Smart Multisensor-Based Machine Learning for Multiclass Freshwater Fishpond Water Quality Degradation Classification

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ABSTRACT

Water quality degradation in freshwater fishponds results from interactions among physicochemical parameters, limiting the effectiveness of single-parameter threshold monitoring. This study presents a multisensor-based Machine Learning (ML) framework for multiclass classification of water quality degradation in a monitored earthen freshwater pond. A dataset comprising 2153 data points was labeled into four degradation levels (Normal, Caution, Warning, Severe) using a predefined rule-based multi-parameter scoring protocol derived from aquaculture operational standards, ensuring independence from model training. Seven physicochemical parameters—Oxidation–Reduction Potential (ORP), Electrical Conductivity (EC), Total Dissolved Solids (TDS), turbidity, temperature, pH, and Dissolved Oxygen (DO)—were analyzed. Four baseline classifiers: Random Forest (RF), XGBoost, Support Vector Machine (SVM) with RBF kernel, and distance-weighted K-Nearest Neighbors (KNN) were evaluated using stratified 5-fold cross-validation, with performance reported as mean ± standard deviation. RF achieved the highest performance, obtaining an accuracy of 0.952 ± 0.013 and a macro-F1 score of 0.955 ± 0.012. To address multicollinearity, Pearson correlation analysis and targeted EC–TDS feature ablation were conducted. The results indicate minimal performance variation when either EC or TDS is removed individually, with noticeable degradation only when both are excluded. SHapley Additive Explanations (SHAP)-based explainability and Principal Component Analysis (PCA) further identify turbidity and EC as dominant degradation indicators. The first two main components capture approximately 58–60% of variance, indicating a multidimensional degradation structure rather than complete separability in two-dimensional space. The proposed framework offers a structured and reproducible engineering-oriented approach for assessing multiclass freshwater fishpond degradation under moderate class imbalance.

Keywords-water quality degradation; freshwater fishpond monitoring; multisensor systems; machine learning classification; random forest

I. INTRODUCTION

Freshwater fishponds play a significant role in aquaculture systems by providing controlled environments for fish growth and food production [1]. However, maintaining stable water quality is a crucial operational challenge [2]. Accumulation of feed residues, metabolic waste, sediment disturbance, temperature fluctuations, and limited water exchange create interacting physicochemical processes that may progressively degrade pond conditions [3-5]. In earthen pond systems, degradation commonly manifests through increased turbidity, elevated dissolved ionic concentrations, oxygen depletion, and redox imbalance, which collectively influence fish stress and survival [6]. Conventional aquaculture monitoring typically relies on single-parameter threshold evaluation, such as pH, Dissolved Oxygen (DO), turbidity, or Electrical Conductivity (EC) [7, 8]. While regulatory thresholds provide practical guidance, they do not capture nonlinear interactions among multiple parameters [9]. In practice, degraded pond conditions rarely result from a single parameter exceeding its limit; instead, they emerge from cumulative deviations across several interacting indicators [10]. Consequently, threshold-based monitoring may inadequately represent transitional or borderline degradation states, particularly in moderately imbalanced environmental datasets.

Machine Learning (ML) has been adopted to analyze environmental monitoring data by learning complex relationships directly from multisensor measurements. In [11-13], ML was applied for environmental observation analysis across various sensing modalities, while in [14], ML was employed for water quality monitoring under climate variability. Ensemble learning methods such as Random Forest (RF) and gradient boosting have shown strong predictive capability and practical deployment potential [15, 16]. In aquaculture-related contexts, ML-based approaches have been used for water quality or water condition assessment [17, 18]. However, many existing studies rely on limited parameter sets or focus on binary classification tasks. In [17], only three parameters were utilized for freshwater water quality classification, limiting environmental representation. Similarly, several works concentrate on binary detection or regression scenarios [19-22], which simplify degradation into two-state outcomes and overlook progressive transitional stages that are common in freshwater fishpond environments. Another significant aspect in environmental monitoring is interpretability. Black-box predictions without physically meaningful explanations may reduce practitioner trust and hinder operational adoption [23]. Explainable artificial intelligence techniques, such as SHapley Additive Explanations (SHAP), have been used to identify dominant environmental drivers in water quality models [24, 25]. Additionally, Principal Component Analysis (PCA) has been applied to explore underlying structures in aquatic datasets [26]. Nevertheless, the integration of structured multiclass degradation modeling, multicollinearity-aware analysis, and explainable ML within freshwater fishpond monitoring remains limited. The present study addresses these gaps by proposing a multisensor-based ML framework for four-level water quality degradation classification in a freshwater fishpond environment. Seven physicochemical parameters—Oxidation–Reduction Potential (ORP), EC, Total Dissolved Solids (TDS), turbidity, temperature, pH, and DO—are integrated to represent complementary degradation mechanisms. Unlike clustering-based or model-derived labeling approaches, degradation classes are defined using a predefined rule-based multi-parameter scoring protocol grounded in aquaculture operational standards [7, 8]. This labeling scheme is constructed independently of model training to ensure transparency and avoid circularity.

The study adopts a snapshot-based classification approach, where each multisensor measurement represents an independent degradation state. While pond conditions evolve gradually over time, periodic multisensor snapshots remain operationally relevant for routine monitoring scenarios. Temporal forecasting extensions are acknowledged as future work. Four baseline classifiers, namely RF, XGBoost, Support Vector Machine (SVM), and distance-weighted K-Nearest Neighbors (KNN), are evaluated using stratified 5-fold cross-validation with class-aware metrics. Correlation analysis and targeted feature ablation are incorporated to assess the impact of multicollinearity, particularly the known linear relationship between EC and TDS. Explainability analysis using SHAP and dimensionality exploration using PCA are applied to interpret model behavior and environmental structure.

The primary contributions of this work are threefold: (1) the introduction of a structured and reproducible four-level degradation labeling protocol for freshwater fishpond monitoring; (2) the integration of multicollinearity-aware feature analysis and targeted ablation to support explainability claims; and (3) a multiclass evaluation framework using interpretable ensemble learning under moderate class imbalance.

This study offers a case-study validated engineering framework specifically designed for monitoring conditions in freshwater earthen ponds, rather than asserting universal generalization. Thus, it establishes a reproducible basis for future cross-site and temporal extensions.

II. METHODOLOGY

A. *Smart Multisensor Freshwater Fishpond Monitoring System*

This study employs a multisensor monitoring system designed for continuous freshwater fishpond data acquisition and structured degradation classification. The system architecture, illustrated in Figure 1, consists of multisensor data acquisition, preprocessing, supervised classification, performance evaluation, and explainability analysis.

The hardware subsystem is built using a single ESP32-S3 microcontroller integrating seven physicochemical sensors: ORP (mV), EC (μS/cm), TDS (mg/L), turbidity (NTU), temperature (°C), pH, and DO (mg/L). These parameters represent complementary aspects of pond dynamics, including suspended solids, ionic concentration, redox state, thermal variation, acidity–alkalinity balance, and oxygen availability.

Sensor measurements are displayed locally via an I²C LCD module and transmitted via Wi-Fi to a remote database and web-based dashboard. Data collection was conducted in a natural earthen freshwater fishpond located at Telkom University, Bandung, Indonesia. The resulting dataset comprises 2153 multisensor data representing realistic operational aquaculture conditions.

The study employs a snapshot-based monitoring paradigm, where each multisensor measurement represents an independent degradation state. Although water quality evolves temporally, periodic multisensor snapshots are operationally relevant for routine monitoring and management decision support.

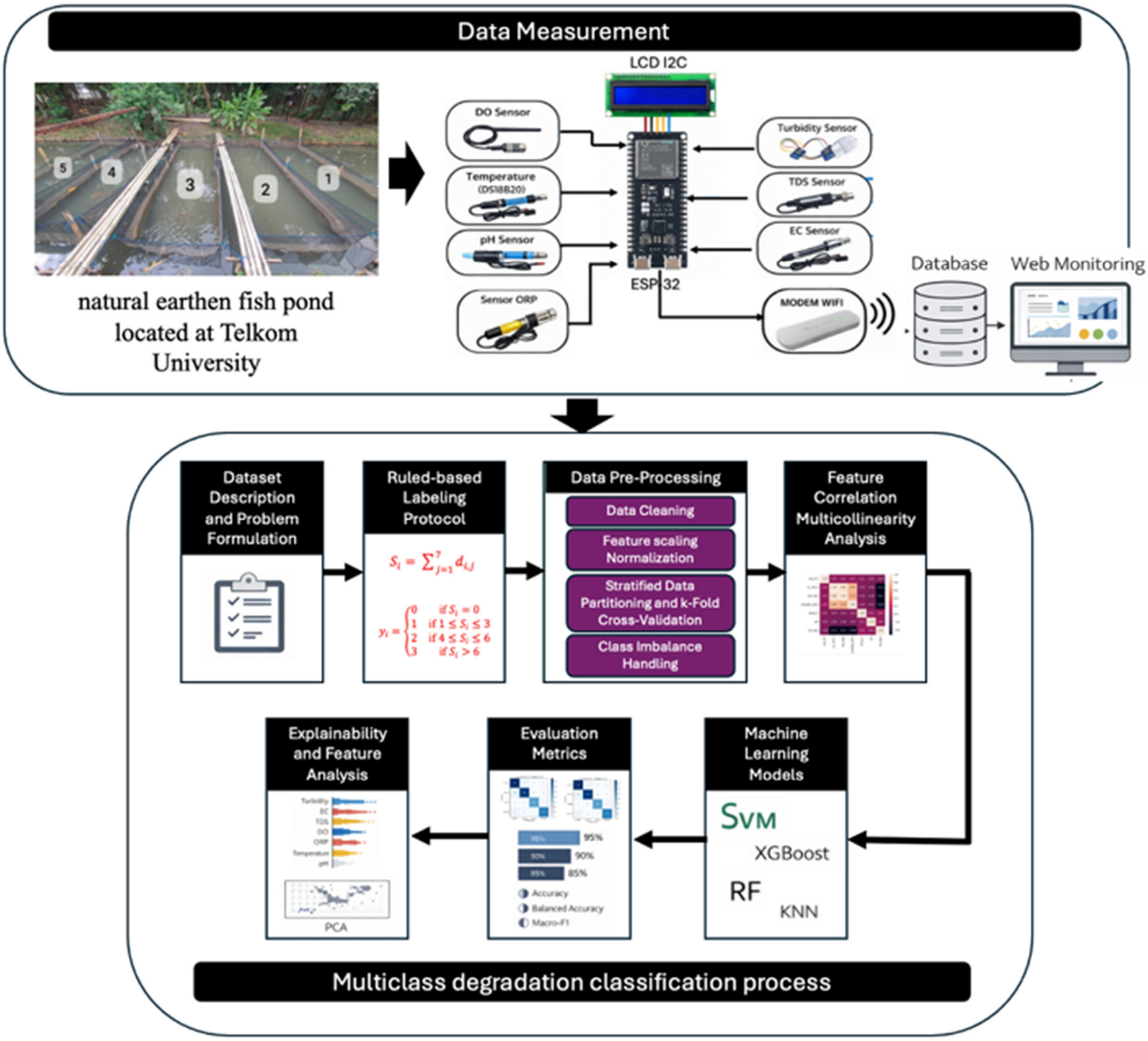

Fig. 1. Proposed smart multisensor-based ML framework for freshwater fishpond degradation classification.

B. Dataset Description and Problem Formulation

The dataset consists of 2153 multisensor data collected from a natural earthen freshwater fishpond deployed as a field monitoring site at Telkom University. Measurements were obtained periodically under operational aquaculture conditions. Each data point is represented by a seven-dimensional feature vector as given in:

$$x_i = ORP_i, EC_i, TDS_i, Turb_i, T_i, pH_{i,}, DO_i] \in \mathbb{R}^7 \quad (1)$$

where ORP_i denotes ORP (mV), EC_i denotes EC (µS/cm), TDS_i denotes TDS (mg/L), $Turb_i$ denotes turbidity (NTU), T_i denotes temperature (°C), pH_i denotes acidity–alkalinity level, and DO_i denotes DO concentration (mg/L). Each observation is assigned to one of four degradation levels in (2), where 0 represents Normal, 1 represents Caution, 2 represents Warning, and 3 represents Severe degradation level:

$$y_i \in \{0,1,2,3\} \quad (2)$$

The classification task is formulated as:

$$\hat{y}_i = f(x_i), \quad f : \mathbb{R}^7 \to \{0,1,2,3\} \quad (3)$$

The dataset exhibits moderate class imbalance. The natural distribution was preserved to maintain ecological realism and avoid artificial distortion of degradation characteristics.

C. Rule-Based Water Quality Degradation Labeling Protocol

1) Parameter Threshold Definition

To ensure transparency and reproducibility, degradation levels were assigned using a predefined rule-based multi-parameter scoring protocol grounded in aquaculture operational standards [7, 8]. The labeling scheme was constructed prior to model development and independently of ML training to avoid circularity. Each data point was evaluated based on parameter-wise deviations from proposed operational ranges. Deviation severity was categorized into four levels (0–3), corresponding to Normal through Severe thresholds. Table I summarizes the operational threshold ranges used for deviation scoring.

TABLE I. RULE-BASED OPERATIONAL THRESHOLDS

Parameter	Normal range	Caution range	Warning range	Severe range
DO (mg/L)	≥ 5.0	4.0–4.9	3.0–3.9	< 3.0
pH	6.5–8.5	6.0–6.4 or 8.6–9.0	5.5–5.9 or 9.1–9.5	<5.5 or >9.5
Turbidity (NTU)	≤ 25	26–50	51–80	> 80
EC (μS/cm)	≤ 400	401–600	601–900	> 900
TDS (mg/L)	≤ 300	301–500	501–800	> 800
ORP (mV)	≥ 200	150–199	100–149	< 100
Temperature (°C)	25–30	23–24 or 31–32	21–22 or 33–34	<21 or >34

2) Multi-Parameter Scoring Mechanism

A multi-parameter severity scoring approach was employed to encapsulate the cumulative and interrelated aspects of freshwater pond degradation. Instead of designating class labels solely based on a singular threshold breach, the protocol assesses concurrent deviations across all seven physicochemical indicators. For each data x_i, every parameter j is assigned a deviation level, where $d_{i,j} \in \{0,1,2,3\}$. The cumulative degradation score S_i is then computed as:

$$S_i = \sum_{j=1}^{7} d_{i,j} \tag{4}$$

In this study, equal weighting was applied across all parameters. This design choice was made to avoid subjective bias in prioritizing specific sensors and to maintain methodological transparency. Future work may explore weighted schemes informed by biological impact studies. The final class label was assigned as defined in:

$$y_i = \begin{cases} 0 & \text{if } S_i = 0 \\ 1 & \text{if } 1 \leq S_i \leq 3 \\ 2 & \text{if } 4 \leq S_i \leq 6 \\ 3 & \text{if } S_i > 6 \end{cases} \tag{5}$$

The score boundaries were selected to reflect progressive accumulation of multi-parameter deviations rather than proportional linear scaling. This formulation ensures that isolated mild deviations do not immediately trigger high-risk classification, while multiple concurrent deviations elevate degradation level in a structured manner.

This cumulative scoring mechanism aligns with operational aquaculture monitoring practices, where adverse pond conditions typically arise from interacting physicochemical stressors rather than isolated threshold violations. The labeling protocol was applied uniformly across all data prior to model training, thereby eliminating circular dependency between labeling and classification.

D. Data Preprocessing

Following dataset construction and rule-based labeling, preprocessing procedures were applied to ensure stable model training, fair classifier comparison, and reproducible evaluation. These steps include data cleaning, feature normalization, stratified data partitioning, cross-validation, and class-aware training configuration.

1) Data Cleaning

The dataset was inspected for missing values, duplicate records, and physically implausible sensor measurements. Data containing incomplete observations were excluded to maintain data integrity. Additionally, measurements outside physically feasible ranges, such as negative DO values, were removed. No synthetic data augmentation or oversampling techniques were applied. The original class distribution was preserved to maintain ecological realism and prevent artificial distortion of minority class characteristics.

2) Feature Scaling and Normalization

Because the seven physicochemical parameters exhibit different physical units and numerical scales, z-score normalization was applied prior to model training. This standardization is particularly important for distance-based and margin-based classifiers such as SVM and KNN. Each feature was transformed as shown in:

$$x'_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j} \tag{6}$$

where $x_{i,j}$ denotes the j^{th} feature of the i^{th} data, μ_j and σ_j represent the mean and standard deviation of the feature j, computed exclusively from the training set. The same normalization parameters were subsequently applied to validation and test sets to prevent data leakage.

3) Stratified Data Partitioning and k-Fold Cross-Validation

To evaluate the generalization performance under moderate class imbalance, the dataset was divided into training (70%) and testing (30%) sets using stratified sampling. This approach preserves the proportional distribution of degradation classes in both subsets, preventing biased performance estimates toward majority classes. In addition to the hold-out split, stratified 5-fold cross-validation was employed on the training data to assess model stability and reduce variance in performance estimation. For each fold, four subsets were used for training and one subset for validation. The final performance metrics are reported as accuracy, balanced accuracy, macro-F1, and weighted-F1.

4) Class Imbalance Handling

Due to the moderate imbalance in class distribution, class-aware learning strategies were integrated during the model training process. In classifiers that incorporate weighting mechanisms, such as RF and SVM, class weights were allocated inversely to class frequency. The performance evaluation focused on class-balanced metrics, such as balanced accuracy and macro-F1 score, to guarantee fair consideration of minority degradation levels.

E. Feature Correlation and Multicollinearity Analysis

To assess potential multicollinearity among physicochemical parameters, pairwise linear correlation analysis was conducted prior to model training. The Pearson correlation coefficient was employed to quantify the strength of linear relationships between features. The Pearson correlation coefficient between two variables x_i and y_i denotes the i^{th} observation of variables x and y, $\bar{x}$ and $\bar{y}$ represent their respective means, and n is the number of data, as defined in:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (7)$$

Pearson correlation was selected due to the continuous nature of the sensor measurements and the objective of detecting linear multicollinearity effects. Correlation analysis was conducted using training data only to avoid information leakage. High inter-feature correlation may influence feature importance distribution, particularly in explainability analysis, and can affect coefficient-based linear models. To evaluate model robustness under correlated predictors, an ablation experiment was conducted, where highly correlated features were selectively removed during training. Comparative performance analysis was performed to determine whether multicollinearity significantly affected predictive stability.

F. ML Models

1) Baseline Model Classifiers

Four baseline classifiers were selected to evaluate the effectiveness of classical and ensemble ML approaches under moderate class imbalance and correlated predictors. The four-baseline classifiers are: RF, XGBoost, SVM (RBF Kernel), and distance-weighted KNN. These models represent ensemble learning, boosting, margin-based, and distance-based paradigms, allowing comparative evaluation across different learning mechanisms. While deep learning architectures may provide advantages in large-scale temporal datasets, the present study focuses on interpretable classical ML methods due to the moderate dataset size and the requirement for explainability in operational aquaculture monitoring.

2) Training Configuration and Hyperparameter Settings

To ensure fair comparison and reproducibility, default or lightly tuned hyperparameters were employed rather than extensive optimization. This strategy avoids dataset-specific overfitting and enables transparent benchmarking. The key configuration for the RF model included 100 trees, unconstrained maximum depth, and class_weight set to balanced. For the XGBoost model, the learning rate was set to 0.1, the number of estimators was 100, and the maximum depth was set to 6. The SVM model with an RBF kernel was configured with a regularization parameter C of 1.0. Furthermore, the KNN model was configured with $k = 5$ using distance-based weighting.

Hyperparameter values were selected based on commonly adopted defaults in environmental ML studies. Systematic optimization was left for future investigation. All experiments were implemented in Python using Scikit-learn and XGBoost libraries. A fixed random seed was applied to ensure reproducibility.

G. Evaluation Metrics

Model performance was evaluated using accuracy, balanced accuracy, and macro-averaged F1-score, which are suitable for multiclass and moderately imbalanced datasets. Accuracy is defined as shown in:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

Balanced accuracy is computed as the average recall across classes in (9), and the macro-averaged F1-score is given by (10), where C denotes the number of classes. These metrics ensure equitable treatment of minority degradation classes:

$$\text{Balanced Accuracy} = \frac{1}{C}\sum_{c=1}^{C}\frac{TP_c}{TP_c+FN_c} \quad (9)$$

$$\text{Macro} - \text{F1} = \frac{1}{C}\sum_{c=1}^{C}\frac{2\cdot Precision_c\cdot Recall_c}{Precision_c+Recall_c} \quad (10)$$

H. Explainability and Feature Analysis

To enhance interpretability, SHAP was employed to quantify feature contributions to model predictions. SHAP analysis was conducted on the RF model due to its superior balanced performance and stability. Additionally, PCA was applied as an unsupervised dimensionality reduction technique to visualize feature space structure and class separability in reduced-dimensional space. Furthermore, targeted feature ablation (EC removal, TDS removal, EC–TDS removal) was conducted under stratified 5-fold cross-validation to evaluate performance stability under correlated predictors.

III. RESULTS AND DISCUSSION

A. Experimental Setup

Model evaluation followed a stratified 70–30 train–test split. Within the training subset, stratified 5-fold cross-validation was performed to assess model stability and reduce variance in performance estimation. The results correspond to mean ± standard deviation across cross-validation folds unless otherwise specified. Consistent hyperparameter configurations were applied across models to avoid dataset-specific over-optimization. Class weighting was incorporated where applicable to address moderate class imbalance. Performance was evaluated using accuracy, balanced accuracy, macro-F1, and weighted-F1 scores, with emphasis placed on balanced accuracy and macro-F1 due to their sensitivity to class imbalance. A fixed random seed was used during data partitioning and model initialization to ensure reproducibility.

B. Dataset Characteristics and Class Distribution

The final labeled dataset comprises 2153 multisensor data categorized into four degradation levels: Normal, Caution, Warning, and Severe. The class distribution is illustrated in Figure 2.

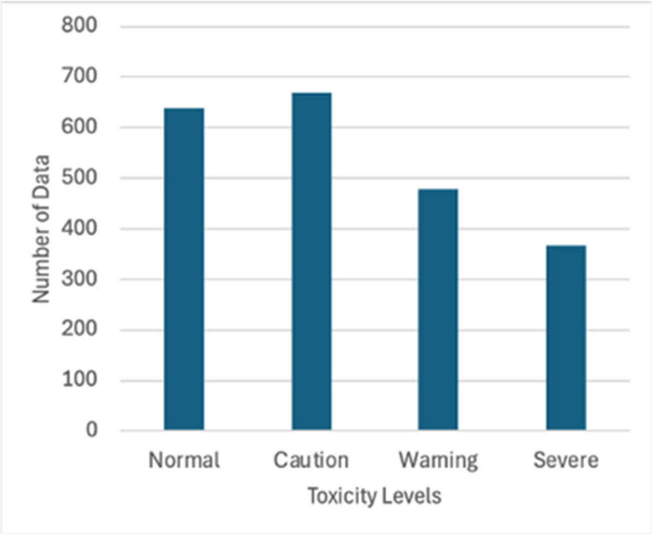

Fig. 2. Class distribution of the freshwater fishpond degradation dataset across four degradation levels: Normal, Caution, Warning, and Severe.

The dataset exhibits moderate class imbalance, with Normal and Caution data slightly dominating the distribution, whereas Warning and Severe remain sufficiently represented for multiclass evaluation. This distribution reflects realistic freshwater fishpond monitoring conditions, where severe degradation states occur less frequently than stable operational states. Table II outlines the statistical characteristics of the monitored physicochemical parameters.

TABLE II. STATISTICAL CHARACTERISTICS OF THE DATASET

Parameter	Minimum	Mean	Maximum
ORP (mV)	115.9	262.27	429.56
EC (µS/cm)	46.46	254.13	888.63
TDS (mg/L)	90.10	621.39	994.29
Turbidity (NTU)	11.43	41.43	127.97
Temperature (°C)	15.37	27.41	34.37
pH	4.720	7.560	10.21
DO (mg/L)	0.290	6.370	11.22

The dataset spans broad dynamic ranges across several parameters, particularly turbidity, TDS, and ORP, indicating substantial variability under field conditions. In contrast, temperature and pH exhibit comparatively narrower ranges, consistent with regulated aquaculture environments. Although partial feature overlap exists among degradation levels, observable distributional shifts across parameters suggest that progressive multiclass discrimination is feasible, particularly under nonlinear classification models.

C. Baseline Model Performance Comparison

The classification performance of the four baseline models is presented in Table III. Performance values correspond to the mean across stratified 5-fold cross-validation. RF achieved the highest overall performance, with an accuracy of 0.952 and a macro-F1 score of 0.955. Its balanced accuracy of 0.952 indicates consistent behavior across degradation classes despite moderate imbalance. XGBoost demonstrated competitive performance, achieving 0.938 accuracy and 0.942 macro-F1, slightly below RF while maintaining stable balanced performance.

TABLE III. BASELINE MODEL PERFORMANCE COMPARISON

Model	Accuracy	Balanced accuracy	Macro-F1	Weighted-F1
RF	0.952	0.952	0.955	0.952
XGBoost	0.938	0.941	0.942	0.938
SVM (RBF)	0.930	0.933	0.934	0.930
KNN (distance)	0.839	0.837	0.847	0.838

SVM (RBF) produced comparable results, with an accuracy of 0.930 and a macro-F1 score of 0.934, indicating that nonlinear margin-based classification can effectively model the dataset, though with slightly reduced robustness compared to ensemble tree methods. KNN exhibited the lowest performance among the evaluated models, with 0.839 accuracy and 0.847 macro-F1 score. The larger performance gap suggests that distance-based classifiers are more sensitive to overlapping feature distributions and correlated predictors. Overall, ensemble tree-based models (RF and XGBoost) demonstrated superior stability within the evaluated dataset for multiclass freshwater fishpond degradation classification.

D. Confusion Matrix

To further examine class-wise behavior, the confusion matrices of the four classifiers are presented in Figure 3. RF demonstrates the most consistent performance across all degradation levels. Misclassifications primarily occur between adjacent classes, particularly between Caution and Normal, as well as between Warning and Severe. This pattern reflects the gradual and progressive nature of freshwater fishpond degradation, where boundaries between intermediate stages are inherently less distinct. XGBoost exhibits a similar misclassification structure, with minor confusion between neighboring classes but strong recognition of Severe data. SVM shows slightly increased misclassification in intermediate classes, especially between Caution and Normal, while maintaining high detection accuracy for Severe cases. KNN presents the highest degree of confusion among adjacent classes, particularly between Caution and Warning, indicating sensitivity to overlapping feature distributions in normalized feature space. Across all models, misclassification between extreme classes (Normal and Severe) is minimal. This suggests that the degradation scoring mechanism produces sufficiently separable boundary conditions at the lowest and highest severity levels, while intermediate transitions remain more challenging due to progressive physicochemical shifts.

E. Feature Correlation and Robustness Analysis

To assess multicollinearity, Pearson correlation analysis was conducted using training data. The resulting correlation matrix is displayed in Figure 4. A strong linear relationship was observed between EC and TDS (r = 0.96), confirming substantial multicollinearity. Turbidity also exhibited a strong correlation with EC (r = 0.80) and TDS (r = 0.78). Moderate negative correlations were observed between DO and both EC (r = –0.53) and TDS (r = –0.51), reflecting inverse relationships between ionic concentration and oxygen availability under degraded conditions.

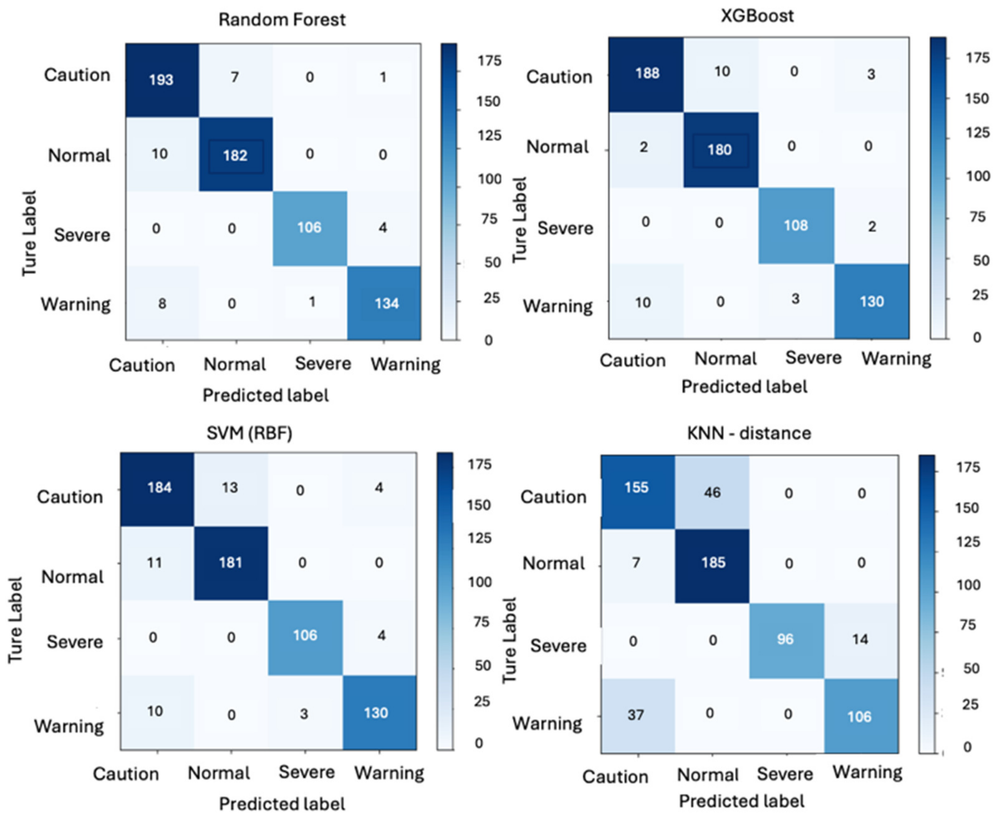

Fig. 3. Confusion matrices of RF, XGBoost, SVM, and KNN.

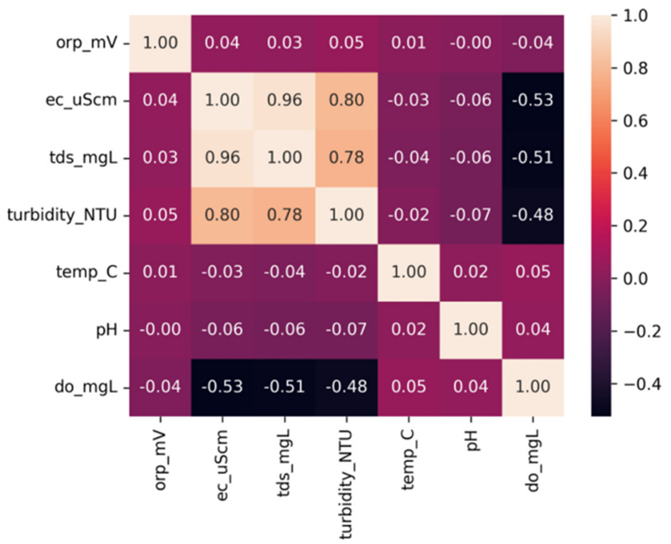

Fig. 4. Pearson correlation map.

Given the high EC–TDS correlation, a targeted ablation study was performed using stratified 5-fold cross-validation, with the results summarized in Table IV. RF achieved an accuracy of 0.945±0.013 using all features. Removing EC resulted in a moderate decrease to 0.931±0.013, while removing TDS alone maintained comparable performance, 0.944±0.016 accuracy. When both EC and TDS were removed simultaneously, accuracy dropped significantly to 0.881±0.014. A similar trend was observed for XGBoost. The results indicate that removing either EC or TDS individually results in only minor performance degradation (<1.5% in macro-F1 score), while simultaneous removal of both features causes a substantial decline (>6%). This suggests that although EC and TDS are strongly correlated, each retains complementary predictive information. The minimal performance reduction under single-feature removal further indicates that multicollinearity does not substantially inflate classification performance or explainability outcomes.

F. Feature-Level Analysis and Dimensional Structure

To better understand the behavior of physicochemical parameters across degradation levels and to interpret model decision mechanisms, descriptive distribution analysis, model-based explainability, and unsupervised dimensionality reduction were conducted.

1) Distributional Analysis Across Degradation Levels

Figure 5 presents the boxplot distributions of the seven monitored parameters across the four degradation classes. Parameters associated with suspended solids and ionic concentration—particularly turbidity, EC, and TDS—exhibit progressive upward shifts in median values as degradation severity increases. These variables also display wider interquartile ranges in the Warning and Severe classes, reflecting greater environmental instability under deteriorating pond conditions.

TABLE IV. PERFORMANCE UNDER EC–TDS FEATURE REMOVAL (5-FOLD CV)

Model	Accuracy	Balanced accuracy	Macro F1	Weighted-F1
All features				
RF	0.945±0.013	0.945±0.013	0.946±0.012	0.945±0.013
XG Boost	0.937±0.012	0.937±0.013	0.938±0.012	0.937±0.012
Remove EC				
RF	0.931±0.013	0.932±0.015	0.933±0.013	0.931±0.013
XG Boost	0.922±0.014	0.921±0.016	0.923±0.014	0.922±0.014
Remove TDS				
RF	0.944±0.016	0.945±0.016	0.947±0.014	0.944±0.016
XG Boost	0.938±0.013	0.938±0.013	0.940±0.012	0.938±0.013
Remove EC and TDS				
RF	0.881±0.014	0.883±0.013	0.887±0.014	0.881±0.014
XG Boost	0.856±0.012	0.858±0.011	0.861±0.012	0.856±0.012

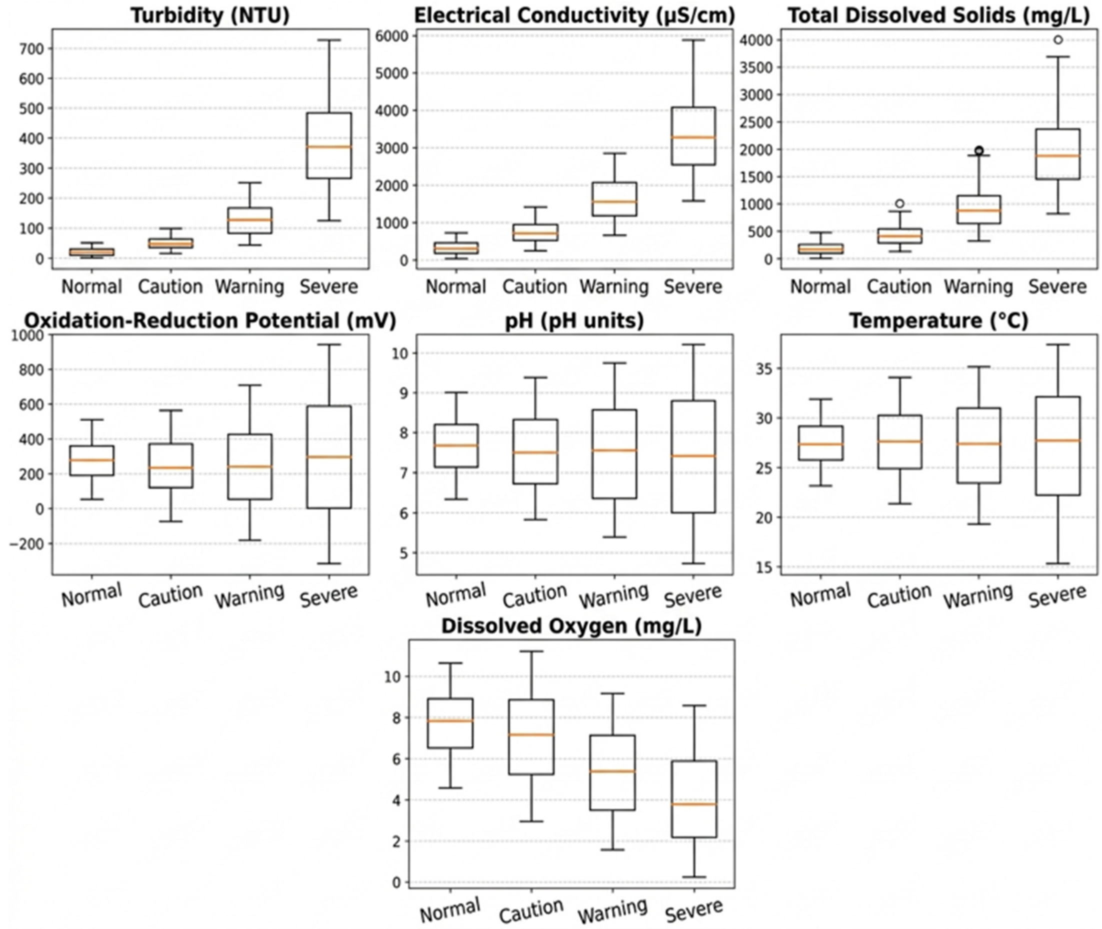

Fig. 5. Boxplot distribution of the seven monitored parameters.

DO demonstrates a monotonic decreasing trend with increasing degradation severity, consistent with oxygen depletion driven by organic load accumulation and microbial activity. In contrast, temperature and pH remain relatively constrained within operational aquaculture ranges, showing narrower dispersion across classes. Although partial overlap is observed between intermediate levels (Caution and Warning), the overall monotonic trends support the feasibility of multiclass degradation modeling using nonlinear classifiers.

2) Model-Based Explainability Using SHAP

To interpret feature contributions to model predictions, SHAP was applied to the RF classifier, which demonstrated the highest balanced performance among the evaluated models. The global SHAP importance ranking, as shown in Figure 6, identifies turbidity, EC, and TDS as the most influential contributors to model output magnitude.

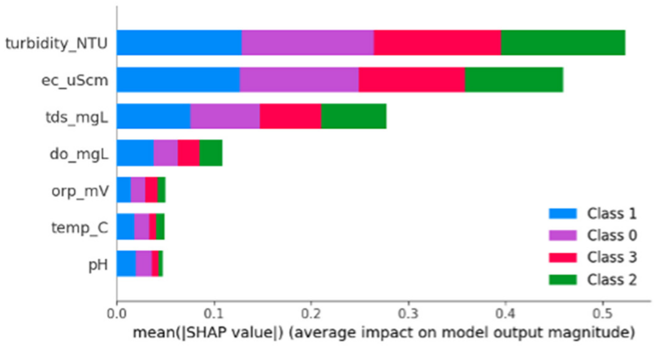

Fig. 6. Global feature importance derived from mean absolute SHAP values for the multiclass freshwater fishpond degradation classifier.

From an environmental perspective, this result is physically consistent. Elevated turbidity reflects suspended solids and sediment disturbance, while increased EC and TDS indicate rising dissolved ionic concentrations associated with feed residues and metabolic by-products. DO and ORP exhibit moderate contributions, whereas temperature and pH contribute comparatively less to classification decisions. Because EC and TDS are strongly correlated in freshwater systems, multicollinearity analysis and targeted feature ablation were conducted. The ablation results confirm that removing either EC or TDS individually results in only minor performance reduction, whereas simultaneous removal of both features leads to substantial degradation in predictive performance. This indicates that although correlated, EC and TDS encode complementary information rather than artificially inflating feature importance.

3) *PCA and Variance Structure*

To explore the intrinsic structure of the normalized feature space, PCA was performed. The scree plot shown in Figure 7 illustrates the explained variance ratio of all seven principal components. The first main component accounts for 43.98% of total variance, while the second explains 14.59%, yielding a cumulative variance of 58.57% for the first two components. The fact that more than 40% of variance remains distributed across higher-order components indicates that degradation patterns are inherently multidimensional. Therefore, the two-dimensional PCA projection depicted in Figure 8 should be interpreted as a visualization aid rather than a complete representation of class separability.

The PCA projection reveals clearer separation between extreme degradation levels (Normal and Severe), while intermediate levels (Caution and Warning) exhibit partial overlap. This transitional structure is consistent with the cumulative multi-parameter scoring mechanism and with confusion matrix patterns, where misclassifications predominantly occur between adjacent classes rather than between extreme categories.

Overall, the combined distributional analysis, explainability results, and dimensional structure assessment provide coherent evidence that degradation classification emerges from interacting physicochemical deviations rather than from isolated single-parameter thresholds.

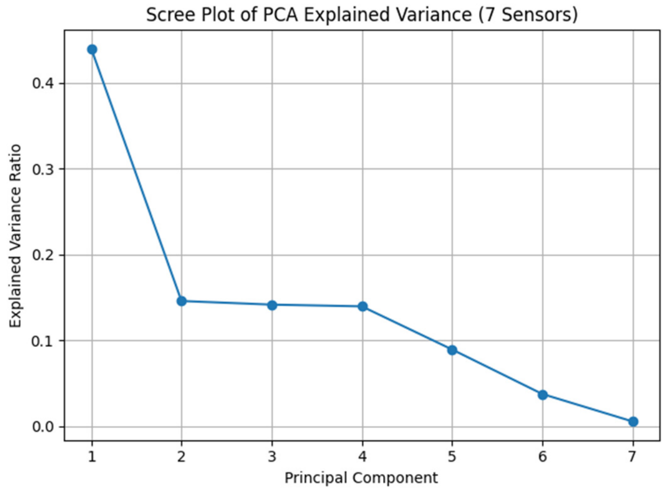

Fig. 7. Scree plot of seven components (sensors).

G. *Discussion and Environmental Implications*

The experimental results demonstrate that ensemble tree-based classifiers, particularly RF, provide consistent and balanced performance for multiclass freshwater fishpond water quality degradation classification. The superior performance of tree-based models indicates that nonlinear interactions among physicochemical parameters play a substantial role in degradation characterization. This observation aligns with the cumulative multi-parameter scoring protocol adopted during label construction, where degradation levels emerge from interacting deviations across multiple indicators rather than isolated threshold violations.

Feature-level distribution analysis further supports this interpretation. Progressive upward shifts in turbidity, EC, and TDS are observed as degradation severity increases. These parameters exhibit broader dispersion in the Warning and Severe classes, indicating greater environmental instability under deteriorating pond conditions. DO demonstrates a decreasing trend across degradation levels, consistent with oxygen depletion driven by organic load accumulation and microbial respiration. In contrast, temperature and pH remain comparatively constrained within operational aquaculture ranges and contribute less significantly to classification decisions. This pattern suggests that degradation is mainly governed by suspended solids and ionic dynamics rather than by thermal or acidity fluctuations within the studied environment.

SHAP-based explainability analysis identifies turbidity, EC, and TDS as dominant contributors to model predictions. From an environmental standpoint, this is physically plausible. Elevated turbidity reflects sediment disturbance and suspended particulate accumulation, while increased EC and TDS indicate rising dissolved ionic concentrations associated with feed residues and metabolic by-products. These parameters function as integrated indicators of physicochemical instability rather than direct measurements of specific toxicants. The alignment between feature importance rankings and known aquaculture dynamics strengthens the environmental interpretability of the model.

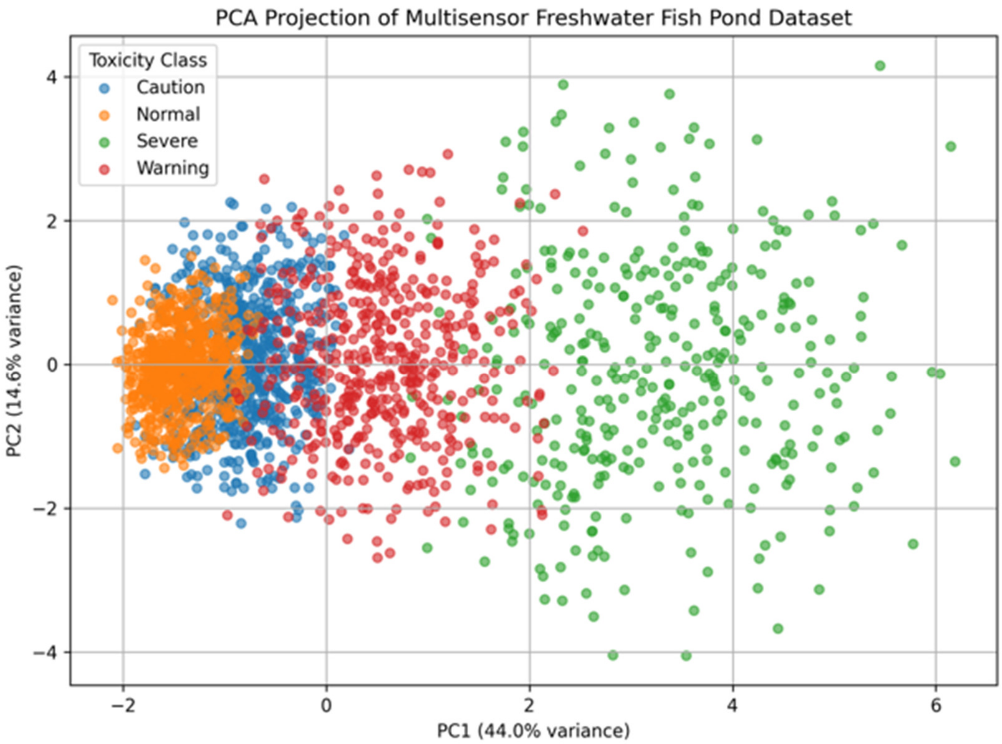

Fig. 8. PCA projection of the multisensor freshwater fishpond dataset onto the first two principal components (PC1 and PC2).

Given the strong linear correlation between EC and TDS ($r \approx 0.96$), Pearson correlation analysis and targeted feature ablation were conducted to evaluate potential multicollinearity effects. Performance remained stable when either EC or TDS was removed individually, but declined substantially when both were excluded simultaneously. These results indicate that although strongly correlated, EC and TDS encode complementary predictive information rather than artificially inflating model performance or explainability outcomes. The combination of correlation analysis and ablation testing enhances the robustness and credibility of the interpretability claims.

PCA provides additional insights into the intrinsic structure of the dataset. The first principal component (PC1) accounts for approximately 44% of total variance, while the first two components (PC1 and PC2) together capture around 58–60%. This distribution suggests that freshwater fishpond degradation patterns are inherently multidimensional rather than dominated by a single linear gradient. In real-world environmental systems, degradation arises from interacting physicochemical processes—including suspended solids, ionic concentration, oxygen availability, and redox balance—that do not collapse into a single dominant axis of variation. Therefore, the moderate cumulative variance captured by the first two components should not be interpreted as a dataset limitation, but rather as evidence of complex multivariate coupling among environmental parameters.

The multidimensional variance structure also justifies the use of nonlinear ensemble classifiers. If most variance was concentrated within one or two principal components, simpler linear decision boundaries might suffice. However, the observed variance dispersion across multiple components indicates that degradation states cannot be fully represented in low-dimensional linear projections. This finding is consistent with the superior performance of tree-based models relative to distance-based approaches and reinforces the necessity of multisensor fusion for efficient multiclass degradation classification.

Confusion matrix analysis further reflects the gradual nature of freshwater degradation processes. Misclassifications predominantly occur between adjacent degradation levels (e.g., Caution–Normal or Warning–Severe), while confusion between extreme states (Normal–Severe) is minimal. This behavior is environmentally coherent, as pond degradation typically progresses through transitional stages rather than abrupt discontinuities. The structured rule-based scoring protocol, therefore, produces realistic class boundaries that align with progressive physicochemical shifts.

Although degradation in freshwater systems evolves temporally, the present framework adopts a snapshot-based classification paradigm. Each multisensor measurement represents a periodic operational monitoring instance capturing the instantaneous physicochemical condition of the pond. In practical aquaculture management, interventions such as aeration adjustment, feeding regulation, or water exchange are triggered based on current state assessment rather than long-term trajectory forecasting. Thus, snapshot-based degradation classification remains operationally relevant for routine monitoring and early-warning decision support. Nevertheless, incorporating temporal dependencies through sequential modeling approaches—such as recurrent neural networks or temporal convolutional networks—represents a meaningful extension for future investigation.

Compared with prior studies that focus on binary classification or limited parameter sets, this work introduces a structured four-level degradation framework grounded in explicit rule-based labeling and reproducible multi-parameter scoring. The integration of multicollinearity assessment, explainable ML, and dimensional structure analysis enhances transparency and engineering rigor. Given the moderate dataset size (2153 data) and the emphasis on interpretability and deployment feasibility, classical ensemble learning offers a balanced methodological choice.

Finally, the present study is based on data collected from a single freshwater earthen pond under specific operational conditions. Site-dependent factors—including pond geometry, fish species, stocking density, feeding strategy, and seasonal variability—may influence physicochemical dynamics and degradation patterns. Although the proposed framework demonstrates stable performance within the studied environment, broader generalization requires cross-site validation. Future research should incorporate multi-pond datasets, seasonal variability analysis, and domain adaptation techniques to evaluate transferability across heterogeneous aquaculture systems.

IV. CONCLUSIONS

This study presented a smart multisensor-based Machine Learning (ML) framework for multiclass freshwater fishpond degradation classification using seven physicochemical parameters. A transparent rule-based multi-parameter scoring protocol was defined prior to model training to establish four progressive degradation levels—Normal, Caution, Warning, and Severe—thereby ensuring reproducibility and eliminating circular dependency between labeling and classification.

Experimental evaluation shows that ensemble tree-based models, particularly Random Forest (RF), achieve consistent and balanced performance under moderate class imbalance. Correlation analysis and targeted feature ablation demonstrate that although Electrical Conductivity (EC) and Total Dissolved Solids (TDS) are strongly correlated, their inclusion does not introduce artificial performance inflation, and each retains complementary predictive value. Explainability analysis identifies turbidity and EC as dominant contributors to classification outcomes, aligning with established environmental dynamics in freshwater aquaculture systems.

The proposed framework provides an interpretable and operational approach to structured water quality degradation assessment based on multisensor snapshots. However, the dataset was collected from a single freshwater pond, and site-specific environmental and operational factors may influence degradation patterns. Future research should incorporate multi-site datasets, seasonal variability analysis, and domain adaptation techniques to evaluate generalizability across heterogeneous aquaculture environments. Integration into scalable real-time monitoring platforms also represents an important direction for practical deployment.

DECLARATION OF COMPETING INTERESTS

The authors declare no conflicts of interest.

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DATA AVAILABILITY

The dataset used in this study is publicly available at [27].

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