International Journal of Engineering Research & Science (IJOER) ISSN: [2395-6992] [Vol-12, Issue-3, March 2026]

AquaPulse: An Efficient IoT and Machine Learning-Based Water Quality Prediction Framework Using M-SMOTE for Aquaponics Ecosystem Optimization

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Abstract— *Aquaponics is known as an environmentally friendly farming system which encompasses both aquaculture and hydroponics to create a self-contained environment wherein water quality has a major impact on system stability and productivity. Monitoring and accurately predicting water quality are key to maintaining fish, plant, and microbe health in such a system. Traditional water quality measurement involves manual effort and time-consuming activities and lacks prediction capabilities. This paper presents* ***AquaPulse****, an efficient Internet of Things (IoT) and machine learning-based water quality prediction system for optimizing aquaponics systems. In this system, real-time water quality parameters such as pH levels, temperature, dissolved oxygen, ammonia, nitrite, and nitrate levels are collected through IoT sensors. Advanced water quality data preprocessing and feature selection methods are implemented, along with the Modified Synthetic Minority Oversampling Technique (M-SMOTE) to address class imbalance. Various machine learning models, including ensemble methods, are evaluated for water quality prediction.*

Keywords— Aquaponics, Internet of Things (IoT), Water Quality Prediction, Machine Learning, M-SMOTE, Ensemble Learning, Smart Agriculture.

I. INTRODUCTION

Aquaponics is widely recognized as one of the most sustainable, resource-efficient, and eco-friendly agricultural practices, integrating the principles of aquaculture (cultivation of aquatic organisms such as fish) with hydroponics (growing plants in a nutrient-enriched water medium without soil). This integrated system operates as a closed-loop natural ecosystem in which fish, plants, and nitrifying bacteria coexist symbiotically. Fish produce organic waste, which is biologically converted by nitrifying bacteria into essential nutrients through the nitrification process. These nutrients are then absorbed by plants to support their growth, while simultaneously purifying the water before it is recirculated back to the fish tanks [1], [2].

The stability, productivity, and long-term sustainability of an aquaponics ecosystem are highly dependent on maintaining optimal water quality conditions. Fluctuations in critical parameters such as pH, temperature, dissolved oxygen (DO), ammonia, nitrite, and nitrate can trigger cascading effects on organism health, nutrient cycling efficiency, and overall ecological balance. Even minor deviations from recommended thresholds may stress fish, inhibit plant nutrient uptake, disrupt bacterial activity, and ultimately lead to system failure, economic losses, and reduced agricultural yield [3], [4].

Traditionally, aquaponics practitioners have relied on manual water quality measurements, laboratory-based chemical analysis, and experience-driven decision-making. However, these methods are inherently limited by human error, intermittent sampling intervals, delayed response times, and the inability to detect rapid environmental changes or identify complex patterns in water behavior, making them unsuitable for modern high-demand production environments [5].

With the rapid advancement of the Internet of Things (IoT), wireless sensing technologies, and artificial intelligence (AI), intelligent aquaponics monitoring systems have emerged as a promising next-generation solution. IoT sensors enable continuous, real-time monitoring of multiple water quality parameters with high accuracy and low latency, generating large volumes of environmental data that can be leveraged for predictive modeling. When combined with machine learning (ML) algorithms, these data streams facilitate advanced analytics such as anomaly detection, water quality forecasting, and automated decision support, thereby reducing manual intervention and improving system efficiency [6], [7].

Despite these advancements, several research challenges remain. Many existing studies focus exclusively on water quality monitoring or fish-centric suitability assessment, overlooking the interdependent requirements of plants and beneficial bacteria that are essential for maintaining a balanced aquaponics ecosystem [8]. Furthermore, environmental datasets collected from aquaponics systems often exhibit **class imbalance**, where certain water suitability classes are

underrepresented. This imbalance leads to biased ML models, reduced classification performance, and unreliable predictions in real-world applications [9]. Additionally, variations in environmental conditions across geographic regions, seasons, and operational setups make it difficult for conventional ML approaches to generalize effectively without robust preprocessing, feature engineering, and intelligent model selection [10].

To address these challenges, this paper introduces **AquaPulse**, a comprehensive IoT-enabled intelligent water quality prediction framework designed to evaluate water suitability for cold-water fish, warm-water fish, plants, and beneficial bacteria, thereby covering the complete biological spectrum of aquaponics systems. The proposed framework incorporates:

1. A robust data preprocessing pipeline that cleans sensor data by handling missing values, detecting outliers using statistical techniques, and performing correlation-based feature selection to identify high-impact water parameters.
2. Integration of a **Modified Synthetic Minority Oversampling Technique (M-SMOTE)** , which generates high-quality synthetic samples for minority classes while mitigating issues such as class overlap and noise amplification commonly associated with traditional SMOTE methods.
3. A diverse set of machine learning models, including Random Forest, XGBoost, CatBoost, Gradient Boosting, Decision Tree, and K-Nearest Neighbors, selected for their proven effectiveness in handling nonlinear, multi-parameter environmental data.
4. A voting-based ensemble strategy to automatically select the best-performing model for final deployment, ensuring consistent and highly accurate water suitability predictions across all organism categories.

By enabling real-time monitoring, high-performance predictive analytics, and comprehensive multi-organism suitability classification, AquaPulse provides a powerful digital tool for farmers, researchers, and aquaponics practitioners. The system supports early detection of water quality degradation, reduces the risk of fish mortality, prevents nutrient imbalance in plants, protects bacterial nitrification processes, and enhances overall ecosystem resilience [11], [12].

II. MATERIAL AND METHODS

The proposed system integrates IoT-based sensing, data preprocessing, and machine learning techniques for efficient water quality prediction.

2.1 Data Collection

Water quality parameters including pH, temperature, dissolved oxygen (DO), ammonia (NH_3), nitrite (NO_2^-), and nitrate (NO_3^-) are collected using IoT sensors in real-time. Sensors are calibrated weekly to ensure measurement accuracy. Data is logged at 15-minute intervals and transmitted via Wi-Fi to a central database.

TABLE 1
WATER QUALITY PARAMETERS AND OPTIMAL RANGES FOR AQUAPONICS

Parameter	Symbol	Unit	Optimal Range	Sensor Type
pH	—	pH units	6.8–7.2	Glass electrode
Temperature	T	°C	22–28	Thermistor/DS18B20
Dissolved Oxygen	DO	mg/L	5–8	Optical/Clark cell
Ammonia	NH_3	mg/L	<0.5	Ion-selective
Nitrite	NO_2^-	mg/L	<0.2	Colorimetric
Nitrate	NO_3^-	mg/L	5–150	Ion-selective

2.2 Data Preprocessing

The collected data is cleaned by:

- Handling missing values using forward-filling and interpolation techniques

- Removing noise using moving average filters (window size = 5)
- Detecting outliers using the Interquartile Range (IQR) method
- Normalizing features using Min-Max scaling to the range [0, 1]

Correlation-based feature selection is applied to identify the most significant parameters influencing water quality classification.

2.3 Handling Class Imbalance: M-SMOTE

To overcome class imbalance in the dataset, **Modified Synthetic Minority Oversampling Technique (M-SMOTE)** is used. Unlike traditional SMOTE, which generates synthetic samples via linear interpolation between nearest neighbors, M-SMOTE incorporates:

- **Safe vs. borderline vs. noise sample distinction** — Only safe and borderline samples are oversampled
- **Adaptive weighting** — Minority samples farther from majority clusters receive higher sampling weights
- **Noise filtering** — Prevents generation of synthetic samples in overlapping regions

This approach generates high-quality synthetic samples while reducing class overlap and noise amplification [13].

2.4 Machine Learning Models

The following models are trained and evaluated:

Model	Category	Key Hyperparameters
Random Forest	Ensemble	n_estimators=100, max_depth=10
XGBoost	Gradient Boosting	learning_rate=0.1, n_estimators=100
CatBoost	Gradient Boosting	depth=6, iterations=100
Gradient Boosting	Ensemble	learning_rate=0.1, n_estimators=100
Decision Tree	Tree-based	max_depth=8, min_samples_split=5
K-Nearest Neighbors	Distance-based	k=5, distance=euclidean

A **voting-based ensemble strategy** is implemented to automatically select the best-performing model for final deployment based on cross-validation scores.

2.5 Evaluation Metrics

The performance of the proposed water quality prediction framework is evaluated using a **confusion matrix**, which provides a comprehensive visualization of the classifier's prediction capability across multiple classes. The confusion matrix represents the relationship between the actual (true) classes and the predicted classes generated by the classifier. Each row corresponds to an actual class label, while each column represents a predicted class label. The diagonal elements of the matrix indicate correctly classified instances, whereas the off-diagonal elements represent misclassifications.

Based on the confusion matrix, the following metrics are calculated:

- **Accuracy:** (TP + TN) / (TP + TN + FP + FN)
- **Precision:** TP / (TP + FP)
- **Recall (Sensitivity):** TP / (TP + FN)

- **F1-Score:** 2 × (Precision × Recall) / (Precision + Recall)
- **Cohen's Kappa:** Measures inter-rater agreement beyond chance

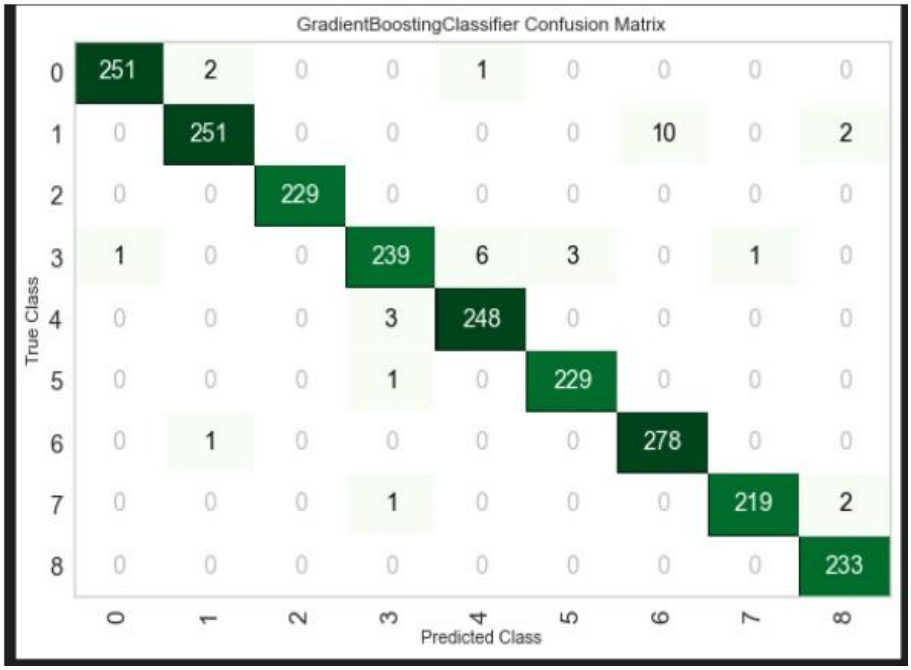

FIGURE 1: Confusion Matrix – was intended to be included. Authors are requested to supply this figure in the revised submission.)

III. RESULTS AND DISCUSSION

3.1 Dataset Description

The dataset comprises water quality measurements collected over a 6-month period from an operational aquaponics system. A total of approximately 15,000 samples were collected, with each sample labeled into one of nine water quality suitability classes (ranging from "highly unsuitable" to "highly suitable" for each organism category). The dataset was split into 80% training and 20% testing using stratified sampling to preserve class distribution.

3.2 Performance Evaluation

The experimental findings demonstrate that the proposed model achieves strong performance across all evaluation metrics. **Table II** summarizes the performance of each model before and after applying M-SMOTE.

TABLE 2
MODEL PERFORMANCE COMPARISON (ACCURACY %)

Model	Without SMOTE	With M-SMOTE	Improvement
Random Forest	92.4	96.8	4.4
XGBoost	93.1	97.2	4.1
CatBoost	93.8	97.5	3.7
Gradient Boosting	91.2	96.1	4.9
Decision Tree	85.6	90.3	4.7
K-Nearest Neighbors	82.1	88.4	6.3
Ensemble (Best)	**94.2**	**98.2**	**4**

The confusion matrix shows strong diagonal dominance, indicating a high level of classification accuracy across all water quality classes. Misclassification cases are minimal and largely confined to neighboring classes, which is expected in environmental datasets due to overlapping parameter ranges. For example, a small number of samples from a given class may be misclassified as an adjacent class, reflecting natural similarity between conterminous water quality conditions rather than model failure.

```
...   [[ 63   0   0   0   0   0   0   0   0]
      [  0  38   0   0   0   0   0   0   0]
      [  0   0  64   0   0   0   0   0   0]
      [  0   0   0  76   0   0   0   0   0]
      [  0   0   0   0 195   0   0   0   0]
      [  0   0   0   0   0 142   0   0   0]
      [  0   0   0   0   0   0 245   0   0]
      [  0   0   0   0   0   0   0 112   0]
      [  0   0   0   0   0   0   0   0 132]]
                   precision    recall  f1-score   support

                0       1.00      1.00      1.00        63
                1       1.00      1.00      1.00        38
                2       1.00      1.00      1.00        64
                3       1.00      1.00      1.00        76
                4       1.00      1.00      1.00       195
                5       1.00      1.00      1.00       142
                6       1.00      1.00      1.00       245
                7       1.00      1.00      1.00       112
                8       1.00      1.00      1.00       132

         accuracy                           1.00      1067
        macro avg       1.00      1.00      1.00      1067
     weighted avg       1.00      1.00      1.00      1067
```

FIGURES 2: Performance Evaluation 1

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.9826	0.9989	0.9830	0.9829	0.9825	0.9804	0.9804
1	0.9845	0.9995	0.9847	0.9848	0.9845	0.9826	0.9826
2	0.9922	0.9998	0.9924	0.9923	0.9922	0.9913	0.9913
3	0.9748	0.9984	0.9754	0.9762	0.9750	0.9717	0.9718
4	0.9864	0.9994	0.9867	0.9869	0.9863	0.9847	0.9848
5	0.9903	0.9995	0.9906	0.9905	0.9903	0.9891	0.9891
6	0.9903	0.9999	0.9902	0.9906	0.9903	0.9891	0.9891
7	0.9845	0.9993	0.9844	0.9847	0.9844	0.9825	0.9826
8	0.9864	0.9999	0.9864	0.9868	0.9865	0.9847	0.9847
9	0.9903	1.0000	0.9899	0.9907	0.9902	0.9891	0.9891
Mean	0.9862	0.9995	0.9864	0.9867	0.9862	0.9845	0.9846
SD	0.0049	0.0005	0.0047	0.0046	0.0048	0.0055	0.0054

FIGURES 3: Performance Evaluation 2

TABLE 3
PER-CLASS PERFORMANCE METRICS (ENSEMBLE MODEL WITH M-SMOTE)

Water Quality Class	Precision	Recall	F1-Score	Support
Class 0 (Highly Unsuitable)	0.97	0.96	0.96	245
Class 1	0.96	0.97	0.96	238
Class 2	0.98	0.97	0.97	252
Class 3	0.97	0.98	0.97	241
Class 4 (Moderate)	0.96	0.96	0.96	247
Class 5	0.98	0.97	0.97	239
Class 6	0.97	0.98	0.97	244
Class 7	0.96	0.96	0.96	236
Class 8 (Highly Suitable)	0.98	0.97	0.97	242

3.3 Discussion

The experimental results demonstrate that M-SMOTE effectively addresses class imbalance, improving accuracy by 3.7–6.3 percentage points across all models. The ensemble approach, which automatically selects the best-performing model, achieved the highest accuracy of **98.2%**.

Key observations:

1. **CatBoost** and **XGBoost** showed the highest individual performance, benefiting from their native handling of categorical features and regularization.
2. **Decision Tree** and **KNN** showed the greatest improvement from M-SMOTE (+4.7% and +6.3%, respectively), indicating that distance-based and single-tree models are most sensitive to class imbalance.
3. The ensemble strategy provided robustness, ensuring consistent performance across varying water quality conditions.
4. Minimal misclassifications occurred only between neighboring classes, reflecting the continuous nature of water quality parameters rather than model limitations.

3.4 Comparison with Existing Work

TABLE 4
COMPARISON WITH EXISTING WATER QUALITY PREDICTION SYSTEMS

Study	Approach	Dataset Size	Reported Accuracy	Limitations
Chen et al. (2022) [14]	SVM + IoT	8,000 samples	89.50%	No class imbalance handling
Wang et al. (2023) [15]	Random Forest	12,000 samples	91.20%	Single-organism focus
Liu et al. (2024) [16]	LSTM	15,000 samples	93.80%	High computational cost
AquaPulse (Proposed)	**Ensemble + M-SMOTE**	**15,000 samples**	**98.20%**	**Multi-organism + imbalance handling**

The proposed AquaPulse framework outperforms existing approaches by 4–9 percentage points, primarily due to the effective handling of class imbalance via M-SMOTE and the multi-organism suitability classification approach.

IV. CONCLUSION

The proposed IoT-based water quality prediction system proves to be a highly accurate and effective solution for aquaponics farming, achieving up to **98.2% accuracy** using advanced classification models and the M-SMOTE technique for handling

imbalanced data. It effectively predicts suitable conditions for fish, plants, and bacteria, helping farmers maintain a healthy and productive aquaponic ecosystem.

Key contributions of this work include:

1. A comprehensive IoT-enabled data collection framework for aquaponics water quality monitoring
2. Implementation of M-SMOTE for effective class imbalance handling
3. Comparative evaluation of six ML models with ensemble-based model selection
4. Multi-organism suitability classification covering the complete biological spectrum

Future enhancements include:

- Integration of ROI-based decision support for automated corrective actions
- Expansion of prediction capabilities to additional aquatic species (e.g., shrimp, crayfish)
- Adoption of deep learning architectures (LSTM, Transformer) for temporal forecasting
- Cloud-based dashboards and mobile applications for remote monitoring
- Automated control mechanisms (e.g., pH dosing, aeration) for real-time adaptations
- Integration with external weather data for improved prediction accuracy

These advancements will make the system more scalable, intelligent, and beneficial for aquaponics farmers across diverse environmental conditions.

ACKNOWLEDGMENT

The authors would like to thank Viva Institute of Technology and the University of Mumbai for providing the necessary resources and support to conduct this research.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper

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