

Optimizing radial basis function networks for harmful algal bloom prediction: a hybrid machine learning approach

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ABSTRACT

The deployment of artificial intelligence in environmental monitoring demands models balancing efficiency, interpretability, and computational cost. This study proposes a hybrid radial basis function network (RBFN) framework integrated with fuzzy c-means (FCM) clustering for predicting harmful algal blooms (HABs) using water quality parameters. Unlike conventional approaches, our model leverages localized activation functions to capture non-linear relationships while maintaining computational efficiency. Experimental results demonstrate that the RBFN-FCM hybrid achieved high accuracy (F1-score: 1.00) on test data and identified Chlorophyll-a as the strongest predictor ($r=0.94$). However, real-world validation revealed critical limitations: the model failed to generalize datasets with incomplete features or distribution shifts, predicting zero HAB outbreaks in an unlabeled 11,701-record dataset. Comparative analysis with Random Forests confirmed the RBFN-FCM's advantages in training speed and interpretability but highlighted its sensitivity to input completeness. This work underscores the potential of RBFNs as lightweight, explainable tools for environmental forecasting while emphasizing the need for robustness against data variability. The framework offers a foundation for real-time decision support in ecological conservation, pending further refinement for field deployment.

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1. INTRODUCTION

Artificial neural networks (ANNs) have become fundamental in modern artificial intelligence, empowering diverse applications in healthcare, finance, environmental monitoring, and smart cities by enabling pattern recognition, data-driven prediction, and adaptive control systems [1], [2]. Among various ANN architectures, radial basis function networks (RBFNs) have emerged as a particularly efficient model for function approximation, classification, and regression tasks. Distinguished by their localized activation functions, such as Gaussian kernels, RBFNs exhibit strong generalization capabilities and fast

training convergence, especially when applied to problems involving non-linear and spatially distributed features [3], [4].

Recent advancements in RBFNs have improved their robustness and accuracy, particularly through the integration of clustering techniques and hybrid learning strategies [5]. For instance, combining RBFNs with fuzzy c-means (FCM) clustering enhances center selection by capturing underlying data structures, thus improving predictive reliability in complex environments [6]. Moreover, hybrid models that integrate RBFNs with ensemble techniques or deep learning paradigms have shown improved performance across various domains, such as financial forecasting, climate prediction, and engineering applications [7], [8]. These innovations address key limitations of traditional RBFNs, including sensitivity to center initialization, limited scalability in high-dimensional spaces, and susceptibility to overfitting.

In the context of environmental monitoring, machine learning models have shown considerable promise in forecasting harmful algal blooms (HABs), a recurring phenomenon that disrupts marine ecosystems, fisheries, and water quality management. Traditional monitoring approaches, which rely heavily on manual water quality sampling, are often time-consuming and reactive. By contrast, predictive models offer a proactive strategy for early warning and response. Despite growing interest in using machine learning for HAB detection, limited studies have explored the performance of RBFNs in this domain or benchmarked them against alternative algorithms such as random forests (RFs) or support vector machines (SVMs) [9], [10].

This study proposes a hybrid machine learning framework that combines RBFNs with FCM clustering to predict HAB events based on key water quality parameters. The model leverages real-world sensor data, public domain datasets, and synthetic datasets generated through comparative statistical methods to ensure sufficient variability and generalizability. A comparative analysis is conducted to evaluate model performance against RF classifiers, emphasizing classification accuracy, generalization to unseen data, and sensitivity to incomplete or noisy inputs.

The contributions of this paper are threefold. First, it presents an optimized RBFN architecture tailored for environmental prediction tasks, enhanced with fuzzy clustering for improved center initialization. Second, it demonstrates the comparative advantage of this hybrid RBFN model over conventional models, including RF, particularly in real-time, low-resource settings. Third, the study provides insights into deployment challenges, such as data completeness and overfitting risks, and proposes future research directions toward improving model robustness.

The remainder of this paper is structured as follows: section 2 reviews the fundamentals of RBFNs and training methodologies. Section 3 describes the dataset, preprocessing steps, and model architecture. Section 4 presents experimental results and a detailed discussion comparing the proposed model with existing techniques. Finally, section 5 concludes the paper.

2. LITERATURE REVIEW

Table 1 summarizes some of the key recent advancements in RBFN research. These developments span enhanced training algorithms through hybridization with deep learning models, highlighting a trend toward integrating RBFNs with more complex neural architectures. Furthermore, the research also focuses on practical implementations, including advancements in hardware acceleration for computational efficiency and applications in emerging areas such as behavior recognition.

RBFNs differentiate themselves from other ANN architectures due to their unique structure and training methodology. Compared to multi-layer perceptrons (MLPs) and convolutional neural networks (CNNs), RBFNs offer several advantages but also have some limitations [16]–[22]. Table 2 provides a comparative analysis of different learning algorithms used in RBFN training, focusing on their methodologies, advantages, and typical applications.

Table 1. Recent developments in RBFNs

Research Area	Advancement	Details	Reference
Enhanced training algorithms	Hybrid RBFNs	RBFNs integrated with deep learning models, enhance performance in cyber-physical systems.	[11]
Deep learning and RBFNs	Hybridization with deep learning	RBFNs combined with NLP and vision models improve classification accuracy.	[12], [13]
Hardware acceleration and computational efficiency	AI in Enterprises	Enterprise-scale artificial intelligence (AI) models leverage RBFNs for efficient scaling.	[14]
Emerging application areas	Crowd dynamics and behavior recognition	AI-based surveillance utilizes RBFNs for behavior analysis.	[15]

Table 2. Learning algorithms of RBFNs

Learning algorithm	Description	Advantages	Application
Ensemble clustering [23]	Combines multiple clustering methods to determine RBF centers, enhancing robustness and accuracy.	Improved center selection, enhanced model robustness	Educational performance modelling
RBF-ARX Integration [24]	Combines RBFNs with Autoregressive with exogenous inputs (ARX) models for predictive control	Enhanced predictive accuracy, robust control strategies	Control systems in engineering
Hybrid RBFNs [25]	Integrates RBFNs with other machine learning techniques to improve time series forecasting.	Increased forecasting accuracy, versatility	Financial forecasting, weather prediction
K-Means and gradient descent [7]	Employs k-means for center determination and gradient descent for weight optimization in reservoir characterization.	Effective modelling of geological data, robust predictions	Geological reservoir characterization

3. METHOD

This study adopted a hybrid machine learning approach to predict Harmful Algal Bloom (HAB) events using water quality data. The methodology consisted of five main stages which data preparation, synthetic data generation, feature normalization, model design, and performance evaluation. An overview of the full workflow is illustrated in Figure 1. Two types of machine learning models were used, a standard RF classifier and the proposed hybrid model that combines RBFNs with FCM clustering.

Model training and evaluation were performed using consistent data split for all models, with 70% of the data used for training and 30% reserved for testing. The models were assessed based on accuracy, precision, recall, and F1-score, with the latter prioritized due to its balanced representation of sensitivity and precision, especially under imbalanced class conditions. This evaluation approach ensures that the model is not only accurate in general classification but also effective in identifying minority class instances, which in this case are the rare HAB events.

The models were developed using Python and MATLAB and executed on Google Colab platform. Libraries such as Scikit-learn, NumPy, Pandas, and KERAS were utilized for data manipulation, model training, and evaluation. This hybrid programming environment enabled efficient experimentation and ensured compatibility across tools. All code and datasets used in this study have been structured to support reproducibility and future extension by other researchers.

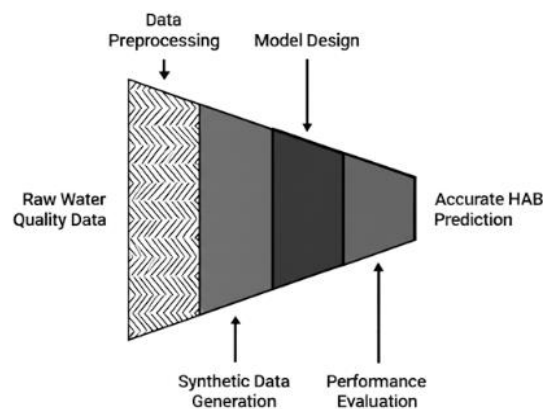


Figure 1. Workflow of the HAB prediction framework

3.1. Training approach

The training process in RBFNs follows a two-step approach, determining center vectors where centers are typically selected using clustering algorithms such as k-means or random sampling, and optimizing weights once centers are fixed, weights in the output layer are optimized using methods like least squares regression or gradient-based techniques. The separation of center selection from weight optimization allows RBFNs to train efficiently, avoiding backpropagation through multiple layers as in deep learning models. This training process is generally categorized into supervised and unsupervised learning approaches.

Supervised learning involves adjusting network parameters based on labeled training data. The primary goal is to minimize the error between the predicted outputs and the actual target values [26]. Unsupervised learning utilizes clustering techniques, such as k-means clustering, to determine the centers of the radial basis functions without requiring labeled data. This method is commonly used in the initial training phase to identify representative data points before fine-tuning the network's weights [27]. Several algorithms are fundamental to the training of RBFNs according to Table 3.

Table 3. Training algorithm of RBFNs

Algorithm	Functionality
K-Means clustering	An unsupervised algorithm used to identify the centers of the RBFs by partitioning the input data into clusters. Each cluster center serves as a center vector for a corresponding RBF neuron.
Gradient descent	A supervised learning method employed to optimize the weights of the output layer by iteratively adjusting them to minimize the prediction error.
Ensemble clustering	Combines multiple clustering methods to enhance the robustness and accuracy of center selection, thereby improving the overall performance of the RBFN.

3.2. Data preprocessing

To prepare the dataset for model training, multiple Excel files containing water quality measurements were consolidated into a unified dataset. Standardization steps included renaming columns for consistency, selecting relevant features, and encoding the target variable as a binary classification (1 for HAB outbreak, 0 for no outbreak). Key environmental parameters such as temperature, total dissolved solids (TDS), salinity, and nutrient concentrations were retained, while non-relevant or redundant features were excluded. Missing values were handled through imputation where possible, while records with excessive missing data were removed to ensure model reliability.

Following data cleaning and feature selection, the dataset was normalized to ensure consistent value ranges across features, which is essential for optimizing the performance of machine learning algorithms, particularly those sensitive to scale differences. Since the dataset exhibited class imbalance with significantly fewer HAB outbreak records compared to non-outbreak cases, synthetic minority over-sampling technique (SMOTE) was used to address this issue. SMOTE generates synthetic samples of the minority class by interpolating between existing minority class instances, effectively balancing the class distribution. This step was crucial to prevent the models from being biased toward the majority class and to enhance the reliability of the classification outcomes.

3.3. Exploratory data analysis and feature relationships

A correlation matrix was computed to examine relationships between water quality parameters and HAB occurrences. Figure 2 shows the Chlorophyll-a exhibited the strongest positive correlation (0.94) with HAB outbreaks, reinforcing its significance as a key predictive feature. Other parameters, such as temperature, TDS, and pH, resulted in weaker correlations, indicating that HAB occurrence is influenced by complex, non-linear interactions. Kernel density estimation (KDE) plots revealed substantial overlap in feature distributions between outbreak and non-outbreak conditions, suggesting that simple linear models may be insufficient for accurate classification.

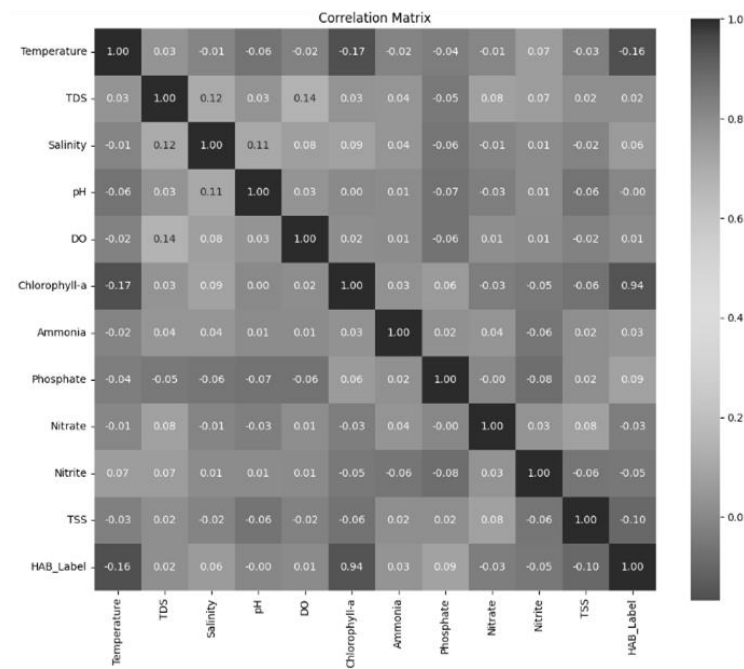


Figure 2. Correlation matrix between water quality parameters and target variables

Overlapping distributions were observed for most features, including temperature, pH, and DO, highlighting the complexity of separating the classes using linear methods. Figure 3 indicates the Chlorophyll-a showed the most distinct separation, aligning with its strong correlation to the target variable.

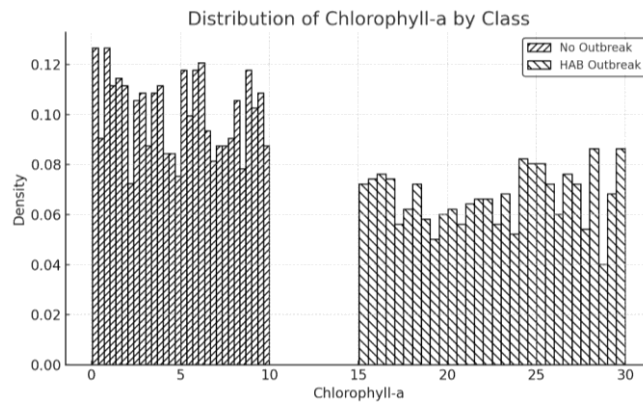


Figure 3. Correlation plot between Chlorophyll-a and target variables

4. RESULT AND DISCUSSION

RBFNs have attracted considerable interest due to their ability to efficiently approximate complex functions while maintaining interpretability in neural computations. However, like any computational model, RBFNs come with both strengths and weaknesses. This section provides the results obtained from the data training and a comprehensive discussion including the advantages and limitations of RBFNs, supported by relevant literature.

4.1. Prediction on real-world unlabeled dataset

To evaluate the practical applicability of the proposed model, the trained RBFN-FCM model was tested on an unlabeled dataset referred to as “Datan HL7 2023–2024.” This dataset comprised 11,701 records containing real-time water quality readings. Only three input parameters, which are temperature, pH, and chlorophyll-a, were directly available from the data source, while other features used during training were unavailable. To maintain consistency in the input shape, missing values were filled with zeros. The model predicted all instances in the dataset as “No Outbreak.” Table 4 shows some of the predicted data:

Although this result may indicate that no HAB events occurred during the period of data collection, it also reflects a potential limitation of the model when applied to datasets with incomplete feature sets. The reliance on multiple parameters for classification suggests that the model’s performance may decline when only a subset of inputs is available. This outcome emphasizes the need for a more robust model that can adapt to missing or imbalanced data without significant performance degradation.

Table 4. Sample predicted data

Date	Time	Temperature	pH	Chlorophyll-a	Predicted HAB Outcome
2024-04-08	17:10:00	32.2	8.32	4.11	No Outbreak
2023-10-07	17:50:00	31.96	8.09	3.15	No Outbreak
2023-12-28	23:00:00	29.4	8.25	4.61	No Outbreak
2024-09-21	00:00:00	29.77	7.85	2.62	No Outbreak
2024-03-25	16:50:00	32.46	8.31	4.87	No Outbreak

4.2. Model performance and evaluation

During the training phase, the model achieved perfect performance metrics, including 100% accuracy, precision, recall, and F1-score on the test dataset. The confusion matrix confirmed the absence of both false positives and false negatives, indicating that the model learned the patterns in the training data exceptionally well. However, this level of performance also raises concerns regarding potential overfitting, particularly given the synthetic nature of part of the training data. To assess the model’s generalization capability, it was tested on an outlier dataset with feature distributions that differed significantly from those in the training set. The results showed a complete failure to classify HAB outbreak cases, resulting in a recall score of 0.00 for the positive class. This outcome underscores the challenge of generalizing from synthetic or uniform datasets to real-world environments, where the data may contain noise, imbalance, or variability

does not present during training. The confusion matrix indicates perfect predictions, with no false positives or false negatives, as shown in Table 5.

Table 5. RBFNs classification report

	Precision	Recall	F1-Score	Support
No Outbreak	1.00	1.00	1.00	20990
HAB Outbreak	1.00	1.00	1.00	20989
Accuracy			1.00	41979
Macro Avg	1.00	1.00	1.00	41979
Weighted Avg	1.00	1.00	1.00	41979

5. CONCLUSION

This study proposed and evaluated a hybrid RBFN integrated with FCM clustering for predicting HAB events based on key water quality parameters. The experimental results demonstrate that the RBFN-FCM model achieved excellent predictive performance on balanced and clean datasets, with an F1-score of 1.00, and identified Chlorophyll-a as the most influential predictor of HAB occurrences. The model outperformed random forest classifiers in terms of training speed and interpretability, suggesting its suitability for real-time, low-resource environmental monitoring systems. However, testing on a real-world, incomplete dataset highlighted critical limitations in the model’s generalization capability, as it failed to detect any HAB events under feature constraints. These findings underscore the challenges of deploying AI models in dynamic, noisy environments and highlight the importance of robust handling of missing or imbalanced data for reliable field performance. This research contributes to the growing body of work on lightweight, explainable AI for ecological monitoring and offers a foundation for integrating hybrid RBFNs into early warning systems for aquaculture and coastal management. Future work should focus on improving resilience to data variability through adaptive kernel functions, advanced imputation strategies, and incorporating online learning mechanisms for continuous model refinement in real-world deployments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization	I : Investigation	Vi : Visualization
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in IEEE Xplore at <https://doi.org/10.1109/SCORED64708.2024.10872705>.

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