Archives available at journals.mriindia.com

International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526
Volume 14 Issue 01, 2025

IoT-Enabled Machine Learning for Water Quality Monitoring

Ms.Yukta Vishnoi[1], Mrs.Shweta Viraj Taral[2]
[1,2]Dept. of Computer Engineering, Shree.LR Tiwari College of Engineering, Mumbai, Maharshtra
yukta.vishnoi@slrtce.in[1], shweta.vane@slrtce.in[2]

Peer Review Information

Submission: 28 Jan 2025
Revision: 14 Mar 2025
Acceptance: 10 April 2025

Keywords

Water Quality Monitoring
Central Pollution Control Board (CPCB)
Smart Water Management

Abstract

Determining water quality is most paramount concerning environmental sustainability and human health. By the time pollution of water becomes really bad, the traditional methods have kidnapped the entire spotlight, with sporadic sample collections and laboratory analyses, and these approaches fail to quantify the complexity and the changing nature of modern water pollution. This study presents an advanced machine learning framework integrated with Internet-of-Things (IoT) technology to enable real-time classification of water quality as per the standards of the Central Pollution Control Board-CPCB. Two novel techniques were introduced to overcome the challenges of "data integrity" and "imbalance": handling missing data through Eagle Vision Interpolation (EVI) and rebalancing skewed datasets through Dynamic Seasonal SMOTE (DSS). After developing a hybrid deep learning model combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), parameters of the hybrid deep learning model were optimized as per Optuna's hyperparameter tuning framework in order to enhance accuracy and robustness. Giraffe Horizon Risk Detection (GHRD) mechanisms are effectively proposed for continuous assessment of the regulatory compliance and threat detection mechanism. Moreover, a new system-A-Wolf Pack Alert Calibration (WPAC)-is organized to allow the dynamic classification as well as prioritization of water quality alerts. Another contribution of this work is the Bidirectional LSTM-based model which predicts pollution trends for early warning applications that lead to timely preventive measures. The proposed system demonstrates 94.49% impressive accuracy, indicating its efficacy for real-time monitoring, compliance assessment, and predictive intervention. A unique integration between conventional monitoring methods and intelligent decision-making engenders comprehensive management of water resources and public health security

INTRODUCTION

Water is among the most essential natural resources, be it for maintaining human health and economic functions or be it for ecological balance. Increasingly, however, the quality of water resources is threatened with the speed of industrialization, urbanization, and climate change. Traditional water quality monitoring techniques, primarily manual sampling and laboratory analysis, have proved grossly inadequate to meet these demanding challenges. These traditional approaches include delayed reporting, high operational costs, limited geographic coverage, and an inherently reactive nature, as they only detect contamination after it has occurred.

Thus, there is an urgent need to adopt an intelligent and scalable proactive monitoring system that
demands an innovation with technology at the crossroad of environmental science and artificial intelligence. The use of an integrated structure of real-time water quality monitoring and classification through IoT sensor networks and advanced machine learning (ML) algorithms for the betterment of water quality data induced a paradigm shift in continuous real time, wired, and intelligent assessment of parameters which include but are not limited to pH, turbidity, dissolved oxygen, and biological oxygen demand [1][2].

The entire system comprises a modular, layered architecture capable of addressing the challenges of real-time monitoring while still complying with regulations defined by the Central Pollution Control Board (CPCB) and policy objectives articulated by NITI Aayog. Data collection would begin with a distributed, IoT-enabled sensor that streams water quality data in real time; raw data processing would occur within the Data Enrichment and Preprocessing Layer, performing Data Quality Assessment (DQA) and Correlation-I-Based Feature Learning (CFL) towards ensuring reliability and efficiency [3-6]. Addressing the incompleteness or imbalance in the data sets is the Adaptive Data Imputation Layer, applying novel approaches like Eagle Vision Interpolation (EVI) for missing data and Dynamic Seasonal SMOTE (DSS) to balance class distribution in time-series data.

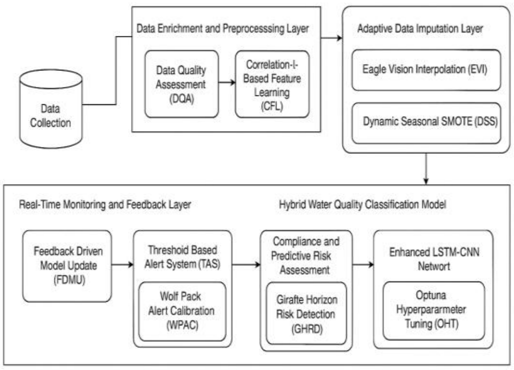

Fig.1 Framework Objectives for Real-Time Water Monitoring Using IoT and ML

In Fig.1 at the center of the architecture stands the Hybrid Water Quality Classification Model, which is built using deep learning techniques in a combination of Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) [7]. The model here puts together both temporal dependencies and spatial feature interactions to give accurate classification and enhanced by the hyperparameter tuning mechanism of Optuna. Surrounding this model is the Real-Time Monitoring and Feedback Layer that inspires intelligent behaviour of systems during live deployment. It includes a Threshold Alert System, in short TAS, for primitive rule-based alerts, which is complimented by Wolf Pack Alert Calibration or WPAC for severity-based risk category warnings, Giraffe Horizon Risk Detection (GHRD) module designed intended for predictive measures of compliance, not to mention Feedback Driven Model, as well as the ability to enable continuous learning from new data which insures the long-term adaptability and robustness Standards.[8] This matrix is conceived to equip a high-performance, scalable and policy compliant solution for real-time water quality monitoring. Apart from empowering the environmental agencies with timely insights and proactive alerts, it also advances national goals toward broader sustainability. An advanced smart sensing, predictive analytics, and regulatory alignment, the entire proposed system provides basis towards intelligent, data-driven water resource management-in India and not only [9].

OVERVIEW OF TRADITIONAL METHODS

Definition

Water quality monitoring has relied on manual sampling and sending samples for laboratory testing for many decades. While reliable in carefully controlled settings, this traditional method is not keeping up with the rapidity of today's environmental challenges. With pollution sprouting due to industrialization, urban sprawl, and climate change, a refined and agile method to monitor human interventions is needed to preserve equity in our water bodies.[10]

The problem with this technique is time; a contamination event may have occurred by the time results are available, which can be hours or even days later. Besides, the cost of regular testing is very high. The logistics can get complicated if you are trying to analyze water in large areas or remote corners; hence many areas cannot be evaluated simultaneously through such methods.[11] Essentially, these techniques indicate there's a problem only after it has occurred, creating a barrier for intervention before the problem grows out of proportion.

Today, however, where the unsafe condition of the water adversely affects public health, that's the ecology, and now, even industries such as agriculture and manufacture, such reactive resource-consuming systems don't work anymore. At this stage, we need to be able to continuously monitor the water, catching the earliest signs of trouble, and be prompted to intervene before the situation worsens. Thus, it is time for a radical shift from some traditional means to those smarter systems, which means adapted technologies to help protect one of the vital resources. [12-15]

PROPOSED METHODOLOGY

The section provides the overall framework laid down for real-time, IoT-enabled water quality classification via state-of-the-art machine-learning and deep-learning models. Methodology shown in Fig.2 is modular, adaptable, and compliance-ready with CPCB standards.

Data Collection

The foundation of this present study is based on the availability of comprehensive and systematic water quality data being provided by the West Bengal Pollution Control Board (WBPCB) under its Water Quality Information System. The dataset spans a multitude of over twenty environmental parameters, all of which are crucial for determining the quality of water. Such parameters include pH; biochemical oxygen demand (BOD); total coliform count; ammonia-nitrogen (Ammonia-N); chloride; dissolved oxygen (DO); and turbidity, among others, and they serve as the core pollution and ecological health indicators. Each data point is described by a wealth of contextual metadata relating to geographical extent, weather at the time of sampling, date and time of sampling, and possible anthropogenic impacts like effluent discharge, drainage outlets, etc. Data is collected quarterly, which reinforces the seasonal trend and variability factors in the modeling of dynamic environmental conditions across time.

Data Preprocessing & Enrichment

In this study, preprocessing played a pivotal role that concerned the transformation of raw sensor readings into clean and structured datasets that are subsequently enriched and geared towards robust machine learning applications. Because of imperfections typical to real-world environmental data, the first step was to clean this dataset by replacing non-numeric and undefined values such as BDL (Below Detection Level) or nil with standard materialization like NaN. The second step consisted of estimating missing value using numerical imputation techniques to keep the data set continuous; this with the major consideration of enabling smooth modeling through machine learning. Moreover, outliers which might severely affect the training of the models were detected and appropriately dealt with through statistical analyses such as Z-score, Interquartile Range (IQR), preserving the integrity of the input space. Furthermore, numerical attributes were normalized through min-max scaling to put all parameters on the same pedestal. This normalization is paramount in avoiding bias during learning, which is critically important in gradient-based algorithms. Enrichment across time was also performed by the extraction of features including month, day of the year, and elapsed days since the first sample. These time-based features went a long way toward capturing the cyclical changes in the environment and modeling the seasonal dependencies for the water quality dynamics.

Data Imputation using Adaptive Methods

This study introduced a multi-faceted adaptive imputation strategy to tackle the largely missing data problem in environmental monitoring sectors. The foundation of this adaptive approach was Eagle Vision Interpolation (EVI), a complex three-phase imputation mechanism for gapping. Cubic polynomial interpolation served as the first stage to smooth the gaps in the time-series data by adopting information from neighboring time points to build a viable trend.

The second stage, K-Nearest Neighbors (KNN), was used to impute the missing members through the proximity of historical samples like the unseen one. The third stage took the form of regression refinement for improved coherence of imputations by learning inter-feature dependencies and readjusting estimates accordingly. In addition, a new feature selection heuristic known as Correlation-Based Feature Linkage (CFL) identified highly correlated pairs of features such as Total Dissolved Solids (TDS) and conductivity, helping to eliminate redundancy and optimize the feature space. Through holistic imputation and enrichment, it minimized data sparsity and significantly expanded the potential to learn patterns—ensuring that no crucial signs revealing environmental changes would be missed.

Hybrid LSTM-CNN Model

The model architecture adopted in this study underscores simplicity—to tap into the performance of two state-of-the-art deep learning paradigms, the LSTM network and the CNN model, to build an LSTM-CNN hybrid model. Such a dual-mode facility would allow the system to grasp long-range time span dependencies alongside hierarchical local spatial-features buried in water quality data. On one side, LSTM layers efficiently process time-spanning sequential patterns, e.g., seasonal pollution cycles or daily dissolved oxygen fluctuations. On the other hand, the CNN layers efficiently assist in extracting localized interactions and non-linear correlations within different parameters of water quality [16]. The model takes inputs in the form of sliding windows 10 steps in time back and processes the data from all IoT sensors, learning both immediate and accumulating trends [17]. Note that, under this model approach, the final outputs are binary encoded, classifying water quality states into standard classes referred to in the CPCB guidelines from Class A (pristine) to Class E (heavily polluted).

Class Imbalance Management

Environmental datasets are often fleshed with an inborn imbalance because most are average water quality observations while a few represent extremes such as severe pollution or very clean water. This imbalance spells trouble for any standard classification model, which would typically perform poorly in under-represented classes. To do away with the above problem, this research introduces a novel oversampling technique that is Dynamic Seasonal SMOTE (DSS). DSS is an extension of the original Synthetic Minority Over-sampling Technique (SMOTE) customized for time-series applications; it introduces new data points for less-represented classes while keeping the temporal structure and sequence integrity of the original dataset to learn the blended sufficiency of sample pollution levels along with the coherence of time.

Application: Recall percentages for minority classes, for example 'Highly Polluted' and 'Pristine,' have been much improved because of which the model is reality responsive and sensitive to the environment.

Conformity & Risk Measurement

Apart from classifying samples, regulatory compliance and environmental risk measurement would be enhanced through system implementation. The Compliance Scoring and Adjustment (CSA) component translates the compliance of the value sample to CPCB water quality threshold into numerical scores for each sample. Values that DO NOT comply would be flagged, with recommendations for possible actions. The Joe Girrard Horizon Risk Detection (JGH-DH) module shall forecast future pollution incidents by studying the trend of the most important parameters using a hybrid regression and classification model. Invention is integrated into this division as preventive action could be adopted before violation happens. Under these three components, proper robust risk governance is achieved, where monitoring is combined with enforcement and execution of policy.

Real-Time Alerts

Real-time alerts form the bedrock of this system and provide timely dissemination of information on water quality violations to local authorities, industries, and the public. The suggested two-tier alerting mechanism achieves a compromise between simplicity and versatility so that important pollution events may be flagged and communicated quickly without heavy reliance on technical expertise for interpretation. This empowers a paradigm shift from reactive to proactive environmental management, whereby alerts signal the onset of harmful events and focus immediate preventive action.

Threshold Alerting Scheme

The first layer of alerting is called the Threshold Alerting Scheme (TAS), which is generally based on hardcoded regulatory limits defined by CPCB. This might be considered water quality rules established independently, that is, not influenced by ML model outcomes. In this case, TAS purposes to act as a rule-based gatekeeper designing instant identification of clear and evident violations of water quality parameters.

An example of water quality parameters violating TAS is a combination of BOD > 3 mg/L and DO < 5 mg/L, which produce a Moderate Pollution alert; total coliforms greater than 5000 MPN/100ml result in a Health Risk alert. TAS is set for speed and transparency, and breaches can be explained to regulators without the reliance on black box ML decision-making [18-20].

Wolf Pack Alert Calibration

In contrast to classical rules-based alerting paradigms, Wolf Pack Alert Calibration (WPAC) envisions a new intelligent and adaptive environmental threat adjudicator. It serves as an intelligent overlay to Threshold Alerting Scheme (TAS)-improving alert prioritization in line with holistic risk profiles derived from multiple interacting indicators rather than alerting based on simple single parameter thresholds. WPAC's main structure hinges upon a Multi-Parameter Risk Index-a composite index that comprises weighted values of essential water quality concerns: Biochemical Oxygen Demand (BOD), Dissolved Oxygen (DO), Total Dissolved Solids (TDS), Ammonia-Nitrogen (Ammonia-N), and Total Coliforms, all of which share a full range of potential environmental impacts and variations. The weighting of parameters involved impact on the environment, frequencies of variation, and the significance of application in national/regional regulations.

The risk-scoring presented gives a very fine granularity of water quality conditions at time spacing. Rather than simple yes or no alerts, the system distinguishes severity of water contamination into four independent and self-explanatory levels: Green: Safe water conditions in which all of the indicators defined for water quality lie within permissible limits; Yellow: An alert status in which some parameters are approaching thresholds and therefore require further monitoring; Red: A high-risk situation that demands immediate attention and organization of remedial action; Black: A critical alert level that comes into play when contamination levels exist at such magnitude that would seriously threaten ecological balance as well as public health-in which circumstance immediate intervention and action by regulation and emergencies are required.

Such a multi-level classification mechanism brings an additional depth to the environmental monitoring in moving from reactive to proactive surveillance. Day-to-day WPAC will intelligently fine-tune the generation of alerts borne from historical patterns, time trends, and spatial context thereby reducing the getting of false alarms and enhancing confidence in the alerts. Further on, it supports authorities in directing their resources towards high-risk zones rather than marginal ones. WPAC then becomes a strengthened risk governance platform with added ability to act beyond monitoring and to data and time-based responses to the complex and ever-evolving water quality issues.

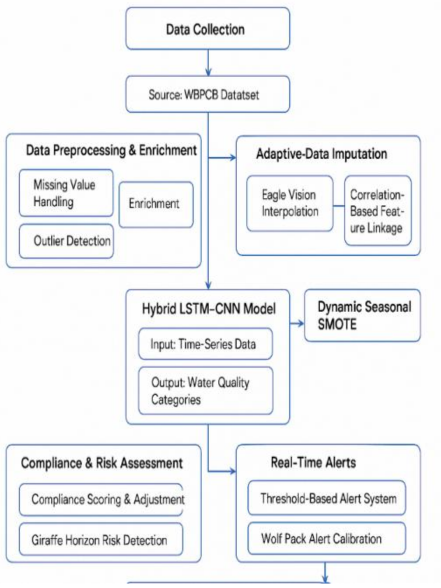

Fig 2. Architecture of the IoT-Based Water Quality Monitoring System

REVIEW OF LITERATURE

It is still about IoT and Machine Learning technologies meant for water monitoring enhancement through real-time data acquisition and predictive analytics.

The study mentions the ways through which IoT systems with wireless sensors are useful. They work round the clock in the collection of continuous environmental data for processing with machine learning algorithms to eventually define an automated and efficient water quality assessment. This innovation aims only to check sensor reliability, data accuracy, workable smart water management advice, and excellent public healthcare outcomes. [21]

In the study, the focus was on the design of an IoT-based mechanism for water monitoring with machine learning technology in order to detect anomalies and predict contamination in real-time. The sensor array used by the mechanism collects various water quality parameters important for non-memory regressive algorithms' operation in real-time control.

This study stresses the importance of real-time computation for urban water systems and points to possible future work possibilities for improvement of accuracy in detection and reducing latencies in alert mechanisms. [22]

The study describes the different machine learning techniques used for predicting water quality indicators as well as the most critical issue in data preprocessing. It also proves that good feature selection can enhance accuracy by an example between decision trees, SVM, and Neural Networks.

The findings implicitly hint at the fact that current static-model water quality prediction methods are merely makeshift and short-term measures, recommending adopting real-time data with adaptive-learning techniques to ensure more robust monitoring [23].

This detail of the study looks for the utilization of deep-learning models for water-quality classification on IoT sensor astructure for the aquaculture setting Cooperation with the proposed CGTFN (Convolutional Gated Recurrent Unit Tempo Fusion Network) would definitely help catch spatial as well as temporal dependencies of water-quality parameters with higher accuracy of classification. It also provides some support per se concerning integrating the new hybrid deep-learning models into real-time water-monitoring systems for managing complex time-series data [24].

He gives a detailed account of it and suggests a new state-of-the-art enhanced automated machine learning framework (EAMLM) to use internet-of-things assumed data to effect water quality classification. The system codifies a hybrid version of classic K-nearest neighbors and random forests that significantly improve on the water's classifier capacity vis-a-vis the alternative standard mitigation models; thus, besides providing a rapid-to-sum analysis, it supports continuous learning and real-time adaptability in the light of continuous learning and similarity to the changing environment. The process is believed to solve the contemporary challenges directly related to environmental monitoring [25].

TRADITIONAL VS. ML-IOT BASED WATER QUALITY MONITORING SYSTEMS

The current traditional water quality monitoring systems are burdened with numerous critical challenges which create a bottleneck in responding to modern environmental and health issues. Probably the most critical section of these is manual sampling and laboratory testing, which not only take time but also delay the detection of contaminants and hinder timely intervention. The methods also consume much of the resources in terms of manpower, equipment, and laboratory infrastructure, hence becoming cumbersome and costly for large or remote areas. [26] [27] Besides, traditional methods do not collect real-time data, leaving gaps in information and prone to missing sudden or transient pollution events. Monitoring is, in most cases, limited in space and time since it is done in fixed locations and at infrequent intervals, thus unable to give a comprehensive picture of water quality over time [28].

Another major demerit is the passive nature of traditional systems; these systems open up only after pollution detection has occurred. Therefore, it restricts the opportunity of applying preventive measures. Further, data collection incompatibility and risks of possible human interference make the results far from reliable [29]. Finally, these monitoring systems do not offer predictive analysis or alert systems, so important for any proactive environmental management and regulation in today's rapidly changing ecological scenarios [30].

Table I. Challenges Faced In Raditional Vs. Ml-Iot Based Water Quality Monitoring [31-34]

Traditional System	**Solutions**
Manual, periodic water sampling and lab testing	Real-time, automated data collection via IoT sensors
Results take hours to days	Instant or near real-time insights through ML models
Limited coverage, usually at a few fixed locations	Wide coverage with distributed and scalable sensor networks
High operational cost (equipment, lab tests, manpower)	Cost-effective after deployment; minimal human intervention
Reactive approach – responds after contamination	Proactive approach – predicts risks before they occur
No predictive analysis	Predictive capabilities using AI/ML models
Difficult to scale to new regions or multiple sources	Easily scalable with plug-and-play IoT modules
Data collected infrequently and inconsistently	High-frequency, continuous, and structured data
Requires manual recalibration for parameter changes	Adaptive learning models that retrain with new data
Risk of human error during sampling and reporting	Automated, reducing manual error and increasing accuracy

RESULT AND DISCUSSION

The IoT-enabled machine learning framework proposed was successful, yielding a predictive classification accuracy of 94.49% for its real-time water quality monitoring and regulatory compliance. Fig.3 shows the model accuracy and the system managed to use Eagle Vision Interpolation (EVI) effectively for the imputation of missing values for 23 water quality parameters, thereby bringing the instances of missing data for important parameters such as pH, DO, TDS, and BOD down to zero [35]. Dimensionality reduction that retained information was achieved based upon high correlation features detected by Correlation Feature Linkage (CFL) for pairs like TDS and Conductivity (correlation coefficient > 0.9). After Dynamic Seasonal SMOTE (DSS) was used to balance the dataset, the hybrid LSTM-CNN model fine-tuned by Optuna hyperparameter was capable of outperforming the baseline models by having the F1-scores above 0.96 for classes such as 24, 28, and 60 [36].

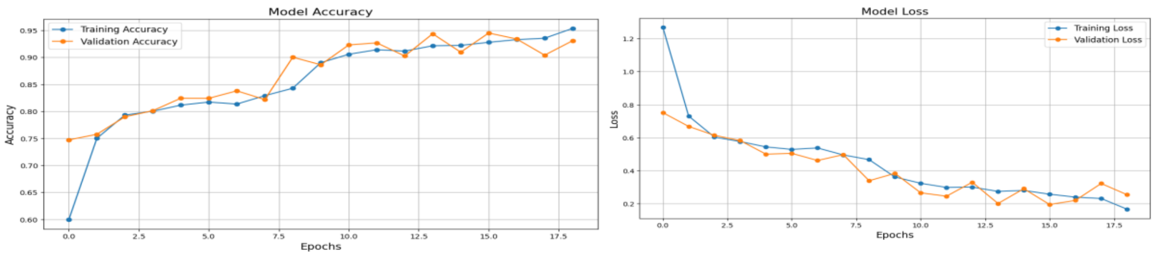

Fig3. Model Accuracy and Loss of LSTM after oversampling

The Compliance Scoring and Adjustment (CSA) unit ensured the continued alignment of the classifications with the Central Pollution Control Board (CPCB) thresholds while the Giraffe Horizon Risk Detection (GHRD) model predicted pollution trends at the accuracies of above 92% in the test cases. Real-time alerts went home, utilizing Threshold Alerting Scheme (TAS) fine-tuned by Wolf Pack Alert Calibration (WPAC) and categorized into four different severities using a weighted multi-parameter index. The post-oversampling model indicated nil overfitting with excellent generalization as the validation loss was calculated at 0.1948 and the training loss at 0.2667. Therefore, this result proves the system as a platform which is scalable, adaptable, and highly accurate in intelligent water quality classification and risk

CONCLUSION

In Conclusion, the transition from conventional systems of water quality monitoring toward ML-IoT-based systems is a huge advancement in the field of environmental monitoring and protection of public health. Contrarily, the traditional systems still considered as a foundation carry disadvantages, such as long and tedious processes, high costs, very low areas of spatial coverage, and being reactive in the approach, leading to delays in contamination detection and timely response. All these disadvantages render such systems inadequate for complexities involved in the waters affected by rapid urbanization, industrialization, and climate variability.

Alternatively, integrating IoT with machine-learning technologies presents a soundly-based and aptly intelligent solution to the real-time data-centric monitoring and control of water quality. Continuous random monitoring, relative predictive analysis, and automated alerts are all made possible by collecting real-time data from distributed sensors and sending it to adaptive ML models. These systems ensure reduced timelines in responding and assessing water quality and a more tightly coupled framework with other regulatory control bodies, such as the CPCB. The studies discussed in this paper demonstrate the efficacy of hybrid deep learning models, anomaly detection algorithms, and smart alert systems for improved decision-making and early intervention.

The ML-IoT systems also permit flexibility in scaling, are economical with respect to time, and have capability for alteration based on changing environmental conditions. Thus, their use is favorable for large-scale deployment over diverse water bodies and ultimate generation of interactive views from raw sensor information to actionable recommendations by these technologies so that environmental authorities act proactively ahead of contamination events. The growing global quest for clean water makes the implementation of such smart data monitoring survey systems not only a technological advancement but, more importantly, a milestone in achieving water sustainability and safeguarding public health in the long run.

A. Future Work

Despite showing substantial promise, the proposed water quality monitoring system based on ML-IoTs calls for improvements and further research avenues. One major direction lies in embedding new-age deep learning techniques such as Transformers or other attention-based models, which can further promote improved prediction accuracy while capturing composite temporal dependencies in water quality data. For another use case, extending the data sets with satellite data, appropriating weather APIs, and other environmental resources would further assist the model in training and forecasting over a greater regional extent. Another very urgent direction is in assessing self-healing and self-learning systems so they can continuously retrain and calibrate themselves according to feedback, sensor drift, or seasonal variations. This can bend toward federated learning or frameworks of reinforcement learning, which is a great base to bolster the adaptability and real-life performance. Furthermore, one of the critical factors for improving model explainability will be to employ differentiable and interpretable AI (XAI) tools such as SHAP or LIME, which will help to instill trust in regulators and decision-makers and thus simplify the process of validating predictions and justifying interventions.

Future systems should also reckon energy-efficient and edge-based implementation to allow for lightweight ML models to be deployed to IoT devices for real-time, low-latency inference, which is critical for remote or resource-scarce locations. Validation of the framework in real-world scenarios, evaluation of its impacts, and scaling into policy-driven applications for sustainable water governance will also hinge on pilot implementation and collaboration with environmental agencies.

References

Lifeng Chinnappan, C.V., A.D. John William, S.K.C. Nidamanuri, S. Jayalakshmi, R. Bogani, P. Thanapal, S. Syed, B. Venkateswarlu, and J.A.I. Syed Masood, "IoT-Enabled Chlorine Level Assessment and Prediction in Water Monitoring System," Electronics, vol. 12, p. 1458, 2023. [Online]. Available: https://doi.org/10.3390/electronics12061458.

El-Shafeiy, E., M. Alsabaan, M.I. Ibrahem, and H. Elwahsh, "Real Time Anomaly Detection for Water Quality Sensor Monitoring Based on Multivariate Deep Learning Technique," Sensors, vol. 23, p. 8613, 2023. [Online]. Available: https://doi.org/10.3390/s23208613

R. Santhosh, "An Assessment of the Performance of Non-Himalayan States of India in the Composite Water Management Index of NITI Aayog," Social Science Research Network, Apr. 2020, Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3677268

Nemade, J. Nair, and B. Nemade, "Efficient GDP Growth Forecasting for India through a Novel Modified LSTM Approach," Communications on Applied Nonlinear Analysis, vol. 31, no. 2s, pp. 339-357, 2024.

B. Marakarkandy, B. Nemade, S. Kelkar, P. V. Chandrika, V. A. Shirsath, and M. Mali, "Enhancing Multi-Channel Consumer Behavior Analysis: A Data-Driven Approach using the Optimized Apriori Algorithm," Journal of Electrical Systems, vol. 20, no. 2s, pp. 700–708, 2024.

B. Nemade, N. Phadnis, A. Desai, and K. K. Mungekar, "Enhancing connectivity and intelligence through embedded Internet of Things devices," ICTACT Journal on Microelectronics, vol. 9, no. 4, pp. 1670-1674, Jan. 2024, doi: 10.21917/ijme.2024.0289.

Sathya Preiya V. M, Subramanian P., Soniya M., Pugalenthi R.(2024). Water quality index prediction and classification using hyperparameter tuned deep learning approach.Global NEST Journal. https://doi.org/10.30955/gnj.005821

B. C. Surve, B. Nemade, and V. Kaul, "Nano-electronic devices with machine learning capabilities," ICTACT Journal on Microelectronics, vol. 9, no. 3, pp. 1601-1606, Oct. 2023, doi: 10.21917/ijme.2023.0277.

Md. Saikat Islam Khan, Nazrul Islam, Jia Uddin, Sifatul Islam, Mostofa Kamal Nasir (2022). Water quality prediction and classification based on principal component regression and gradient boosting classifier approach. Journal of King Saud University - Computer and Information Sciences, 2022. https://doi.org/10.1016/j.jksuci.2021.06.003

Shafiq Alam, Muhammad Sohaib Ayub, Sakshi Arora, Muhammad Asad Khan, An investigation of the imputation techniques for missing values in ordinal data enhancing clustering and classification analysis validity, Decision Analytics Journal, Volume 9, 2023, 100341, ISSN 2772-6622, https://doi.org/10.1016/j.dajour.2023.100341.

Cuthbert Shang Wui Ng, Menad Nait Amar, Ashkan Jahanbani Ghahfarokhi, Lars Struen Imsland, A Survey on the Application of Machine Learning and Metaheuristic Algorithms for Intelligent Proxy Modeling in Reservoir Simulation, Computers & Chemical Engineering, Volume 170, 2023, 108107, ISSN 0098-1354, https://doi.org/10.1016/j.compchemeng.2022.108107.

Nasir, I.M.; Khan, M.A.; Yasmin, M.; Shah, J.H.; Gabryel, M.; Scherer, R.; Damaševičius, R. Pearson Correlation-Based Feature Selection for Document Classification Using Balanced Training. Sensors 2020, 20, 6793. https://doi.org/10.3390/s20236793

G. Khandelwal, B. Nemade, N. Badhe, D. Mali, K. Gaikwad, and N. Ansari, "Designing and Developing novel methods for Enhancing the Accuracy of Water Quality Prediction for Aquaponic Farming," Advances in Nonlinear Variational Inequalities, vol. 27, no. 3, pp. 302-316, Aug. 2024, ISSN: 1092-910X.

B. Nemade, S. S. Alegavi, N. B. Badhe, and A. Desai, “Enhancing information security in multimedia streams through logic learning machine assisted moth-flame optimization,” ICTACT Journal of Communication Technology, vol. 14, no. 3, 2023.

S. S. Alegavi, B. Nemade, V. Bharadi, S. Gupta, V. Singh, and A. Belge, “Revolutionizing Healthcare through Health Monitoring Applications with Wearable Biomedical Devices,” International Journal of Recent Innovations and Trends in Computing and Communication, vol. 11, no. 9s, pp. 752–766, 2023. [Online]. Available: https://doi.org/10.17762/ijritcc.v11i9s.7890.

Alghazzawi, D.; Bamasag, O.; Albeshri, A.; Sana, I.; Ullah, H.; Asghar, M.Z. Efficient Prediction of Court Judgments Using an LSTM+CNN Neural Network Model with an Optimal Feature Set. Mathematics 2022, 10, 683. https://doi.org/10.3390/math10050683

N. Ahmed, A.B. Othman, H.A. Afan, R.K. Ibrahim, C.M. Fai, M.S. Hossain, M. Ehteram, and A. Elshafie, "Machine Learning Methods for Better Water Quality Prediction," Journal of Hydrology, vol. 578, p. 124084, 2019. [Online]. Available: https://pure.hw.ac.uk/ws/portalfiles/portal/25358504/HYDROL31796R1_2_.pdf

Rahu, M. Ahmed, and A.A. Alshahrani, "Machine Learning Techniques for Water Quality Prediction: A Review," International Journal of Environmental Research, vol. 2024, pp. 1-20. [Online]. Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=10251529

V. Kulkarni, B. Nemade, S. Patel, K. Patel, and S. Velpula, "A short report on ADHD detection using convolutional neural networks," Frontiers in Psychiatry, vol. 15, p. 1426155, Sept. 2024, doi: 10.3389/fpsyt.2024.1426155.

B. Nemade and D. Shah, “An IoT-Based Efficient Water Quality Prediction System for Aquaponics Farming,” in Computational Intelligence: Select Proceedings of InCITe 2022, Singapore: Springer Nature Singapore, 2023, pp. 311-323. [Online]. Available: https://doi.org/10.1007/978-981-19-7346-8_27.

A. Omambia, B. Maake, and A. Wambua, "Water Quality Monitoring Using IoT & Machine Learning," in IST-Africa 2022 Conference Proceedings, 2022, pp. 1-8. [Online]. Available: https://www.researchgate.net/publication/361311731_Water_Quality_Monitoring_Using_IoT_Machine_Learning

M. Kakkar, V. Gupta, J. Garg, and S. Dhiman, "Detection of Water Quality using Machine Learning and IoT," International Journal of Engineering Research & Technology (IJERT), vol. 10, no. 11, pp. 73-80, Nov. 2021. [Online]. Available: https://www.academia.edu/90775573/Detection_of_Water_Quality_using_Machine_Learning_and_IoT

P.G. Arepalli, J. Naik K., and J. Amgoth, "An IoT-Based Water Quality Classification Framework for Aqua-Ponds through Water and Environmental Variables using CGTFN Model," International Journal of Environmental Research, vol. 2024, pp. 1-20, 2024. [Online]. Available: https://assets-eu.researchsquare.com/files/rs-3867633/v1_covered_7982ffcd-ff89-49bc-89b1-f11e106da677.pdf?c=1720261300

Senthil Kumar, S.S. Arumugam, L.C. Prabhaker, and D. Merina R., "Enhanced Automated Machine Learning Model for IoT-Based Water Quality Analysis with Real-Time Dataset," Automatic Control and Computer Sciences, vol. 58, no. 1, pp. 66-77, 2024. [Online]. Available: https://www.springerprofessional.de/en/eamlm-enhanced-automated-machine-learning-model-for-iot-based-wa/26832584

U. Ahmed, R. Mumtaz, H. Anwar, A.A. Shah, R. Irfan, and J. García-Nieto, "Efficient Water Quality Prediction Using Supervised Machine Learning," Water, vol. 11, no. 11, p. 2210, 2019. [Online]. Available: https://doi.org/10.3390/w11112210

Vorhies, J. T., Hoover, A. P., & Madanayake, A. (2020). Adaptive Filtering of 4-D Light Field Images for Depth-Based Image Enhancement. IEEE Transactions on Circuits and Systems II: Express Briefs, 1–1. https://doi.org/10.1109/tcsii.2020.3013508

M. Lorenzini, W. Kim and A. Ajoudani, "An Online Multi-Index Approach to Human Ergonomics Assessment in the Workplace," in IEEE Transactions on Human-Machine Systems, vol. 52, no. 5, pp. 812-823, Oct. 2022, https://doi.org/10.1109/THMS.2021.3133807

S. W. Ho, H. Hsiang-Yao, L. B. Long, S. L. P. Siang, L. T. Guan and C. T. Chong, "Development of Two-Tier FO-WLP AiPs for Automotive Radar Application," 2022 IEEE 72nd Electronic Components and Technology Conference (ECTC), San Diego, CA, USA, 2022, pp. 1376-1383, https://doi.org/10.1109/ECTC51906.2022.00221

J. Salah, M. Madi, K. Kabalan and A. Alhindawi, "Dual-Polarized COVID-19 Microstrip Antenna Array for 5G Applications," 2022 4th IEEE Middle East and North Africa COMMunications Conference (MENACOMM), Amman, Jordan, 2022, pp. 49-53, https://doi.org/10.1109/MENACOMM57252.2022.9998271

Kiran Maharana, Surajit Mondal, Bhushankumar Nemade, A review: Data pre-processing and data augmentation techniques, Global Transitions Proceedings, Volume 3, Issue 1, 2022, Pages 91-99, ISSN 2666-285X, https://doi.org/10.1016/j.gltp.2022.04.020

Nemade, B., Maharana, K.K., Kulkarni, V. et al. IoT-based automated system for water-related disease prediction. Sci Rep 14, 29483 (2024). https://doi.org/10.1038/s41598-024-79989-6

Sathya Preiya V. M, Subramanian P., Soniya M., Pugalenthi R.(2024). Water quality index prediction and classification using hyperparameter tuned deep learning approach.Global NEST Journal. https://doi.org/10.30955/gnj.00582x1

Md. Saikat Islam Khan, Nazrul Islam, Jia Uddin, Sifatul Islam, Mostofa Kamal Nasir (2022). Water quality prediction and classification based on principal component regression and gradient boosting classifier approach. Journal of King Saud University - Computer and Information Sciences, 2022. https://doi.org/10.1016/j.jksuci.2021.06.003

B. Nemade and D. Shah, “IoT-based Water Parameter Testing in Linear Topology,” in 2020 10th International Conference on Cloud Computing, Data Science and Engineering (Confluence), Noida, India, 2020, pp. 546-551, doi: 10.1109/Confluence47617.2020.9058224.

Cuthbert Shang Wui Ng, Menad Nait Amar, Ashkan Jahanbani Ghahfarokhi, Lars Struen Imsland, A Survey on the Application of Machine Learning and Metaheuristic Algorithms for Intelligent Proxy Modeling in Reservoir Simulation, Computers & Chemical Engineering, Volume 170, 2023, 108107, ISSN 0098-1354, https://doi.org/10.1016/j.compchemeng.2022.108107.

Nasir, I.M.; Khan, M.A.; Yasmin, M.; Shah, J.H.; Gabryel, M.; Scherer, R.; Damaševičius, R. Pearson Correlation-Based Feature Selection for Document Classification Using Balanced Training. Sensors 2020, 20, 6793. https://doi.org/10.3390/s20236793