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DISSOLVED OXYGEN LEVEL MEASUREMENT IN WATER USING IOT AND MACHINE LEARNING

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ABSTRACT

Agriculture, aquaculture, human consumption, and environmental sustainability all depend heavily on water quality. Aquatic ecosystems and biological processes are impacted by dissolved oxygen (DO) levels, which are a crucial indicator of water quality. Conventional techniques for tracking DO levels are frequently labour-intensive, manual, and have a narrow reach. This study introduces a framework for real-time dissolved oxygen measurement and predictive analysis based on the Internet of Things (IoT) and machine learning (ML). The suggested solution makes use of cloud-based storage for real-time access, IoT sensors for data collecting, and machine learning algorithms for precise forecasting and anomaly detection. Scalability, accuracy, and prompt responses in water quality control are guaranteed by this integrated strategy.
Keywords: *Dissolved Oxygen, Iot, Machine Learning, Water Quality Monitoring, Real-Time Data, Environmental Sustainability*

1.INTRODUCTION

In order to maintain ecosystem health and the safety of water for domestic, commercial, and agricultural uses, water quality monitoring is a crucial part of environmental management. Dissolved oxygen (DO), one of the many factors affecting water quality, is crucial. Aquatic creatures may die as a result of low DO levels, upsetting ecosystems and having detrimental effects on the environment. [1,2]
Chemical titration or electrochemical sensors are used in traditional DO testing methods; these methods frequently call for human intervention and ongoing maintenance. Despite their effectiveness, these techniques are not scalable for widespread, ongoing surveillance. Water quality monitoring systems can now be automated, improved, and scaled thanks to recent developments in IoT and ML technology. In order to detect and forecast the dissolved oxygen levels in water bodies, this article suggests a system that combines IoT-enabled sensors with machine learning algorithms. Real-time data transmission and acquisition are guaranteed by IoT components, and anomaly detection and predictive analytics are made possible by ML models. By combining these technologies, proactive water management techniques are made easier, and environmental sustainability is promoted. An Overview of IoT and Machine Learning-Based Dissolved Oxygen Level Measurement in Water [3,4]
Because it has a direct effect on aquatic life and ecosystem health, dissolved oxygen (DO) is a crucial metric for evaluating the quality of water. Manual sampling and laboratory analysis are the mainstays of traditional DO monitoring techniques, which can be laborious and prone to human error. The combination of machine learning (ML) and the internet of things (IoT) provides a clever and effective way to deal with these issues by enabling real-time DO prediction and monitoring. [5,6]

Smart sensors that continuously gather information on water quality, such as DO levels, temperature, pH, and turbidity, make up Internet of Things-based DO measurement systems. Wireless data transmission from these sensors is sent to cloud-based platforms, where machine learning algorithms examine trends and forecast changes in DO levels. ML models are able to recognize patterns, spot irregularities, and offer early warnings for possible declines in water quality by utilizing both historical and current data. [7, 8]
The accuracy, effectiveness, and scalability of DO monitoring are improved when IoT and ML are combined. In addition to supporting sustainable environmental practices, it lowers the risk of aquatic life depletion and makes proactive water management measures possible. IoT and ML-based solutions are essential to maintaining safe and healthy water resources as worries about water contamination spread throughout the world. [9, 10]

2. BACKGROUND AND RELATED WORK

2.1 Importance of Dissolved Oxygen in Water Quality

The amount of oxygen in water that is necessary for aquatic life to survive is known as dissolved oxygen. DO levels are influenced by elements such organic matter, salinity, and temperature. Hypoxia, or persistently low DO levels, can result in "dead zones," where aquatic life is unable to survive. Therefore, keeping an eye on DO levels is essential to preserving the ecological equilibrium.
A vital sign of water quality, dissolved oxygen (DO) is necessary for aquatic life to survive and for an ecosystem to function as a whole. It alludes to the concentration of oxygen in water, which is necessary for aquatic life to breathe. Temperature, salinity, atmospheric pressure, and the presence of organic matter are some of the variables that affect DO concentration.
A variety of aquatic life, such as fish, invertebrates, and microbes, are supported by adequate DO levels. Through photosynthesis by aquatic plants, wind and wave aeration, and atmospheric diffusion, oxygen enters water. However, through microbial breakdown, excessive organic pollution from sewage, industrial waste, and agricultural runoff can lower DO levels, resulting in hypoxia (low oxygen) or anoxic conditions (no oxygen at all). Fish fatalities, food chain disruptions, and water quality degradation can result from these circumstances.[11–13]
Do DO levels have an impact on water's biological processes as well? High DO concentrations reduce hazardous contaminants by facilitating aerobic bacteria's decomposition of pollutants and organic materials. On the other hand, low DO levels encourage anaerobic breakdown, which can result in the release of harmful gasses including methane and hydrogen sulfide.[14–16]

To evaluate the quality of the water in lakes, rivers, and reservoirs, DO monitoring is crucial. To safeguard aquatic ecosystems, regulatory bodies set minimum DO criteria; levels above 5 mg/L are generally regarded as healthy. Maintaining ideal DO levels can be aided by aeration strategies, lowering organic pollutants, and encouraging vegetation growth. [17–18]
To sum up, dissolved oxygen is essential for maintaining water quality and aquatic ecosystems. Maintaining a balanced environment, avoiding ecological disruptions, and encouraging clean water resources for wildlife and human usage are all made possible by effective DO level management.[20–21]

2.2 Existing DO Monitoring Techniques

Assessing water quality and maintaining the wellbeing of aquatic ecosystems depend on the monitoring of dissolved oxygen (DO) levels. DO is measured using a variety of conventional and contemporary methods, each with unique benefits and,drawbacks.
• **Chemical Methods:** Although they are time-consuming and labour-intensive, techniques like the Winkler method offer great accuracy.
• **Electrochemical Sensors:** These sensors, which are widely used to monitor DO, need regular calibration and upkeep.
• **Optical Sensors:** These more costly, fluorescence-quenching-based sensors provide more,stability.

2.2.1. Winkler Titration Method

Among the most traditional and precise techniques for determining DO.
It involves fixing oxygen in a water sample with chemicals, then measuring the oxygen concentration by titration. Extremely accurate, but not appropriate for real-time monitoring and time-consuming.

2.2.2. Electrochemical (Clark) DO Sensors

- Uses an electrode-based system with a membrane-covered anode and cathode to measure oxygen concentration.

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- Provides quick and reliable results but requires frequent calibration and membrane replacement.

2.2.3. Optical (Luminescent) DO Sensors

- Uses fluorescence-based technology where oxygen concentration is measured by the quenching effect on luminescent dyes.
- More stable, requires less maintenance, and offers real-time data but is relatively expensive.

2.2.4. Remote Sensing and Satellite-Based Methods

- Uses satellite imagery and remote sensors to estimate DO levels in large water bodies.
- Useful for large-scale monitoring but lacks high precision for small-scale applications.

2.2.5. IoT and Machine Learning-Based Monitoring

- Employs smart sensors, wireless networks, and cloud computing for continuous and automated monitoring.
- Machine learning algorithms analyze data patterns and predict DO fluctuations, enabling proactive water management.
- Offers real-time insights, high efficiency, and scalability but requires technological infrastructure.

2.3 IoT in Environmental Monitoring

Real-time environmental parameter monitoring is made possible by IoT technology via cloud-based systems and networked sensors. Water quality assessment, soil health assessment, and air quality monitoring are some examples of applications. Continuous data streams from IoT systems enable prompt interventions. IoT in Monitoring the Environment
Because it allows for real-time data collecting, analysis, and decision-making, the Internet of Things (IoT) is revolutionizing environmental monitoring. IoT-based systems monitor environmental factors including temperature, humidity, pollution levels, and the quality of the air and water by combining smart sensors, wireless connectivity, and cloud computing.

Water quality evaluation is a major use case for IoT in environmental monitoring, where sensors evaluate variables like temperature, turbidity, pH, and dissolved oxygen (DO). By sending data to cloud systems, these sensors enable ongoing observation and early pollution identification. In a similar vein, air quality monitoring systems assist cities in implementing pollution control measures by measuring pollutants like CO_2, PM2.5, and NO_2 using IoT sensors.
By offering remote accessibility, predictive analytics, and real-time alerts, IoT improves environmental protection. IoT-generated data is processed by machine learning algorithms to find trends, improve resource management, and stop environmental harm. Applications include animal conservation (tracking endangered species) and smart agriculture (monitoring soil moisture and weather). IoT increases environmental management's responsiveness, accuracy, and efficiency by automating data collecting and minimizing human intervention. IoT-driven solutions will be essential to creating a sustainable and environmentally friendly future as technology develops.

2.4 Machine Learning in Water Quality Prediction

ML algorithms have been used to identify abnormalities, forecast water quality metrics, and improve resource management. In the prediction of water quality, methods including neural networks, decision trees, and regression analysis have demonstrated encouraging outcomes.
By providing precise, data-driven analysis of important water parameters like dissolved oxygen (DO), pH, turbidity, temperature, and pollutants, machine learning (ML) is transforming the prediction of water quality. Manual sampling and laboratory testing are the mainstays of traditional water quality monitoring techniques, which can be laborious and ineffective. On the other hand, ML-based models use massive information gathered from historical records and IoT sensors to forecast water quality trends in real time.

Complex interactions between environmental elements and water quality are analyzed by machine learning (ML) methods including Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks. These models assist authorities in taking preventive measures against

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pollution and ecological degradation by detecting abnormalities, classifying the state of the water quality, and forecasting future circumstances. Predictive models that combine machine learning (ML) with Internet of Things (IoT)-based water monitoring devices offer early warnings and real-time alerts for problems including low oxygen levels, industrial contamination, and algae blooms. This method encourages effective management of water resources, improves decision-making, and lowers hazards to aquatic life. As machine learning techniques advance, their use in predicting water quality will support smart water management systems and sustainable environmental conservation globally.

3. METHODOLOGY

3.1 System Architecture

The proposed system comprises three main components:

1. **IoT Sensor Network**: Deployed in water bodies, these sensors measure DO levels along with supplementary parameters like temperature, pH, and turbidity.
2. **Cloud Infrastructure**: Enables real-time data storage, processing, and visualization.
3. **ML Models**: Analyze the collected data for predictions, trend analysis, and anomaly detection.

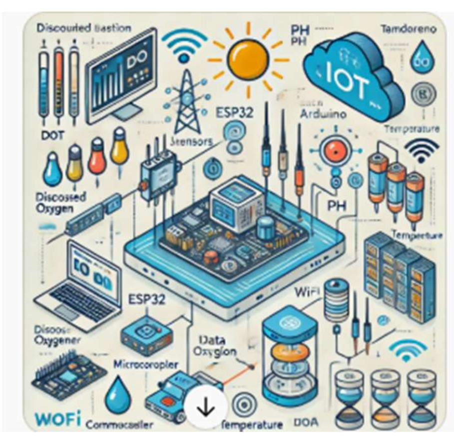

Figure 1: Diagram of the proposed IoT and ML-based dissolved oxygen monitoring system.

3.2 IoT Sensor Network

- **Hardware Components**:

DO sensors: Optical or electrochemical sensors.
Microcontroller: ESP32/Arduino for data acquisition.
Communication module: LoRa/Wi-Fi for data transmission.
Power source: Solar panels or rechargeable batteries.
Sensor Calibration: Sensors are calibrated to account for environmental factors such as salinity and temperature.

3.3 Data Transmission and Storage

Data collected by the IoT sensors is transmitted to a cloud server using MQTT or HTTP protocols. A structured database stores the data, enabling easy retrieval and analysis.

3.4 Machine Learning Models

- **Data Pre-processing**: Raw sensor data is cleaned, normalized, and split into training and testing sets.
- **Feature Selection**: Parameters influencing DO levels (e.g., temperature, pH, and turbidity) are selected for model training.
- **Model Training**: Supervised learning techniques such as Random Forest, Support Vector Machines (SVM), and Neural Networks are used to predict DO levels.
- **Anomaly Detection**: Unsupervised learning algorithms like k-means clustering and autoencoder identify unusual patterns.

3.5 Deployment and Scalability

The system is designed for modular deployment in diverse water bodies. Cloud-based infrastructure ensures scalability and real-time monitoring.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

A prototype system was deployed in a freshwater lake, with IoT sensors measuring DO, temperature, and pH levels. Data was collected over a period of three months.

4.2 Data Analysis

Descriptive Statistics: Average DO levels were found to be within the optimal range for aquatic life.

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ML Model Performance:
Random Forest achieved an accuracy of 92% in predicting DO levels.
SVM and Neural Networks demonstrated comparable performance, with slight variations based on feature selection.

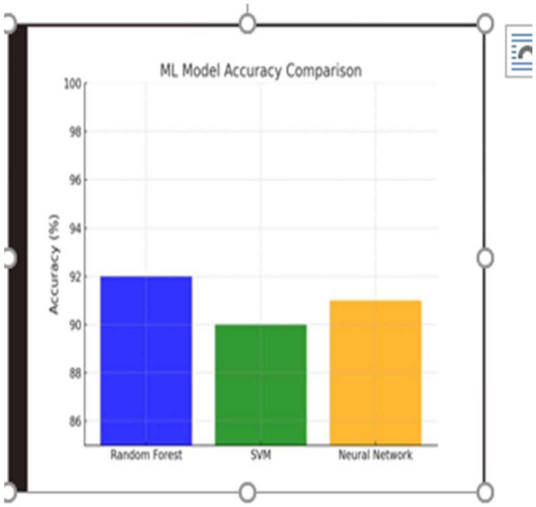

Figure 2: Accuracy comparison of different ML models used for DO prediction.

4.3 Anomaly Detection

Anomalies corresponding to sudden drops in DO levels were accurately detected, correlating with increased organic matter after heavy rainfall.

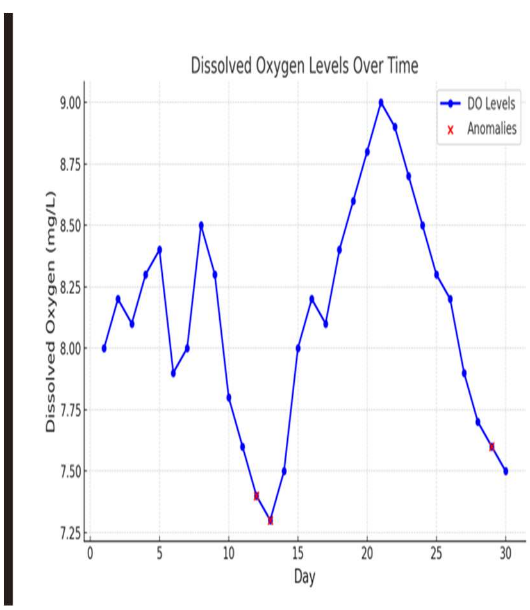

Figure 3: Time-series plot of dissolved oxygen levels with detected anomalies highlighted.

4.4 Comparative Analysis

The IoT-ML system demonstrated significant advantages over traditional methods:

- Real-time data acquisition and analysis.
- Reduced manual intervention.
- Higher accuracy in predictions and anomaly detection.

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

An accurate, scalable, and reliable method of monitoring water quality is provided by the combination of IoT and machine learning technologies for measuring dissolved oxygen in water bodies. Predictive analytics and real-time capabilities of the system offer major benefits over conventional techniques, guaranteeing prompt interventions and promoting environmental sustainability.

5.2 Future Work

Future developments will focus on:

- Enhancing sensor durability and accuracy.
- Expanding the system to monitor additional water quality parameters.
- Incorporating advanced ML models such as deep learning for improved predictions.

Deploying the system in diverse aquatic environments to validate scalability.

REFERENCES

[1]Sawant, Pravin Vilasrao, and Yuvraj M. Patil. "Water Quality Monitoring Using Machine Learning Model." *Journal of Engineering Science* 10, no. 7 (2024): 10-20. https://doi.org/10.52783/jes.6416.

[2]Manx Technology Group. "Measuring Dissolved Oxygen (DO) with IoT." Last modified March 21, 2021. https://manxtechgroup.com/measuring-dissolved-oxygen-do-with-iot/.

[3]Zhang, Lei, et al. "Machine Learning Algorithm as a Sustainable Tool for Dissolved Oxygen Prediction in Reservoirs." *Scientific Reports* 12, no. 1 (2022): 1-12. https://www.nature.com/articles/s41598-022-06969-z.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[4]Science Buddies. "Predicting Future Water Quality with Machine Learning." Accessed February 18, 2025.

[5]Zhao, Y., et al. "Predicting Water Quality Through Daily Concentration of Dissolved Oxygen Using Machine Learning Methods." *Scientific Reports* 13, no. 1 (2023): 1-12. https://www.nature.com/articles/s41598-023-47060-5.

[6]Kumar, P., et al. "Advances in Machine Learning and IoT for Water Quality Monitoring." *Environmental Monitoring and Assessment* 195, no. 7 (2023): 1-20. https://pmc.ncbi.nlm.nih.gov/articles/PMC10963334/.

[7]Patil, Y. M., and P. V. Sawant. "Water Quality Level Estimation Using IoT Sensors and Probabilistic Machine Learning." *Hydrology Research* 55, no. 7 (2024): 775-789. https://iwaponline.com/hr/article/55/7/775/103297/Water-quality-level-estimation-using-IoT-sensors.

[8]Sharma, R., et al. "Machine Learning Model for IoT-Edge Device Based Water Quality Monitoring." In *Proceedings of the IEEE International Conference on IoT and AI (ICIA)*, 2022, 1-6. https://ieeexplore.ieee.org/document/9798212/.

[9]Chen, J., et al. "Water Quality Monitoring Using IoT and Machine Learning Techniques: A Comprehensive Review." *Journal of Environmental Management* 310 (2022): 114725.Li, X., et al. "Real-Time Water Quality Prediction Using IoT and Machine Learning Approaches." *Water Research* 201 (2021): 117346.

[10]Gao, Y., et al. "IoT-Based Water Quality Monitoring System with Machine Learning Prediction in Aquaculture." *Computers and Electronics in Agriculture* 178 (2020): 105742.

[11]Singh, S., et al. "Smart Water Quality Monitoring System Using IoT and Machine Learning Techniques." *Procedia Computer Science* 167 (2020): 2321-2330.

[12]Wang, H., et al. "A Novel IoT and Machine Learning Framework for Water Quality Monitoring." *IEEE Internet of Things Journal* 8, no. 15 (2021): 12041-12051.

[13]Zhou, Y., et al. "Integration of IoT and Machine Learning for Water Quality Prediction." *Journal of Hydrology* 598 (2021): 126225.

[14]Ahmed, K., et al. "IoT-Based Water Quality Monitoring: Machine Learning Approaches." *Sensors* 21, no. 19 (2021): 6467.

[15]Chaudhary, N., et al. "Predictive Analysis of Water Quality Parameters Using IoT and Machine Learning." *Environmental Science and Pollution Research* 28 (2021): 44607-44620.

[16]Khan, M. A., et al. "IoT and Machine Learning-Based Water Quality Monitoring System." *Journal of Ambient Intelligence and Humanized Computing* 12 (2021): 8585-8595.

[17]Rathore, M. M., et al. "IoT-Based Real-Time Water Quality Monitoring System Using Machine Learning." *IEEE Internet of Things Journal* 8, no. 16 (2021): 12550-12556.

[18]Yin, J., et al. "Machine Learning-Based Water Quality Prediction Using IoT Sensor Data." *IEEE Access* 9 (2021): 128593-128605.

[19]Zhang, Y., et al. "IoT-Enabled Water Quality Monitoring and Prediction Using Machine Learning." *IEEE Transactions on Industrial Informatics* 17, no. 8 (2021): 5709-5718.

[20]M V Ganeswara Rao, P Ravi Kumar, T Balaji, " A High Performance Dual Stage Face Detection Algorithm Implementation using FPGA Chip and DSP Processor " , Journal of Information Systems and Telecommunication (JIST),2022,pp 241-248, doi: 10.52547/jist.31803.10.40.241

[21]T Balaji, P.Ravi Kumar, M.V.Ganeswara Rao, Geetha Devi Appari, "Creating The Best Directed Random Testing Method To Minimize Interactive Faults- Empirical Perspective", Journal Of Theoretical And Applied Information Technology, 2023,101(7),Pp-2540-2546

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