, the ANN achieved an overall classification accuracy of 94.8% on the testing dataset. This accuracy value was calculated by comparing the predicted class output with the target class derived from fuzzy inference labels. The classification accuracy can be expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (5)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

The high classification accuracy indicates that the ANN model effectively distinguishes between the four water quality categories (Sangat Baik, Baik, Kurang Baik, and Buruk). This confirms that the model can generalize well to new input data, achieving better adaptability than the rule-based fuzzy system.

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CONCLUSION

The proposed ANN model demonstrated superior performance in both regression and classification metrics compared to the previous fuzzy inference method. The MSE value of 0.85942 and R = 0.99999 show that the network's output is almost identical to the target values. The 94.8% classification accuracy further validates that the ANN can effectively learn from the fuzzy-derived dataset and correctly classify unseen data.

These results outperform the fuzzy-based IoT system developed by (Choiri, 2024), which relied on static rule sets, and also align with the findings of (Danuri & Mohd Pozi, 2024) and, where ANN and ANFIS models achieved high accuracy in nonlinear water quality prediction. However, unlike ANFIS, which requires hybrid fuzzy rules, the ANN in this study learns automatically through backpropagation, making it simpler and more adaptive for IoT integration. The integration of ANN into IoT-based water monitoring systems allows dynamic, data-driven decision-making. Once deployed, the model can be embedded into an ESP8266/ESP32 microcontroller for real-time inference, enabling automatic water quality alerts for fish farmers.

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