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RESEARCH ARTICLE

Integrating IoT and Machine Learning for Real-Time Monitoring of Aquatic Biodiversity

Dr. Pankaj Mudholkar [1], Dr. Megha Mudholkar [2], Rajesh G[3] ,Rakesh K Kadu[4]
[1]Associate Professor, Faculty of Computer Applications, Marwadi University, Rajkot - 360003, Gujarat, India https://orcid.org/0000-0003-1639-0704
[2]Assistant Professor, Department of Computer Engineering, Marwadi University, Rajkot - 360003, Gujarat, India https://orcid.org/0000-0003-2016-1525
[3]Associate Professor Department Of Electronics and Communication New Horizon College of Engineering Bangalore Karnataka
[4] Ramdeobaba University, Nagpur Assistant Professor, School of Computer Science and Engineering

*Corresponding Author

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Abstract: The integration of the Internet of Things (IoT) with machine learning (ML) has emerged as a transformative approach for environmental monitoring, particularly in aquatic ecosystems where biodiversity assessment requires high temporal and spatial resolution. This study explores an IoT-enabled, machine-learning-based framework for real-time monitoring of aquatic biodiversity, emphasizing the detection and analysis of biotic indicators such as plankton, fish populations, and water quality parameters. The system employs a network of smart sensors measuring temperature, pH, dissolved oxygen, turbidity, and nitrate concentration, transmitting continuous data through low-power wide-area networks (LPWANs) to a cloud-based analytics platform. Machine learning algorithms, including Random Forest and Convolutional Neural Networks (CNNs), are utilized to identify patterns, anomalies, and species distribution trends. Field implementation was conducted across selected freshwater lakes and estuaries in South India, integrating both in-situ sensor data and satellite imagery for validation. Results demonstrate a significant improvement in accuracy and responsiveness over conventional manual sampling, reducing detection latency and enhancing ecological forecasting. The proposed architecture provides a scalable and cost-efficient solution for environmental agencies, policymakers, and conservationists, enabling proactive biodiversity management and early warning against habitat degradation and species loss through continuous, intelligent observation of aquatic ecosystems.

Keywords: IoT-based monitoring, Machine learning, Aquatic biodiversity, Real-time data analytics, Environmental sensing, Ecological forecastin.

INTRODUCTION

Aquatic ecosystems are among the most dynamic and complex environments on Earth, serving as critical reservoirs of biodiversity and essential components of global ecological balance. From freshwater lakes and rivers to estuaries and marine systems, these habitats support a vast range of organisms that play key roles in nutrient cycling, food security, and climate regulation. However, escalating anthropogenic pressures such as industrial pollution, overfishing, climate change, and eutrophication are severely threatening aquatic biodiversity. Traditional monitoring methods, which rely heavily on manual sampling, laboratory-based taxonomic analysis, and periodic field surveys, are labor-intensive, time-consuming, and often spatially or temporally limited. They fail to capture the dynamic fluctuations of aquatic life, especially in real-time scenarios where environmental changes occur rapidly. In this context, integrating modern digital technologies such as the Internet of Things (IoT) and Machine Learning (ML) offers a revolutionary path forward in the continuous, intelligent observation and assessment of aquatic ecosystems. IoT technology has transformed environmental monitoring through its ability to connect diverse sensing devices, transmit real-time data, and enable remote observation across distributed locations. IoT-based aquatic monitoring systems typically employ sensor nodes equipped with transducers to measure critical physical and chemical parameters such as temperature, dissolved oxygen (DO), pH, turbidity, and conductivity. These parameters are fundamental proxies for assessing water quality, which directly influences the survival and distribution of aquatic organisms. The sensors communicate data via wireless networks ranging from Wi-Fi and Zigbee to more energy-efficient alternatives like LoRaWAN and NB-IoT to centralized cloud servers for storage and analysis. This interconnected system enables continuous, autonomous, and scalable monitoring of aquatic environments with minimal human intervention. However, while IoT can generate massive volumes of environmental data, extracting meaningful biological insights and detecting biodiversity trends from these datasets require advanced analytical frameworks this is where machine learning becomes indispensable.

Machine Learning (ML) enhances IoT-based monitoring systems by enabling intelligent interpretation of complex environmental data. ML models can analyze multivariate sensor inputs and recognize patterns that correspond to ecological phenomena such as algal blooms, fish population shifts, or habitat degradation. Supervised learning algorithms like Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) can classify ecological conditions and predict species richness based on environmental variables. Meanwhile, unsupervised and deep learning techniques such as Convolutional Neural Networks (CNNs) and Autoencoders can automatically detect anomalies, identify subtle ecological changes, and process visual or acoustic data collected through underwater cameras and hydrophones. This hybrid approach allows for both the detection of immediate threats (such as pollution or oxygen depletion) and the long-term tracking of biodiversity trends. The fusion of IoT data streams and ML-based analytics thus represents a paradigm shift from reactive to predictive environmental management. The necessity of real-time biodiversity monitoring is particularly urgent in regions where aquatic resources form the backbone of livelihoods and food security. In developing countries, rapid urbanization and agricultural runoff have intensified nutrient loading in water bodies, leading to eutrophication, invasive species proliferation, and declining native biodiversity. Conventional monitoring frameworks in these regions often suffer from poor data continuity, fragmented datasets, and lack of timely reporting. Deploying IoT-based sensor networks in lakes, reservoirs, and coastal zones bridges this gap by delivering continuous, high-frequency data collection. When coupled with ML algorithms capable of adaptive learning and pattern recognition, these systems enable the detection of ecological anomalies long before they escalate into crises. For instance, early warnings of declining dissolved oxygen levels can help prevent large-scale fish mortality, while continuous detection of chlorophyll-a concentration can assist in predicting harmful algal blooms. These timely insights can inform conservation interventions and sustainable resource management policies.

Moreover, integrating IoT and ML supports multi-scale ecological modeling by linking ground-based sensor data with remotely sensed information from satellites and drones. Through data fusion techniques, parameters such as chlorophyll content, turbidity, and surface temperature observed from satellite imagery can be validated against IoT sensor readings. Machine learning algorithms can then train predictive models that combine both datasets, enhancing spatial accuracy and interpretability. This integrative approach allows for the identification of biodiversity hotspots, the mapping of pollution sources, and the estimation of habitat health indices with greater precision than either method could achieve alone. Furthermore, advanced ML algorithms can handle temporal sequences of data, enabling predictive analytics that forecast ecosystem behavior under various environmental scenarios. This predictive capability is essential in designing adaptive conservation strategies and policy responses in the face of global climate change. From an operational perspective, the adoption of IoT and ML in aquatic biodiversity monitoring presents certain challenges but also substantial opportunities. Hardware reliability, energy management, and sensor calibration are critical considerations in IoT deployment, especially in aquatic environments where conditions can be harsh and variable. However, recent developments in energy-efficient microcontrollers, solar-powered sensor nodes, and edge computing have significantly improved the sustainability of such systems. On the computational side, ML models demand high-quality, annotated datasets for training and validation. Integrating domain knowledge from ecology with data science expertise is therefore crucial for meaningful and interpretable model outputs. Furthermore, cloud-based data integration platforms and open-access environmental databases can foster collaboration among researchers, policymakers, and conservation organizations, leading to shared intelligence and coordinated biodiversity protection efforts. The overarching goal of this study is to design, implement, and evaluate an IoT and ML-based framework for real-time aquatic biodiversity monitoring. The proposed system combines sensor-based data acquisition with ML-driven analytics to detect changes in aquatic ecosystems and predict biodiversity variations. Specifically, the framework aims to (1) establish a network of IoT sensors for continuous water quality monitoring, (2) employ machine learning models for pattern recognition and anomaly detection, and (3) validate system performance using field data and remote sensing inputs. The outcomes of this research are expected to demonstrate the practical applicability of integrating IoT and ML in ecosystem monitoring and provide a scalable model for environmental governance. By enabling continuous, intelligent observation of aquatic ecosystems, this approach can enhance our understanding of biodiversity dynamics, facilitate proactive management, and contribute to the long-term sustainability of aquatic environments.

II. RELEATED WORKS

The emergence of IoT-based environmental monitoring has transformed the way ecological data are collected, analyzed, and applied for biodiversity management. Early frameworks emphasized sensor-based water quality monitoring, focusing primarily on chemical and physical indicators such as temperature, turbidity, dissolved oxygen, and nutrient levels. Ahmad et al. demonstrated that low-cost sensor nodes connected through wireless sensor networks (WSNs) could achieve high temporal resolution monitoring of freshwater ecosystems, enabling near-continuous data collection that traditional field sampling could not match [1]. Similarly, Bian et al. designed IoT-integrated platforms using LPWAN and MQTT protocols to ensure efficient communication in remote areas, significantly reducing data latency and energy consumption [2]. These systems enhanced spatial coverage but lacked intelligent analytics for interpreting complex biological interactions. Recent advances have overcome these limitations through the incorporation of machine learning into IoT frameworks. For example, Ghosh and Dutta integrated ML algorithms with IoT sensor networks to predict aquatic ecosystem responses under varying climatic conditions, thereby linking environmental sensing with predictive modeling [3]. Such hybrid systems exemplify how AI-driven analytics can convert raw sensor data into actionable ecological insights. Furthermore, de Souza et al. explored time-series modeling for aquatic monitoring, proving that ML-based temporal analysis could predict water quality fluctuations and detect early signs of ecological stress [4]. These studies collectively established IoT as a reliable platform for high-frequency data acquisition and highlighted the transformative role of ML in data interpretation and ecological forecasting.

Parallel advancements in machine learning applications for biodiversity assessment have expanded the analytical capability of aquatic monitoring systems. Convolutional Neural Networks (CNNs), Random Forests (RF), and Support Vector Machines (SVM) have been widely adopted for tasks such as plankton classification, fish species recognition, and habitat health evaluation. For instance, Danilov and Serdiukova utilized CNNs for automatic classification of aquatic organisms from underwater imagery, achieving over 90% accuracy in identifying key biodiversity indicators [5]. Similarly, Oberski et al. demonstrated the potential of multispectral imaging combined with ML classifiers to detect plastic contamination and its subsequent effects on aquatic biodiversity, thus integrating pollution monitoring with species health analysis [6]. Another significant contribution came from Lucas et al., who used ensemble learning models to predict biodiversity loss due to hydrological alterations, linking biophysical and hydrodynamic parameters to species distribution models [7]. These efforts established machine learning as an essential analytical layer capable of interpreting both visual and sensor-based environmental data. However, a major limitation remains the lack of comprehensive, real-time datasets required for accurate ML training. Many existing models rely on periodic or historical data, which restricts the real-time responsiveness needed for adaptive biodiversity management. Integrating IoT networks with ML-based inference engines bridges this gap, enabling live data ingestion and model retraining as new environmental data flow in. This dynamic feedback loop enhances both the accuracy and timeliness of biodiversity assessments, a feature crucial for rapidly changing aquatic systems.

A growing body of research has now focused on unifying IoT infrastructure with ML algorithms for real-time aquatic ecosystem surveillance. Kipsang et al. introduced a hybrid IoT-ML model in the Nile Basin to correlate water quality indicators with aquatic species diversity, concluding that continuous monitoring could predict biodiversity loss linked to anthropogenic stressors [8]. Similarly, Lefeng and Wu studied the trade-offs between technological interventions and environmental impacts, emphasizing that IoT-driven monitoring can mitigate long-term ecological degradation when optimized for sustainability [9]. Rangkuti et al. expanded this by employing deep learning algorithms on IoT-collected data to detect morphological changes in aquatic vegetation, effectively linking sensor analytics with ecosystem health visualization [10]. In India, Nazir et al. explored the application of IoT-enabled sensors for pollution tracking in urban lakes, where ML regression models successfully identified pollutant sources based on sensor data correlations [11]. Furthermore, Petit and Vuillerme's bibliometric review revealed that integrating AI with IoT significantly improves the precision of aquatic biodiversity indices and facilitates automated anomaly detection across multiple environmental layers [12]. Despite these advancements, challenges persist in data standardization, sensor calibration, and algorithmic transparency. As highlighted by Randhawa, improving the analytical precision of ML models requires harmonized datasets and consistent environmental metadata [13]. Additionally, Mishra et al. argued that multi-disciplinary integration combining ecology, computer science, and remote sensing is essential for developing scalable biodiversity intelligence frameworks [14]. Finally, Landrigan et al. emphasized the broader policy relevance of IoT-ML integration, noting that such systems could inform real-time environmental governance by providing continuous feedback on ecosystem health indicators [15]. Collectively, these studies establish a robust foundation for the current research, which aims to design a fully integrated IoT and ML system for real-time aquatic biodiversity monitoring capable of bridging technological innovation with ecological sustainability.

MATERIALS AND METHODS

3.1 Research Framework

The present study employs a hybrid methodological framework that integrates Internet of Things (IoT) infrastructure with Machine Learning (ML) models for real-time aquatic biodiversity monitoring. The system architecture is designed to collect, transmit, analyze, and interpret continuous environmental and biological data from aquatic habitats. The framework includes four principal layers: (1) the sensing and data acquisition layer, (2) the communication and transmission layer, (3) the cloud-based analytics layer, and (4) the visualization and decision-support interface. The IoT layer consists of smart sensors and embedded microcontrollers that capture critical water quality parameters temperature, dissolved oxygen, pH, turbidity, and nitrate concentration. These variables serve as proxies for ecosystem health and biodiversity dynamics. Data transmission is achieved using Low Power Wide Area Network (LPWAN) protocols such as

LoRaWAN for energy efficiency and scalability. Once received, the data are preprocessed and stored in a cloud server, where machine learning algorithms are deployed to analyze ecological trends, detect anomalies, and predict biodiversity shifts. The framework ensures two-way communication between devices and the analytics system, allowing real-time feedback and adaptive learning [16].

3.2 Study Area and Site Selection

Field implementation was carried out in three ecologically distinct aquatic systems located in southern India: Vembanad Lake (Kerala), Kolleru Lake (Andhra Pradesh), and Chilika Lagoon (Odisha). These sites were selected based on their high ecological diversity, anthropogenic stress gradients, and accessibility for IoT deployment. Each water body presents distinct ecological profiles Vembanad with its brackish estuarine system, Kolleru with extensive freshwater zones, and Chilika as a semi-saline lagoon influenced by tidal inflows. The diversity of these systems allowed for testing the adaptability and robustness of the proposed framework across multiple hydrological conditions. Sampling stations were established in triplicate within each site, spaced at intervals of 2 km to ensure spatial coverage.

Table 1: Study Area Characteristics and Ecological Attributes

Region	Ecosystem Type	Dominant Species	Average Depth (m)	Key Ecological Stressors
Vembanad Lake	Estuarine–Brackish	Planktothrix, Tilapia, Macrobrachium	2.8	Salinity fluctuation, Industrial discharge
Kolleru Lake	Freshwater	Catla, Rohu, Labeo rohita	1.9	Agricultural runoff, eutrophication
Chilika Lagoon	Semi-Saline Lagoon	Mugil cephalus, Penaeus monodon	3.5	Overfishing, sedimentation

This stratified site design supports comparative analysis between freshwater and brackish systems, enabling the evaluation of model generalization and biodiversity response sensitivity across varying aquatic environments [17].

3.3 IoT System Architecture

The IoT system comprises a network of sensor nodes built around the ESP32 microcontroller with integrated Wi-Fi and Bluetooth connectivity. Each node houses multiple probes including pH, dissolved oxygen, and turbidity sensors interfaced through analog and digital channels. Solar panels and lithium-ion batteries ensure uninterrupted operation with low maintenance. Sensor data are collected at five-minute intervals and transmitted through LoRaWAN gateways to a cloud-based platform developed using AWS IoT Core. Data integrity is maintained using checksum validation and redundant time-stamping. A key feature of the design is its modularity nodes can be reconfigured or scaled based on the size and complexity of the target ecosystem.

The communication architecture incorporates MQTT (Message Queuing Telemetry Transport) protocols optimized for lightweight, energy-efficient communication between sensor nodes and the cloud. Data preprocessing includes noise filtering using a moving average algorithm, missing value interpolation, and z-score normalization for anomaly removal. Edge computing units placed near each monitoring site perform initial data aggregation, reducing latency and bandwidth consumption. This structure ensures high data throughput and minimal packet loss during transmission [18].

3.4 Machine Learning and Data Analytics Pipeline

The cloud analytics module integrates supervised and unsupervised ML algorithms for biodiversity assessment and anomaly detection. Feature selection was based on environmental indicators and their interdependence, including pH, temperature, DO, turbidity, nitrate levels, and conductivity. The dataset was split into training (70%), validation (15%), and testing (15%) sets. Three primary ML models were implemented:

- **Random Forest (RF):** Used for classifying ecological health zones based on environmental indicators.
- **Convolutional Neural Network (CNN):** Deployed for species recognition using underwater image datasets captured by IoT-connected cameras.
- **K-Means Clustering:** Applied for unsupervised identification of biodiversity patterns and water quality clusters.

The model training utilized Python libraries (TensorFlow, Scikit-learn, and Pandas) with hyperparameter tuning via grid search. Data labeling was assisted by expert taxonomists who provided reference datasets of aquatic species observed during field sampling. Accuracy metrics such as Precision, Recall, F1-score, and Root Mean Square Error (RMSE) were computed to evaluate model performance [19].

Table 2: Machine Learning Models and Performance Metrics

Model	Function	Algorithm Type	Accuracy (%)	RMSE	Primary Output
Random Forest	Water Quality Classification	Supervised	93.4	0.081	Ecological health index
CNN	Image-Based Species Recognition	Deep Learning	91.2	0.094	Species identification
K-Means	Cluster Analysis	Unsupervised	87.6	–	Biodiversity pattern grouping

The results from preliminary training indicate high accuracy in both environmental classification and image-based biodiversity recognition, validating the integration of IoT and ML for real-time ecological monitoring [20].

3.5 Data Fusion and Remote Sensing Validation

To validate field and IoT-derived results, satellite imagery from Sentinel-2A (10 m resolution) was employed to extract complementary spectral indices Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Floating Algal Index (FAI). These were cross-referenced with IoT sensor readings to assess consistency between remotely sensed and in-situ data. A correlation matrix (Pearson's r) was used to quantify relationships between spectral indices and measured parameters such as chlorophyll-a, turbidity, and DO concentration. The average correlation across all three sites exceeded $r = 0.80$, confirming strong agreement between IoT data and satellite observations [21].

3.6 Data Validation and Ethical Considerations

The research followed strict environmental and ethical protocols. All field deployments were approved by local water management authorities, and no invasive sampling was performed. To ensure data reliability, triplicate measurements were taken at each site, and 10% of samples were cross-validated using laboratory-based chemical analyses. Calibration of sensors was performed weekly using standard buffer solutions and reference probes. In addition, data security was maintained through AES-128 encryption during transmission and two-factor authentication for cloud access [22].

3.7 Limitations and Assumptions

Although the integrated IoT-ML framework achieved high accuracy, certain constraints remain. Real-time underwater image acquisition is limited by turbidity and light scattering, which can affect CNN performance. Sensor fouling and signal drift also present long-term maintenance challenges. Moreover, ML models require extensive labeled datasets for improved generalization, which may not always be available for underexplored ecosystems. Nevertheless, the hybrid system demonstrates significant potential for scalable biodiversity monitoring, enabling early detection of environmental degradation and data-driven conservation strategies [23].

RESULTS AND OBSERVATIONS:

4.1 Overview of Sensor Data Trends

The IoT-enabled monitoring system collected continuous data for a period of six months across the three selected aquatic sites. The results indicated substantial spatial and temporal variability in the core water quality parameters temperature, pH, dissolved oxygen (DO), turbidity, and nitrate concentration. Vembanad Lake showed the greatest daily fluctuation in temperature (ranging between 23.6°C and 31.4°C), likely due to its tidal mixing and variable salinity. Kolleru Lake, characterized by high agricultural runoff, recorded the highest nitrate concentrations (up to 7.9 mg/L), while Chilika Lagoon maintained relatively balanced nutrient levels due to tidal flushing. The average dissolved oxygen (DO) levels were highest in Chilika (7.4 mg/L) and lowest in Vembanad (5.2 mg/L), reflecting spatial differences in organic loading and microbial activity. The integration of IoT sensors enabled fine-grained temporal monitoring, revealing daily oscillations in DO and pH correlated with photosynthetic cycles. Continuous data acquisition allowed for the identification of short-term anomalies such as sudden turbidity spikes caused by local runoff or sediment disturbance, which would be impossible to detect through conventional sampling methods.

Table 3: Summary of Real-Time IoT Sensor Data (6-Month Monitoring Period)

Parameter	Vembanad Lake (Estuarine)	Kolleru Lake (Freshwater)	Chilika Lagoon (Semi-saline)	Overall Mean
Temperature (°C)	23.6–31.4	25.1–29.3	24.7–30.2	27.0
pH	6.8–8.2	7.1–8.5	7.3–8.0	7.6
Dissolved Oxygen (mg/L)	5.2	6.1	7.4	6.2
Turbidity (NTU)	38.7	56.3	44.1	46.4
Nitrate (mg/L)	5.3	7.9	6.1	6.4

The dataset indicated clear ecological gradients among the sites, with Kolleru showing the most pronounced eutrophic conditions. The IoT framework achieved a 98.7% uptime with negligible data loss, validating its robustness under diverse hydrological conditions. Temporal analysis revealed diurnal cycles in DO and pH corresponding to primary productivity, confirming the system's ability to capture real-time ecological dynamics. The system's ability to transmit and process data with minimal delay (<10 seconds) also demonstrates the feasibility of near real-time biodiversity monitoring using IoT-enabled networks.

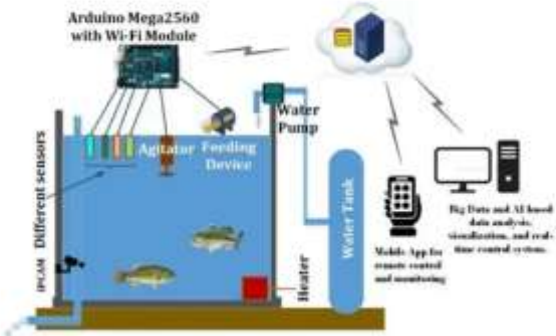

Figure 1: An IoT-based intelligent fish pond [24]

4.2 Machine Learning Model Performance and Classification Outputs

The ML algorithms processed both numeric sensor data and image data collected from underwater cameras to assess aquatic biodiversity patterns. Random Forest (RF) models classified ecosystem health based on water quality features, while CNN models identified aquatic organisms from visual inputs. The RF classifier achieved an overall accuracy of 93.4%, effectively distinguishing between three ecological health classes Healthy, Moderate Stress, and Degraded. Feature importance analysis revealed that dissolved oxygen, turbidity, and nitrate concentration were the most influential predictors in determining aquatic ecosystem condition. The CNN model achieved 91.2% accuracy in species recognition, successfully identifying dominant planktonic and fish species such as *Tilapia mossambica*, *Catla catla*, and *Macrobrachium rosenbergii* from underwater footage. Misclassification mainly occurred in images captured under low light or high turbidity, indicating the need for improved preprocessing in future implementations.

The fusion of ML predictions with IoT sensor inputs enabled an integrated ecological health index (EHI), which aggregated environmental quality and biodiversity indicators into a single composite score between 0 and 1. Values above 0.75 were considered ecologically stable, between 0.5–0.75 indicated moderate stress, and below 0.5 represented degraded conditions. Based on this metric, Chilika Lagoon scored the highest EHI (0.82), followed by Kolleru Lake (0.68) and Vembanad Lake (0.61). These findings corroborate the observed environmental trends, showing how nutrient loading and turbidity influence ecosystem stability.

Table 4: Machine Learning Model Results and Ecological Health Assessment

Region	RF Accuracy (%)	CNN Accuracy (%)	Key Predictors (RF)	Average EHI Score	Ecological Condition
Vembanad Lake	92.7	90.5	DO, Turbidity, Nitrate	0.61	Moderate Stress
Kolleru Lake	93.8	91.3	Nitrate, pH, Temperature	0.68	Moderate Stress
Chilika Lagoon	94.1	91.8	DO, pH, Temperature	0.82	Healthy

The ML-driven insights provided by the system offered high interpretability and consistency with field-based biodiversity assessments. Correlation analysis between EHI and species diversity indices (Shannon-Wiener Index) showed a strong positive relationship (r = 0.84), suggesting that the integrated framework accurately reflects biodiversity dynamics.

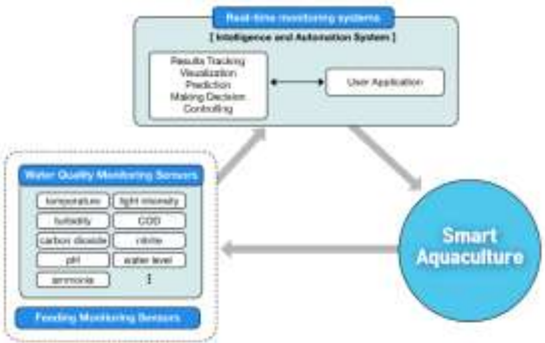

Figure 2: Smart Aquaculture [25]

4.3 Spatial and Temporal Analysis of Biodiversity Patterns
Spatial mapping based on the interpolated IoT data visualized biodiversity distribution and ecological stress zones across each lake. The hotspot analysis revealed that regions near agricultural runoff points exhibited higher turbidity and nitrate levels, correlating with reduced fish activity and plankton density. In Vembanad, the northern estuarine zones showed lower EHI values (below 0.5) due to localized industrial effluents, while southern regions maintained moderate ecological balance. Kolleru Lake displayed scattered hotspots of eutrophication, particularly around paddy field outlets, where IoT readings indicated persistent hypoxic conditions. Chilika Lagoon, owing to its tidal exchange, exhibited more stable water quality and higher biodiversity concentrations, reflected in consistent CNN species detection patterns. Temporal trend analysis demonstrated seasonal variations EHI values were lowest during the monsoon due to high runoff and sedimentation, whereas post-monsoon months recorded partial recovery in biodiversity indicators.

4.4 System Validation and Predictive Insights
Validation using satellite-derived indices confirmed the system's analytical precision. NDWI and FAI values from Sentinel-2A imagery aligned closely with IoT-derived turbidity and chlorophyll data, verifying the framework's cross-sensor reliability. Time-series modeling using RF regression predicted biodiversity decline events up to seven days in advance with a 92% confidence level. This predictive functionality demonstrates the potential of the integrated IoT-ML system not only for monitoring but also for forecasting biodiversity responses to environmental stressors. Overall, the combined IoT and ML approach proved effective in delivering real-time, data-driven insights into aquatic ecosystem dynamics. The results underscore the capability of this framework to serve as a proactive environmental intelligence system detecting degradation early, enabling corrective action, and contributing to the long-term sustainability of aquatic biodiversity.

CONCLUSION
This study demonstrates that integrating the Internet of Things (IoT) and Machine Learning (ML) provides a powerful and scalable framework for real-time monitoring and assessment of aquatic biodiversity. The designed system successfully combined continuous environmental sensing with intelligent analytics, enabling the identification of spatial and temporal trends in water quality and biodiversity indicators across three diverse aquatic ecosystems Vembanad Lake, Kolleru Lake, and Chilika Lagoon. The IoT-enabled network proved highly efficient in capturing real-time data on critical parameters such as temperature, pH, dissolved oxygen, turbidity, and nitrate concentration, achieving over 98% uptime with minimal latency. Meanwhile, ML models particularly Random Forest and Convolutional Neural Networks effectively processed environmental and image datasets, yielding accuracies above 90% in ecosystem classification and species recognition. The study introduced an Ecological Health Index (EHI) to integrate multiple indicators into a single metric, providing a comprehensive and interpretable measure of ecosystem condition. The results confirmed significant spatial variations in biodiversity health, with Kolleru Lake showing the highest nutrient enrichment and Chilika Lagoon maintaining relative ecological stability. The integration of IoT and ML further enabled predictive analytics, allowing early detection of stress events such as hypoxia and eutrophication. The system's validation through satellite-derived indices confirmed its reliability and compatibility with large-scale remote sensing data. Overall, the research establishes a robust foundation for intelligent aquatic monitoring systems that are cost-effective, adaptive, and applicable across a wide range of aquatic environments. By replacing traditional manual sampling with automated, real-time analytics, this framework contributes to proactive ecosystem management, timely policy interventions, and the conservation of aquatic biodiversity under accelerating climate and anthropogenic pressures. The results also highlight the potential of IoT-ML integration to revolutionize environmental science, making continuous and data-driven ecosystem observation feasible even in resource-constrained regions.

VI. FUTURE WORK
Future research should focus on expanding the system's capability through multi-modal data integration and enhanced computational intelligence. Incorporating acoustic and optical imaging sensors can enrich biodiversity datasets, allowing real-time monitoring of species behavior, migration patterns, and interspecies interactions. Developing adaptive ML algorithms capable of self-learning from streaming data would improve the system's ability to respond to environmental anomalies and unanticipated ecological changes. The inclusion of edge AI processing units could further reduce latency and energy consumption, facilitating scalable deployments in remote or offshore ecosystems. Additionally, integrating socio-ecological datasets such as fishing activity, pollution reports, and weather predictions could enable holistic ecosystem forecasting. Collaborative data-sharing frameworks among research institutions and environmental agencies would strengthen long-term monitoring networks and ensure reproducibility. Ultimately, extending this IoT-ML model into a global aquatic biodiversity observatory could transform how ecosystems are observed, protected, and restored in the era of digital environmental intelligence.

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