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Artificial Neural Network-Based Classification of Water Quality Status in Ornamental Fish Farming Using IoT Sensor Data

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Abstract

Water quality plays an important role in sustainable agriculture. Water quality also affects the quality and quantity of fishery production. In ornamental fish cultivation, water quality influences not only production, but also the shape and color of the fish. To achieve optimal results, water quality parameters need to be maintained. Manually monitoring water quality parameters faces many challenges such as being time-consuming and not providing real-time data. This study investigated the application of Artificial Neural Networks (ANNs) in classifying water quality status. This status is based on data collected using sensors in an Internet of Things (IoT)-based monitoring system. The dataset comprised five key parameters: pH, temperature, ammonia, total dissolved solids (TDS), and total suspended solids (TSS). This data was collected from aquariums cultivating the Denison barb (Sahyadria denisonii). Data preprocessing was performed using feature standardization. This aims to improve model performance. The ANN model was constructed with two hidden layers (32 and 16 neurons). This model was trained using the Adam optimizer, with categorical cross-entropy as the loss function. The dataset was divided into 80% for

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training and 20% for testing. The trained ANN model achieved an accuracy of 99.95%. It has low false-positive and false-negative rates. These results demonstrate the effectiveness of ANN in predicting water quality status using sensor-based data. This suggests its potential for real-time monitoring and decision-making support in small-scale ornamental fish aquaculture.

Keywords: aquaculture, artificial neural network, machine learning, ornamental fish, water quality

INTRODUCTION

Water quality plays an important role in sustainable agriculture. Water quality also affects the quality and quantity of fishery production. In ornamental fish cultivation, water quality not only influences production but also affects the shape and color of the fish. Ornamental fish are fish that are appreciated for their shape and color, not for consumption. This type of fish is highly sought after and has significant economic value. One of the most popular ornamental fish is the Denison barb.

Denison barb is among the most commercially valuable ornamental fish species in international markets due to its distinctive coloration and high demand among hobbyists (Jain et al., 2022). However, it is highly sensitive to fluctuations in water quality, particularly changes in pH, temperature, and dissolved solids (Duque et al., 2020). For ornamental fish, maintaining optimal water conditions is directly linked to survival rates, marketability, and farmer profitability (Mihály-Karnai et al., 2025; Simasiku et al., 2024). Maintaining stable water quality parameters is essential to ensure fish health and prevent fish mortality (Atkore et al., 2020; Nagothu et al., 2025). Poor water conditions can cause stress, hinder growth, reduce productivity, and increase the risk of disease or death in sensitive species (Canosa & Bertucci, 2023; K. Zhang et al., 2025). To achieve optimal results in ornamental fish farming, water quality parameters need to be maintained.

In small-scale aquaculture systems, water quality measurement is often conducted manually. Manually monitoring water quality parameters presents several challenges, including time consumption and the inability to provide real-time data. This will limit the frequency, introduce delays, and fail to provide real-time insights (Dharmarathne et al., 2025; Zou et al., 2025). These limitations hinder timely interventions and informed decision-making. To address this, IoT-based monitoring systems have emerged as a solution. This system enables continuous and remote measurements of water quality parameters (Chavhan et al., 2025; Essamlali et al., 2024). However, the large volume of sensor data generated by IoT devices requires intelligent analytical tools to extract meaningful insights in real time (Andersen et al., 2020; Choudhary, 2024; Kumar et al., 2024).

Artificial Neural Networks (ANNs), a subset of machine learning, have shown strong capabilities in learning complex and nonlinear relationships in environmental datasets (Maier et al., 2023; Pasini, 2015). Several studies support the use of ANN and other deep learning models to predict water quality and support decision-making in aquaculture. For example, Chen et al. (2020)

reviewed over 150 studies that used ANN models, such as multilayer perceptrons (MLP), general regression neural networks (GRNN), and backpropagation neural networks (BPNN), to predict variables such as dissolved oxygen (DO), biological oxygen demand (BOD), and chlorophyll-a concentration. Wu et al., (2025) applied deep learning architecture, including CNN-GRU, BiLSTM, and attention-based LSTM, for real-time water quality prediction and behavioral anomaly detection in smart aquaculture systems. There is also a study that explored machine learning models, such as Random Forest, SVM, and XGBoost, combined with sensor data fusion techniques to predict DO and temperature, but noted limitations in handling nonlinear temporal dynamics, which ANN models are better suited to address (Fini et.al., 2025). Deep learning models, such as CNN and LSTM, can enhance real-time monitoring and behavioral assessment in recirculating aquaculture systems (RAS) (Chen & Hao, 2025).

These findings strongly support the integration of ANN into aquaculture monitoring systems, particularly for classifying water quality status using real-time IoT sensor data. Although IoT-based sensing technologies have proven effective for environmental data acquisition (Pasika & Gandla, 2020; Popescu et al., 2024; Ramadan et al., 2024), the real-time classification of water quality using ANN remains underexplored, particularly in the context of ornamental fish farming. Most previous studies have focused on commercial aquaculture species, with limited attention to small-scale ornamental systems.

This study aims to address these gaps by developing and evaluating an ANN-based model for classifying water quality using data from an IoT sensor system. The model categorizes water quality into “good” and “poor” conditions. This condition was based on five key parameters: pH, temperature, ammonia, total dissolved solids (TDS), and total suspended solids (TSS). The classification accuracy was assessed to determine its effectiveness in supporting timely, data-driven decision-making in ornamental fish aquaculture.

Beyond its technical contributions, this study supports broader sustainability goals. It aligns with SDG 6 (Clean Water and Sanitation) by promoting improved water management practices, contributes to SDG 12 (Responsible Consumption and Production) by enabling more efficient use of water resources, and supports SDG 17 (Partnerships for the Goals) through participatory engagement of fish farmers in a citizen science-based monitoring framework.

To achieve these goals, this study investigated whether an Artificial Neural Network (ANN) can accurately classify water quality in ornamental fish farming using real-time data from IoT-based sensors. This study aimed to evaluate the practical value of ANN in processing environmental data and providing reliable classifications to support operational decisions in small-scale aquaculture systems.

METHOD

The dataset comprised water quality measurements collected using sensors from an IoT system in ornamental fish aquariums. The recorded parameters included pH, temperature, ammonia, total dissolved solids (TDS), total suspended solids (TSS), and the corresponding water quality status (good or poor).

Before feeding the data into the ANN model, feature scaling was applied using StandardScaler. This feature will normalize the input variables to have a zero mean and unit variance. This preprocessing step is important in machine learning applications for enhancing convergence speed and training stability. Especially for algorithms that are sensitive to feature magnitudes, such as neural networks. According to Hosseinpour et al. (2025), standardization techniques, such as StandScale (Standard Scaler), have a significant influence on the predictive performance of machine learning models. Particularly when dealing with multivariate sensor data or imbalanced datasets. Their study highlighted that even for robust algorithms, such as Random Forest or CART, applying standard scaling can improve model generalization and mitigate training instability. Therefore, in this study, scaling was used to harmonize the feature magnitudes and ensure that the learning process remained efficient and less susceptible to convergence issues associated with raw data distributions.

Dataset and Preprocessing

The dataset used in this study was collected from ornamental fish aquariums cultivating Denison barb (*Sahyadria denisonii*). These aquariums are located at the Fish Production Laboratory, School of Vocational Studies, IPB University, Indonesia. A set of IoT-based sensors was deployed to monitor five key water quality parameters in real time: pH, temperature, ammonia, total dissolved solids (TDS), and total suspended solids (TSS). Each aquarium unit was equipped with identical sensor configurations to ensure consistency in data acquisition.

The full dataset, named SIMONAIR, consists of 515,066 records with eight attributes: id, machine_id, pH, temperature, ammonia, total dissolved solids (TDS), total suspended solids (TSS), and status. The status column served as the classification label, with values “Good Quality” or “Poor Quality”. The status is determined based on expert evaluation and thresholds established by the Indonesian National Standards (SNI) for the quality of ornamental aquaculture water. From the total records, 87% of the data were categorized as Good Quality and 13% as Poor Quality. This relatively imbalanced class distribution presents a challenge for the classification process. The imbalanced distribution making the choice of normalization method and tuning of model parameters important to avoid prediction bias toward the majority class. A large dataset was continuously generated by multiple IoT devices (machine_id) under real-time monitoring. This ensured that the records captured a wide range of environmental variability relevant to the ornamental aquaculture. Each data record was labeled with the corresponding water quality status. The resulting dataset consisted of structured numerical records, where each instance represented a real-time snapshot of the water quality conditions and its corresponding classification labels.

Prior to model training, all input features were normalized using StandardScaler, a standard feature-scaling technique that transforms variables to have zero mean and unit variance. This preprocessing step was critical for ensuring model stability, accelerating convergence, and preventing the dominance of features with higher magnitudes during training.

Artificial Neural Network (ANN) Architecture

To classify the water quality status, an Artificial Neural Network (ANN) model was developed using a multilayer feedforward architecture. The network consists of the following components. (1) An input layer with five neurons, each corresponding to one of the water quality parameters; (2) Two hidden layers: the first with 32 neurons and the second with 16 neurons, both utilizing the Rectified Linear Unit (ReLU) activation function to introduce nonlinearity and facilitate efficient gradient propagation and (3) An output layer with two neurons, representing the binary classification outcomes ("good" or "poor"). This output generated using the softmax activation function to generate probability distributions across the classes. The softmax activation function returns a probability distribution over mutually exclusive output classes.

The model was trained using the backpropagation algorithm. The Adam optimizer applied for adaptive learning rate adjustment and categorical cross-entropy as the loss function. In backpropagation, the prediction error calculated at the output layer is propagated backward through the network to iteratively adjust the connection weights. It will minimizing the error over successive training cycles. This configuration was chosen for its ability to efficiently handle multiclass classification tasks and non-linear decision boundaries.

The overall architecture of the ANN model is illustrated in Figure 1. It shows the full configuration from the input to the output layers and their respective activation functions.

Model Training and Evaluation

The dataset was randomly divided into 80% training and 20% testing subsets. During training, the ANN model repeatedly adjusted the network weights. This aims to reduce prediction errors by utilizing labeled instances from the training set. The training process was carefully monitored to ensure convergence and prevent overfitting.

The model's performance was assessed on the test set using standard classification metrics, including accuracy, precision, and recall. A confusion matrix was created to visualize the distribution of true positives, true negatives, false positives, and false negatives. This matrix provided a comprehensive evaluation of the model's ability to distinguish between good and poor water quality.

RESULTS AND DISCUSSION

The trained Artificial Neural Network (ANN) model achieved an accuracy of 99.95% on the test dataset. This result demonstrates its strong predictive capability for water quality status. As shown in the confusion matrix (Figure 1), the model correctly identified 14520 instances of poor water quality and 88447 instances of good water quality. Misclassifications were minimal, with only 15 false negatives (good water quality incorrectly classified as poor) and 32 false positives (poor water quality incorrectly classified as good). This indicates the model's reliability in distinguishing between the two classes.

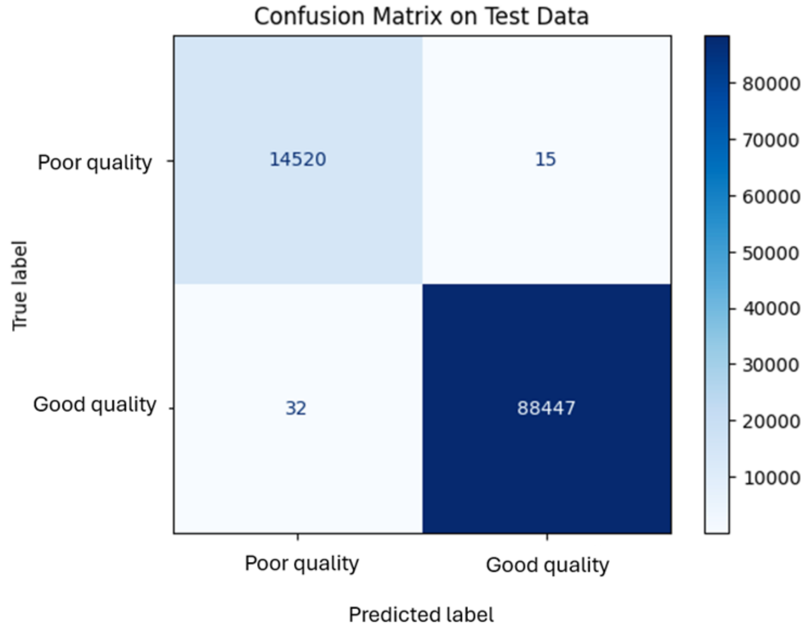

Figure 1. Confusion matrix of the ANN model

The training loss curve (Figure 2) further confirms the effective learning and convergence of the proposed model. Initially, the loss was high due to significant prediction errors. However, as training continued, the loss dropped quickly and eventually leveled off at a very low value. This indicates that the model successfully learned the underlying patterns in the dataset. The smooth convergence also shows that the model did not suffer from overfitting or underfitting, which are common challenges in neural network training.

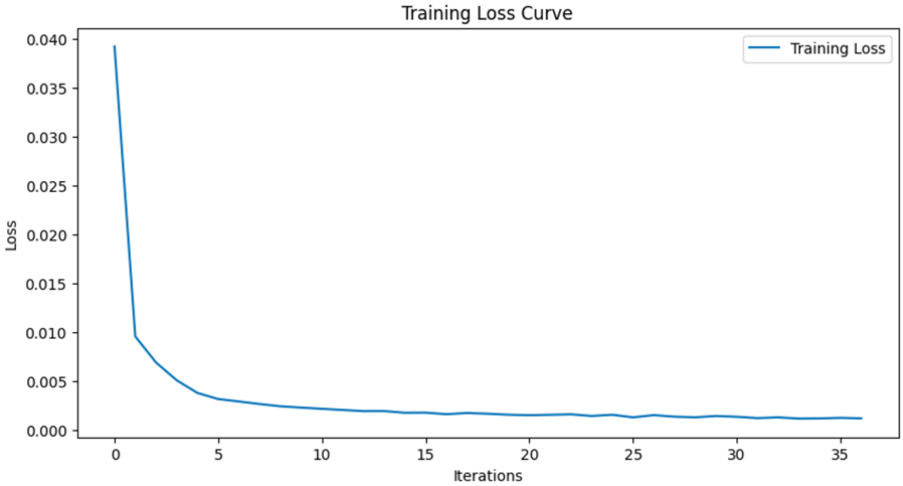

Figure 2. Training loss curve showing convergence of the ANN model

The high classification performance stems from two main factors. First, there was a strong correlation between the measured parameters (pH, temperature, ammonia, TDS, and TSS) and overall water quality. These parameters served as discriminative features that the ANN could utilize effectively for classification. Second, applying feature standardization through the Standard Scaler normalized the input variables, which helped the model converge more quickly and ensured that no single feature had an undue influence on the learning process.

To provide context for these results, it is useful to compare the model's performance with existing studies. For instance, Wu et al. (2025) reported classification accuracies between 92% and 96% using BiLSTM and CNN-GRU models for real-time water quality prediction in smart aquaculture systems. Another study used Random Forest and SVM to predict dissolved oxygen and temperature, reaching about 91% accuracy, though it highlighted difficulties in managing nonlinear interactions among variables (Fini et.al., 2025).

In contrast, the 99.95% accuracy achieved by the ANN model in this study demonstrates superior performance, especially considering the simplicity of the architecture and the constraints of small-scale sensor-based monitoring systems. These results suggest that a well-designed ANN model, when combined with effective preprocessing and relevant features, can match more complex hybrid architectures. It also remains easy to implement in embedded or low-resource environments.

Despite these promising results, deploying ANN models in real-world aquaculture settings faces practical challenges. These include sensor calibration inconsistencies, data loss due to connectivity issues, and environmental variability across aquaculture sites, which may affect the model's generalizability. In particular, a model trained on data from controlled laboratory conditions might perform differently when exposed to fluctuating parameters in field conditions. These factors should be considered when scaling or adapting models for broader use.

From a practical perspective, these results demonstrate that ANN is highly effective for real-time water quality classification in ornamental aquaculture settings. Its capacity to handle multivariate sensor inputs and provide dependable classifications makes it suitable for integration into automated water-quality monitoring systems. Such systems could help small-scale fish farmers identify poor water conditions sooner, allow for timely corrective actions, and reduce fish stress or mortality. This system can also increase the productivity and sustainability of aquaculture.

Importantly, the model's capacity to classify water quality instantly holds significant practical value for ornamental fish farmers. By decreasing reliance on manual sampling and providing early warnings of declining water conditions, the system allows farmers to make timely interventions, lower operational expenses, and protect valuable fish stocks. Additionally, the successful application of ANN in this study supports the broader movement toward smart aquaculture, where machine learning and IoT-based solutions can provide affordable and scalable tools for digital transformation in rural and resource-constrained aquaculture settings.

Although this study demonstrated excellent performance under controlled conditions, several directions for future improvements should be considered. Future studies should focus on expanding the dataset to include a more diverse range of environmental conditions, species, and aquaculture systems to improve the robustness of the model. Incorporating temporal sequence data could also allow the use of recurrent or hybrid neural networks to detect trends and provide early warnings. Furthermore, integrating explainable AI (XAI) methods would provide greater transparency in model decision-making, enhancing trust and usability for end-users, such as fish farmers or aquaculture technicians.

In addition to its technical contributions, this study highlights the potential for integrating AI and IoT technologies into community-driven monitoring systems aligned with citizen science initiatives. By empowering small-scale fish farmers with automated decision-support tools, such systems can promote digital inclusion, resource efficiency, and more equitable access to smart aquaculture solutions. Therefore, this study supports broader sustainability goals, including SDG 6, 12, and 17.

CONCLUSION

This study confirmed the feasibility and effectiveness of using an Artificial Neural Network (ANN) to classify water quality in ornamental fish farming based on real-time data collected from an IoT-based system. The developed model achieved a classification accuracy of 99.95%. It demonstrates strong capability to interpret environmental sensor data and reliably distinguish between good and poor water conditions.

The integration of ANN with IoT systems presents a practical solution for automated, data-driven decision-making in aquaculture. By enabling more accurate and timely detection of water quality issues, such systems can help reduce unnecessary water replacement, minimize fish mortality, and optimize resource efficiency. This will thereby contribute to more sustainable and productive aquaculture practices.

Future research should enhance model generalizability by incorporating a wider range of environmental conditions, aquaculture species, and water quality parameters. Additionally, exploring alternative machine learning algorithms and hybrid deep learning architectures may further improve the classification performance and robustness in dynamic, real-world aquaculture environments. From a practical perspective, these findings highlight the direct benefits for farmers, who can adopt such systems to improve their daily management practices. Fish farmers can ensure healthier stock and reduce unnecessary resource consumption. This strengthens the applicability of ANN and IoT-based monitoring tools as practical decision-support technologies in ornamental fish aquaculture.

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