Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal
of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 6 (2026)

An Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification

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Publication Date: June 13, 2026 DOI: **10.5281/zenodo.20680123**

Abstract

Coastal ecosystems, particularly seagrass meadows, are increasingly threatened by pollution, climate change, and human activities, creating a need for efficient and real-time environmental monitoring systems. This study aimed to develop and evaluate an Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification that combines Internet of Things (IoT), machine learning, image processing, and real-time monitoring technologies to support coastal ecosystem management and marine conservation. The study employed a Developmental and Mixed Methods Research Design using the System Development Life Cycle (SDLC) Prototyping Model. The qualitative phase involved stakeholder consultations and expert validation to determine system requirements, usability, and environmental monitoring needs, while the quantitative phase focused on system testing and evaluation using ISO/IEC 25010:2011 software quality standards. The system utilized temperature, pH, and dissolved oxygen sensors integrated with Arduino Uno, Raspberry Pi, GSM communication, and a web-based monitoring dashboard. A Convolutional Neural Network (CNN) was implemented to automate seagrass identification using underwater image analysis. The developed system was evaluated by seventy (70) Marine Biology students and obtained an overall weighted mean of 4.34, verbally interpreted as Very Satisfactory, indicating high acceptability, reliability, and functionality. The study concluded that integrating IoT, machine learning, and environmental sensing technologies can provide a practical and sustainable solution for real-time coastal ecosystem monitoring. It is recommended that future researchers integrate additional water quality parameters, improve AI models through larger datasets, and incorporate mobile and cloud-based technologies to further enhance monitoring accuracy, accessibility, and long-term environmental sustainability.

Keywords: *Information Technology, Machine Learning, Real-Time Water Quality Monitoring, Seagrass Identification, Sequential Exploratory Mixed-Methods Research Design, Philippines*

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BACKGROUND AND RATIONALE

Coastal ecosystems are among the most productive and ecologically significant habitats on Earth, providing vital services such as carbon sequestration, shoreline protection, and biodiversity support (Orth et al., 2006; Duarte, 2002). Among these ecosystems, seagrass meadows play a pivotal role in maintaining marine health, acting as nurseries for fish, stabilizing sediments, and improving water quality (Waycott et al., 2009). However, these habitats are increasingly threatened by anthropogenic pressures including pollution, climate change, and coastal development (Unsworth et al., 2015). To safeguard these ecosystems, real-time monitoring systems that integrate both physico-chemical water parameters and seagrass identification technologies are essential.

In tropical coastal regions like the Philippines, where seagrass meadows are abundant, monitoring water quality is particularly crucial (Fortes et al., 2018). Elevated nutrient levels, often from agricultural runoff, can lead to eutrophication, reducing light penetration and impairing seagrass growth. Similarly, changes in temperature and salinity can affect seagrass physiology and distribution. By integrating smart sensors with cloud-based analytics, researchers and policymakers can track these changes in real time and implement timely interventions.

Seagrass identification has benefited immensely from the convergence of computer vision, machine learning, and underwater robotics (Mishra et al., 2020). High-resolution underwater cameras mounted on autonomous vehicles can capture detailed images of the seabed, which are then processed using AI algorithms to classify seagrass species and assess coverage. Wibowo et al. (2023) developed a system that combines underwater imaging with convolutional neural networks (CNNs) to accurately identify seagrass patches and monitor their health over time.

These technologies not only improve spatial accuracy but also reduce the need for labor-intensive fieldwork. Furthermore, they enable the detection of subtle changes in seagrass morphology, which may indicate stress or degradation. When coupled with water quality data, these insights provide a holistic view of habitat dynamics, facilitating ecosystem-based management.

The integration of physico-chemical monitoring and seagrass identification into a single platform represents a paradigm shift in marine conservation. Such systems can be deployed in coastal zones to continuously monitor environmental conditions and habitat status. Data from sensors and imaging devices are transmitted to cloud servers, where they are analyzed using machine learning models to detect anomalies, predict trends, and generate actionable insights. Algorithms such as convolutional neural networks (CNNs) are particularly effective for image-based seagrass classification, enabling automated recognition of species and coverage patterns from underwater photographs. For time-series sensor data, methods like random forests and support vector machines (SVMs) can be applied to classify water quality states and identify deviations from normal baselines. Meanwhile, recurrent neural networks (RNNs) and their variants (e.g., LSTMs) are well-suited for forecasting long-term ecological trends by capturing temporal dependencies in environmental variables such as salinity, temperature, and nutrient

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 6 (2026)

levels. By combining these approaches, the platform not only enhances the accuracy of habitat assessments but also provides predictive capabilities that support proactive conservation strategies and adaptive management of fragile coastal ecosystems.

Integrated monitoring systems face several challenges. Sensor calibration, data interoperability, and power management remain persistent technical hurdles, while the deployment of underwater imaging systems requires careful planning to minimize ecological disturbance. Beyond these technological considerations, the active involvement of local communities plays a pivotal role in ensuring the effectiveness and sustainability of such initiatives. Community members contribute not only through participatory monitoring and stewardship but also by providing traditional ecological knowledge that enriches scientific datasets and contextualizes sensor outputs. Their engagement fosters co-production of knowledge enhances the legitimacy of conservation efforts, and strengthens governance frameworks by embedding transparency and accountability into data management practices. Moreover, community participation helps bridge the gap between scientific innovation and social acceptance, ensuring that monitoring outcomes are aligned with local priorities and cultural values. Addressing issues of data privacy and governance in ways that respect community agency is therefore essential, as it builds trust, empowers stakeholders, and ultimately supports the long-term resilience of coastal ecosystems.

This research aligns with Sustainable Development Goals (SDGs), particularly SDG 14 (Life Below Water), by promoting ecosystem-based management and biodiversity protection. Policy makers gain access to empirical, real-time data to guide legislation, funding allocation, and coastal development strategies.

The University of Science and Technology of Southern Philippines (USTP) Panaon Campus is situated in Purok 6, Barangay Punta, within the Municipality of Panaon, Misamis Occidental, Philippines, the campus has evolved into a regional hub for fisheries education, marine research, and community extension services. Panaon is a coastal municipality bordered by rich marine ecosystems, including seagrass meadows, coral reefs, and mangrove forests. These habitats are vital to local biodiversity and support the livelihoods of small-scale fishers and aquaculture practitioners. The proximity of the campus to these ecosystems provides direct access for fieldwork, sensor deployment, and underwater imaging, making it a strategic location for real-time habitat monitoring.

Seagrass meadows are vital to coastal ecosystems, but they face growing threats from pollution, climate change, and human activity (Waycott et al., 2009). Traditional monitoring methods are slow, limited, and lack real-time data, making it difficult to respond quickly to environmental changes. In regions like the Philippines, there's an urgent need for smart, integrated systems that combine water quality sensors with AI-based seagrass identification. Current tools manual sampling, satellite imagery, and field surveys are often inaccurate, weather-dependent, and labor-intensive. This study addresses the lack of unified, real-time habitat monitoring by developing a smart platform that merges physico-chemical water analysis with underwater imaging and machine learning. The goal is to provide continuous, high-resolution data to support conservation, inform policy, and empower local stakeholders.

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REVIEW OF RELATED LITERATURE

Seagrass ecosystems are critical to coastal resilience, biodiversity, and carbon sequestration. However, their monitoring remains challenging due to environmental variability, water turbidity, and the limitations of traditional field-based methods. Recent advances in machine learning (ML), remote sensing, and real-time water quality monitoring have opened new pathways for integrated systems that can simultaneously assess water parameters and identify seagrass distribution.

Machine Learning in Aquatic Ecosystem Monitoring

Water quality monitoring and prediction have become increasingly important due to the growing impacts of population growth, industrialization, climate change, and intensified land-use activities on aquatic ecosystems. Conventional water quality assessment methods, which rely heavily on point sampling and laboratory analysis, are often costly, time-consuming, and limited in spatial and temporal coverage. As a result, researchers have increasingly explored data-driven approaches, particularly machine learning (ML), to overcome these limitations and enhance the accuracy and efficiency of water quality evaluation.

Recent studies have demonstrated that machine learning algorithms are well suited for water quality prediction because they can model complex, nonlinear relationships among physical, chemical, and biological parameters. Rogers and Ambili (2024) reported that ML models such as Random Forest, Support Vector Machines, and Gradient Boosting Machines achieved high predictive accuracy when applied to water quality indicators including pH, dissolved oxygen, and turbidity. Their findings emphasized that ML-based prediction models can support early warning systems and improve sustainable water resource management by identifying key factors influencing water quality variation.

The application of machine learning in marine and coastal environments has also gained attention due to the increasing occurrence of eutrophication and harmful algal blooms. Deng et al. (2021) applied artificial neural networks and support vector machines to long-term marine datasets in Hong Kong and found that ML models were capable of accurately predicting algal growth trends and magnitudes. Their study highlighted the robustness of ML approaches in learning complex relationships between algal dynamics and coastal environmental variables, making them valuable tools for coastal hydro-environment management and early warning systems.

Advancements in ML have further been strengthened by the integration of Internet of Things (IoT) technologies, which enable real-time data collection from distributed sensor networks. Essamlali et al. (2024) explained that IoT-based water quality monitoring systems, when combined with supervised and unsupervised ML algorithms, allow continuous monitoring, anomaly detection, and predictive analysis of water quality conditions. Their review emphasized that such systems improve decision-making, reduce monitoring costs, and enhance the protection of water resources by enabling timely responses to contamination events. Similarly, Shashank et al. (2024) noted that ML-IoT-based monitoring systems provide advantages such as scalability, remote accessibility, and real-time analysis, which are critical for ensuring water safety and sustainability

In addition to real-time monitoring, machine learning has been widely used for assessing ecological conditions such as trophic status in aquatic ecosystems. Uddin et al. (2024) developed a data-driven trophic status assessment model using ML and artificial intelligence techniques to address limitations of traditional trophic status indices. Their results showed that ML-based models, particularly those using advanced algorithms such as XGBoost, produced more reliable and sensitive assessments of eutrophication in coastal and transitional waters compared with conventional approaches.

Remote sensing technologies have further expanded the applicability of machine learning in water quality monitoring by enabling large-scale and repetitive observations of water bodies. Hassan and Woo (2021) conducted a systematic review of ML applications using satellite data and found that algorithms such as ANN, Random Forest, and SVM were effective in estimating water quality parameters including chlorophyll-a, turbidity, suspended solids, temperature, and salinity. Their findings indicated that ML-based remote sensing approaches can successfully complement traditional monitoring methods and support ecosystem restoration and environmental policy implementation. In support of this, Akbari et al. (2020) demonstrated that machine learning classifiers applied to multitemporal Sentinel-1 and Sentinel-2 satellite data could accurately detect aquatic weed infestations in wetlands, highlighting the potential of ML-driven remote sensing for ecosystem monitoring and management.

Broader reviews have reinforced the growing role of machine learning across different water environments. Zhu et al. (2022) reviewed the application of ML in evaluating surface water, groundwater, drinking water, wastewater, and seawater, concluding that ML models offer higher flexibility and precision than traditional statistical and index-based methods. Their study emphasized that ML can effectively handle large datasets and uncover hidden patterns essential for water quality evaluation and pollution control. Likewise, Mohan et al. (2025) highlighted that integrating machine learning with remote sensing enhances the accuracy and efficiency of water quality prediction by capturing complex spatial and temporal variations, while also identifying critical research gaps for future studies.

Machine learning has also been extensively applied in chemical and biological oceanography, where large and complex datasets are common. Sadaiappan et al. (2023) reported that ML techniques have been successfully used to predict chemical properties, classify plankton species, detect marine mammals acoustically, and forecast hypoxic conditions and harmful algal bloom events. Their review demonstrated that ML provides a powerful analytical framework for understanding ocean biogeochemical processes and supporting long-term environmental monitoring.

Smart Water Monitoring Technologies

Water quality monitoring has increasingly become a global priority due to rising water pollution, population growth, and the limitations of traditional laboratory-based testing methods.

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Volume 2 Issue 6 (2026)

Conventional water quality assessment typically involves manual sampling and laboratory analysis, which are time-consuming, costly, and unable to provide real-time feedback. To address these limitations, researchers have emphasized the integration of Internet of Things (IoT), wireless sensor networks (WSNs), and smart sensing technologies to enable continuous, automated, and real-time monitoring of water quality parameters.

Several studies highlight that IoT-based water quality monitoring systems significantly enhance efficiency by enabling real-time measurement of key physicochemical parameters such as pH, turbidity, temperature, dissolved oxygen, conductivity, and total dissolved solids. Spoorthi et al. (2022) emphasized that IoT-enabled systems using sensors and microcontrollers can provide cost-effective and continuous monitoring of drinking water quality, reducing health risks associated with contaminated water. Similarly, Pasika and Gandla (2020) demonstrated that low-cost IoT architectures integrated with cloud platforms such as ThingSpeak allow remote monitoring and data visualization, making water quality information easily accessible to stakeholders.

Recent reviews further indicate that IoT-based water quality monitoring systems outperform earlier WSN-based approaches by addressing issues related to energy efficiency, scalability, communication reliability, and real-time analytics. Jan et al. (2021) noted that while early WSN systems were limited by power consumption and data security challenges, modern IoT-based systems leverage cloud computing and standardized communication protocols to deliver more robust and scalable solutions, particularly for domestic water applications. The study also emphasized alignment with World Health Organization (WHO) standards to ensure safe drinking water.

Empirical studies demonstrate that smart water quality monitoring systems can detect pollution at an early stage, enabling timely intervention and prevention of severe public health and environmental consequences. Lakshmikantha et al. (2021) highlighted that continuous monitoring using IoT sensors allows early detection of contamination, thereby reducing disease outbreaks and economic losses linked to poor water quality. Similar findings were reported by Pushpa et al. (2023), who validated the effectiveness of IoT-based systems through real-world testing using multiple water samples, confirming improved reliability and responsiveness compared to manual monitoring.

Beyond individual monitoring systems, broader smart water management frameworks have been proposed to integrate water quality monitoring with infrastructure management. Palermo et al. (2022) discussed how smart water technologies embedded within smart buildings and urban infrastructure enable efficient water resource management through real-time sensing, leak detection, and consumption analysis, contributing to sustainability goals. Patgar et al. (2023) further expanded this perspective by introducing smart water grids that combine IoT, artificial intelligence, and big data analytics to enhance predictive decision-making and system resilience, although challenges related to cost and cybersecurity remain significant barriers to adoption

Advanced frameworks integrating cloud computing, semantic modeling, and machine learning have also been explored. Mezni et al. (2022) proposed a service-oriented, sensor cloud-based framework that uses knowledge graphs and intelligent analytics to support large-scale monitoring and decision-making for water environments, demonstrating improved accuracy and adaptability in real-world scenarios. Complementing this, Gupta et al. (2020) reviewed smart water technologies across multiple domains, including water treatment plants and natural water bodies, concluding that smart systems significantly reduce water loss and contamination risks, though high implementation costs pose challenges in developing regions.

Earlier foundational surveys, such as that by Dong et al. (2015), provided a comprehensive overview of smart water quality monitoring systems by examining data collection, transmission, and management subsystems. The study underscored the importance of early warning mechanisms, data analytics, and quality assurance processes in ensuring reliable and actionable water quality information. Collectively, the reviewed literature demonstrates clear progression from manual and WSN-based monitoring toward integrated IoT-driven smart water quality monitoring systems, underscoring their critical role in safeguarding public health, improving water governance, and promoting sustainable water resource management.

AI-Based Seagrass Identification

Tallam et al. (2023) applied a deep learning image segmentation technique, DeepLab v3, to classify intertidal eelgrass (Zostera marina) from drone-acquired imagery in Morro Bay, California. Their model achieved high recall (0.954) and an F1 score of 0.809, demonstrating the potential of semantic segmentation for fine-scale eelgrass monitoring compared to traditional manual annotation methods.

Perez et al. (2020) developed two deep learning models—a deep capsule network (DCN) and a convolutional neural network (CNN)—to quantify seagrass distribution using multispectral WorldView-2 satellite imagery. Their approach focused on regression of leaf area index (LAI), with CNN achieving an average RMSE of 0.19, outperforming traditional regression and support vector machine methods. They also introduced transfer learning to generalize models across different coastal locations

Scarpetta et al. (2022) explored the use of U-Net convolutional neural networks for monitoring Posidonia oceanica meadows along the Apulian coastline using high-resolution satellite images. Their model achieved an overall accuracy of 92% and a mean Intersection over Union (IoU) of 0.87, highlighting the effectiveness of CNN-based segmentation for large-scale seagrass mapping.

Islam et al. (2018) introduced a deep capsule network for seagrass detection in Florida coastal waters using multispectral satellite imagery. Their model achieved superior performance compared to CNN and SVM, with cross-validation accuracies exceeding 99% in some locations. They also proposed a generative fine-tuning strategy to enhance transfer learning across sites.

Moniruzzaman et al. (2019) applied Faster R-CNN with an Inception V2 backbone to detect Halophila ovalis from underwater digital images. Using a dataset of 2,699 images, their model achieved mean average precision (mAP) values of 0.261 (field and lab images) and 0.346 (lab-only images), establishing a baseline for underwater seagrass detection.

Raine et al. (2020) proposed a multi-species seagrass detector using CNNs trained on a newly created dataset (DeepSeagrass) from Moreton Bay, Australia. Their patch-based classification approach achieved an overall accuracy of 92.4% when background classes were refined, demonstrating the feasibility of multi-species detection in underwater imagery.

Chowdhury et al. (2024) presented an AI-driven remote sensing framework for monitoring Posidonia oceanica in the Mediterranean using Sentinel-2 data. Their deep learning neural network achieved accuracies between 74% and 92% depending on location and depth, supporting large-scale conservation initiatives such as the Mediterranean Posidonia Network.

Lestari et al. (2021) applied Mask R-CNN to segment Enhalus acoroides from underwater camera recordings in Indonesia. Their model achieved precision of 98.19%, recall of 95.04%, and an F1 score of 96.58%, confirming the suitability of instance segmentation for species-specific monitoring.

Noman et al. (2023) compared YOLOv5 and EfficientDet-D7 detectors for Halophila ovalis detection. EfficientDet-D7 achieved the highest mAP (0.484 on ECUHO-2), while YOLOv5 offered faster inference times (0.043–0.077 s), balancing accuracy and efficiency in underwater seagrass detection.

Halder et al. (2024) developed an AI-based morphology measurement system using YOLO-v6 to classify and measure seagrass components (leaves, rhizomes, roots) of Zostera muelleri. Their model achieved an average recall of 97.5% and an F1 score of 90.1%, providing a novel approach to automate morphometric analysis for ecological monitoring.

Sensor-Based IoT Systems for Aquaculture Monitoring

Gleiser and Moro (2023) implemented an IoT-based water quality monitoring system for aquaculture, employing sensors such as DS18b temperature and turbidity sensors connected to an ESP32 microcontroller. Their system enabled remote monitoring via the Blynk app and incorporated water recycling mechanisms, reducing waste and costs while ensuring optimal growth conditions for aquatic species.

Prapti et al. (2022) provided an overview of IoT applications in aquaculture water quality monitoring, reviewing 30 published studies between 2011 and 2020. They found that inland aquaculture dominated research (81%), with temperature, dissolved oxygen, and pH as the most prioritized parameters. Real-time monitoring was the most common solution offered, highlighting the growing role of IoT in Aquaculture 4.0.

Manoharan et al. (2020) examined aquaculture monitoring using sensor-based technology integrated with machine learning algorithms. Their improved decision machine learning algorithm (IDMLA) optimized monitoring of parameters such as pH, velocity, and pump flow rate. Results demonstrated higher efficiency compared to traditional methods, with MATLAB simulations validating the system's effectiveness.

Flores-Iwasaki et al. (2025) conducted a systematic review and bibliometric analysis of IoT sensors for water quality monitoring in aquaculture systems. Analyzing 217 articles published between 2020 and 2024, they reported significant growth in research output (74.79%). pH sensors were the most studied (98.2%), followed by temperature (92.9%) and dissolved oxygen (62.5%). Their findings emphasized the importance of sensor integration in Biofloc Technology (BFT), Recirculating Aquaculture Systems (RAS), and aquaponics.

Liu, Cheng, and Kuo (2025) presented a narrative review on smart sensors and IoT solutions for sustainable agriculture and aquaculture. They highlighted empirical evidence showing IoT-based aquaculture systems reduced mortality by up to 40% and increased yields by 15–50%. Integration with artificial intelligence enhanced predictive capabilities, though adoption remained constrained by infrastructure costs and sensor robustness.

Rosaline and Sathyalakshimi (2019) designed an IoT-based aquaculture monitoring and control system using multiple sensors (temperature, pH, salinity, dissolved oxygen, ammonia, and water level). Data was transmitted via NodeMCU ESP12E to the Ubidots platform, enabling remote monitoring and alerts. Their system demonstrated improved environmental control and reduced management costs.

Nasir and Mumtazah (2020) developed an IoT-based monitoring system for aquaculture in Malaysia, employing five sensors (temperature, pH, turbidity, air temperature, and light). Data was transmitted to the ThingSpeak cloud via GSM, allowing continuous monitoring. Their study also explored correlations between air and water temperature, light intensity and turbidity, and feeding effects on pH.

Saha, Rajib, and Kabir (2018) implemented an IoT-based automated fish farm monitoring system using Raspberry Pi, Arduino, and smartphone integration. Their system monitored temperature, pH, electrical conductivity, and watercolor, with data processed and stored on Raspberry Pi. An Android app provided real-time monitoring, reducing manual testing and improving aquaculture management.

Bachtiar, Hidayat, and Anantama (2022) proposed an IoT-based aquaculture monitoring system in Indonesia, focusing on pH, temperature, and turbidity. Using NodeMCU and Ubidots, their system achieved success rates of 97.66% for pH monitoring and 94.92% for temperature monitoring. Turbidity levels were categorized into clear, slightly cloudy, cloudy, and very cloudy, providing actionable insights for fish farmers.

Remote Sensing and Image Processing for Seagrass

Campillo-Tamarit, Molner, and Soria (2025) conducted a systematic review of remote sensing methodologies for monitoring marine phanerogams, focusing on Sentinel and Landsat applications. Their study highlighted the use of vegetation indices (NDVI, NDWI, EVI) and supervised classification algorithms such as Random Forest, Maximum Likelihood, and Support Vector Machine. These approaches were applied in Mediterranean and other coastal regions, revealing seagrass cover changes due to anchor damage and trawling scars, thereby informing management actions like restrictions on anchoring and bottom trawling.

Dierssen et al. (2019) evaluated the limits of seagrass remote sensing in turbid waters of Elkhorn Slough, California. They compared broadband satellite imagery (Sentinel-2, Google Earth) with airborne hyperspectral imagery from PRISM. While broadband imagery detected shallow beds, hyperspectral data combined with the HOPE semi-analytical inversion model successfully mapped both shallow and deep eelgrass beds, retrieved water column properties, and quantified bathymetry. Their findings emphasized the potential of hyperspectral imagery in optically complex waters.

Thalib, Faizal, and La Nafie (2019) analyzed seagrass beds in Bontosua Island, Spermonde Archipelago, using Sentinel-2A imagery and the Lyzenga algorithm. Their study demonstrated that water column correction significantly improved classification accuracy, increasing seagrass detection from 19.08 ha (without correction) to 31.27 ha (with correction). The classification achieved 88% accuracy, meeting minimum standards for image reliability.

Veettil et al. (2020) reviewed opportunities for seagrass research derived from remote sensing, discussing current methods and tools. They highlighted the ecological importance of seagrass meadows and described the use of optical, Radar, and LiDAR data. The review emphasized combining remote sensing with traditional methods for validation, noting limitations in spatial resolution and challenges in species-level discrimination. They concluded that the recent expansion of remote sensing tools provides timely opportunities for mapping, monitoring, and quantifying ecosystem services.

Hossain, Bujang, Zakaria, and Hashim (2015) provided an overview of remote sensing applications to seagrass ecosystems. Reviewing 195 studies, they identified advances in optical and acoustic methods, particularly Landsat imagery, for detecting seagrass presence, cover, distribution, and biomass. They emphasized that no single technology can measure all parameters, advocating for integrated approaches combining field data, imagery, and mapping techniques. Their review underscored the need for continued methodological improvements in seagrass remote sensing.

The reviewed literature collectively demonstrates a clear progression toward the integration of machine learning, artificial intelligence, remote sensing, and IoT-based smart monitoring systems to address long-standing limitations in aquatic ecosystem and seagrass monitoring. Traditional field-based and laboratory-dependent methods, while scientifically reliable, are consistently identified as costly, time-consuming, and spatially constrained, making them insufficient for large-scale, real-time, and long-term coastal monitoring. In response, recent studies emphasize data-driven and sensor-enabled approaches capable of capturing complex, nonlinear interactions among water quality parameters, biological indicators, and environmental conditions.

Online ISSN: 3082-5121
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https://journals.aloysianpublications.com
Volume 2 Issue 6 (2026)

Across the literature, machine learning models such as Random Forest, Support Vector Machines, neural networks, and deep learning architectures have proven highly effective in predicting water quality parameters, detecting eutrophication, and supporting early warning systems. These capabilities are further enhanced when combined with IoT and cloud-based technologies, which enable continuous, real-time data acquisition, scalability, and remote accessibility. Empirical evidence from smart water and aquaculture monitoring systems highlights improved efficiency, early contamination detection, and better resource management outcomes, though challenges related to cost, infrastructure, and cybersecurity remain.

Similarly, advances in AI-based seagrass identification using deep learning and remote sensing reveal strong potential for accurate, large-scale, and species-specific seagrass mapping, even in optically complex and turbid waters. While satellite, drone, and underwater imaging approaches have achieved high accuracy, the literature consistently underscores the need for integrated systems that combine sensor-based water quality monitoring with AI-driven image analysis to provide holistic ecosystem assessments.

Taken together, the reviewed studies reveal a methodological gap in fully unified monitoring frameworks that simultaneously integrate real-time water quality sensing, machine learning analytics, and AI-based seagrass detection. This synthesis justifies the present study's research approach, which adopts an integrated, technology-driven framework to enhance coastal and seagrass ecosystem monitoring, support evidence-based management, and contribute to sustainable marine resource conservation.

STATEMENT OF THE PROBLEM

General Problem

Seagrass meadows are vital to coastal ecosystems, but they face growing threats from pollution, climate change, and human activity. Traditional monitoring methods are slow, limited, and lack real-time data, making it difficult to respond quickly to environmental changes. In regions like the Philippines, there's an urgent need for smart, integrated systems that combine water quality sensors with AI-based seagrass identification. Current tools manual sampling, satellite imagery, and field surveys are often inaccurate, weather-dependent, and labor-intensive. This study addresses the lack of unified, real-time habitat monitoring by developing a smart platform that merges physio-chemical water analysis with underwater imaging and machine learning. The goal is to provide continuous, high-resolution data to support conservation, inform policy, and empower local stakeholders.

Specific Problems

- **Labor-Intensive Monitoring Process** - Manual monitoring requires frequent sampling, which is time-consuming and demands substantial human resources.
- **Lack of Continuous Water Quality Monitoring** - Without continuous data, sudden changes in water quality, such as drops in dissolved oxygen or temperature fluctuations, may go unnoticed, resulting in sea grass/fish stress and eventually death.

- **Economic Setbacks from Inadequate Monitoring** – Sea grass/fish mortality due to inadequate monitoring leads to economic setbacks for farmers and threatens the sustainability of aquaculture operations.
- **Limitations of Manual Seagrass Identification Methods –** Manual methods like field surveys and satellite imagery for seagrass identification are often inaccurate, weather-dependent, and labor-intensive, highlighting the need for a smart, AI-driven system that enables real-time, automated habitat monitoring.

OBJECTIVES OF THE STUDY

General Objectives

This Study aim to develop and evaluate an integrated smart monitoring system that combines real-time physio-chemical water quality analysis with AI-based seagrass identification, aimed at enhancing habitat monitoring, supporting coastal conservation, and empowering local stakeholders in regions like the Philippines.

Specific Objectives

- To gather water quality data from aquaculture areas (onshore or offshore) using sensor-based hardware.
- To design and implement an automated monitoring system enhanced with machine learning algorithms for real-time analysis and classification of physicochemical parameters.
- To develop a comprehensive notification system that alerts users in real time about unsafe water conditions and necessary corrective actions, integrating auditory signals (buzzers) to ensure immediate attention and intervention.
- To improve the accuracy and efficiency of seagrass identification by integrating image processing and machine-learning classification techniques that overcome the limitations of manual field surveys and satellite imagery.
- To evaluate the system using researchers made questionnaires aligned with ISO-Standard parameters.

MATERIALS AND METHODOLOGY

This chapter outlines the methodology used in the design, development, and implementation of the An Integrated Machine Learning System for Realtime Water Quality Monitoring for Sea Grass Identification, an IoT-based machine learning solution tailored for aquaculture and coastal ecosystem management. The methodology ensures technical rigor, stakeholder relevance, and iterative refinement through a structured development framework.

Research Design

This study employed a development and mixed-methods research design to integrate technical system validation with user-centered evaluation. The qualitative component involved stakeholder interviews and structured consultations with aquaculture practitioners, environmental researchers, local government unit representatives, and technical experts to identify operational requirements, usability preferences, and deployment constraints of the proposed monitoring system. Such qualitative inquiry is appropriate for capturing contextual insights and stakeholder perspectives that inform system design and implementation (Creswell & Plano Clark, 2018).

The quantitative component focused on sensor calibration, system performance benchmarking, and image processing accuracy evaluation to assess system reliability and technical effectiveness. Water quality parameters and monitoring indicators were selected and adapted based on internationally recognized ISO Standards for water quality measurement to ensure consistency, accuracy, and regulatory alignment. The integration of qualitative and quantitative methods enabled a comprehensive assessment of both functional performance and practical applicability of the system.

Instrument Validation

Instrument validation was established through face and content validity to ensure that the system parameters, monitoring indicators, and evaluation instruments were relevant, clear, and aligned with the study objectives. A panel of six (6) internal and external experts composed of aquaculture specialists, environmental scientists, information technology professionals, and research methodologists reviewed the adapted instruments. Face validity focused on the apparent clarity and suitability of the instruments, while content validity assessed the extent to which the instruments adequately represented the constructs being measured (Polit & Beck, 2006; Taherdoost, 2016).

Face and content validity were established to ensure that the developed questionnaire was appropriate, relevant, and representative of the constructs it intended to measure. The instrument was subjected to expert review to determine whether the items were clearly worded, conceptually sound, and adequately aligned with the ISO/IEC 25010 system quality characteristics relevant to the integrated machine learning system for real-time water quality monitoring and seagrass identification.

For face validity, expert validators examined the questionnaire to assess whether the items appeared understandable, logically structured, and suitable for evaluating the developed system. The reviewers considered the clarity of wording, appropriateness of technical terminology, and overall coherence of the instrument from the perspective of intended respondents. Feedback provided by the experts led to revisions aimed at improving item clarity, eliminating ambiguity, and enhancing readability.

For content validity, the same panel of experts evaluated the extent to which the questionnaire items sufficiently represented each ISO/IEC 25010 quality characteristic included in the study. Validators assessed the relevance and adequacy of each item in capturing the essential aspects of system quality, particularly in relation to machine learning performance, real-time monitoring, and environmental data processing. Items were reviewed using a qualitative decision approach, wherein items were retained, revised, or removed based on expert judgment. Revisions were incorporated to ensure comprehensive coverage and alignment with the system's functional scope.

Through this systematic expert review process, the instrument was refined and deemed to possess acceptable face and content validity, making it suitable for evaluating the performance and quality of the developed integrated machine learning system.

The validators were asked to evaluate each item based on its clarity of wording, appropriateness of terminology, and apparent relevance to the evaluation of the integrated machine learning system for real-time water quality monitoring and seagrass identification. Suggestions provided by the experts were carefully considered, and necessary revisions were made to improve item phrasing, remove ambiguities, and enhance overall comprehensibility. Items that were deemed unclear or redundant were refined or removed accordingly. Through this expert review process, the instrument was judged to possess acceptable face validity for use in evaluating the developed system.

The validation process also ensured that the selected parameters and system indicators were consistent with ISO Standards–based water quality monitoring guidelines, strengthening their scientific rigor and practical relevance. Feedback from the experts was systematically incorporated to refine sensor parameters, threshold values, system functions, and evaluation tools, confirming the appropriateness of the instruments for aquatic ecosystem and seagrass monitoring.

Data Reliability

Data reliability was established through pilot testing and internal consistency analysis. With the assistance of fifteen (15) Information Technology (IT) experts, a pilot test was conducted prior to the full-scale deployment of the system in a controlled aquatic environment to assess system stability, sensor responsiveness, data transmission reliability, and user interaction with the monitoring platform. Pilot testing is a critical methodological step for identifying potential technical and procedural issues and improving instrument performance before full implementation (Thabane et al., 2010).

Following the pilot test, the reliability of the system evaluation instrument was examined using Cronbach's alpha coefficient to determine the internal consistency of the questionnaire items. The results revealed that the instrument demonstrated good to excellent reliability, with Cronbach's alpha coefficients ranging from 0.78 to 0.91 across the ISO/IEC 25010 software quality characteristics. Specifically, the computed reliability coefficients were 0.84–0.86 for Functional Suitability, 0.84–0.89 for Performance Efficiency, 0.85–0.90 for Compatibility, 0.88–0.91 for Usability, 0.78–0.88 for Reliability, 0.79–0.85 for Security, 0.62–0.72 for Portability, and 0.79–0.85 for Maintainability, indicating acceptable to excellent internal consistency of the evaluation instrument. These values exceeded the minimum acceptable threshold of 0.70 recommended for research instruments (Cronbach, 1951; Tavakol & Dennick, 2011), therefore confirming that the questionnaire was sufficiently reliable for evaluating the developed Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification.

The detailed Cronbach's alpha results are presented in this table. Furthermore, compliance with ISO standards-based calibration and measurement procedures enhanced the accuracy, consistency, and reproducibility of the collected data, thereby ensuring dependable and credible results for the system evaluation.

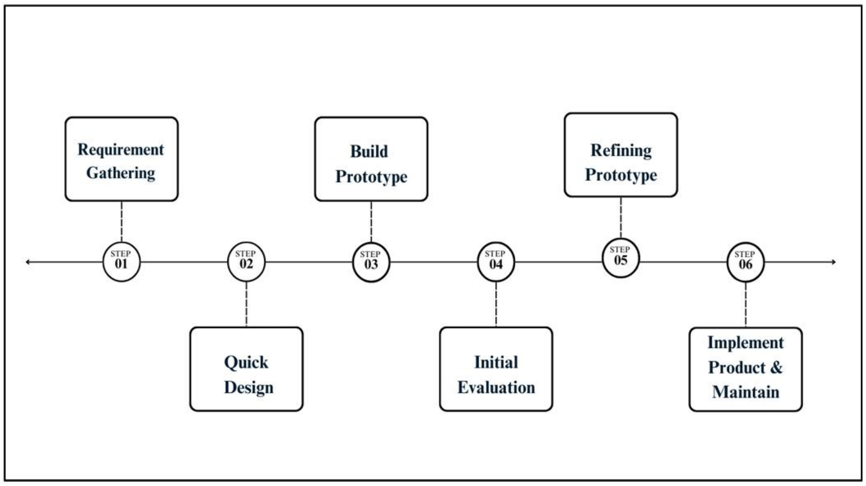
Table 1
Cronbach's Alpha Results

Quality Characteristic	Cronbach's Alpha Range	Interpretation
1. Functional Suitability	0.839 – 0.863	Good Reliability
2. Performance Efficiency	0.840 – 0.892	Good to Excellent Reliability
3. Compatibility	0.846 – 0.902	Good to Excellent Reliability
4. Usability	0.884 – 0.906	Excellent Reliability
5. Reliability	0.777 – 0.879	Acceptable to Good Reliability
6. Security	0.789 – 0.848	Good Reliability
7. Portability	0.623 – 0.718	Marginal to Acceptable Reliability
8. Maintainability	0.789 – 0.848	Good Reliability

Procedures (System Development Framework)

The system was develop using the System Development Life Cycle (SDLC), specifically the Prototyping Model, which supports iterative design and testing ideal for projects involving hardware-software integration and stakeholder feedback. This model allowed the researchers to build functional prototypes, gather user input, and refine system components in successive cycles.

Figure 1
Prototype Model



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This study adopts the **Prototyping Model** as the research design to guide the systematic development and evaluation of the proposed system. The model emphasizes iterative design, continuous user involvement, and progressive refinement, making it suitable for technology-based research that integrates system development with stakeholder feedback.

The research process begins with **requirement gathering**, wherein relevant information is collected from stakeholders to identify system objectives, user needs, and functional requirements. These inputs inform the scope and direction of the system design. This is followed by the **quick design** phase, during which a preliminary system layout and interface are rapidly developed to visualize key components and workflows.

Next, a **working prototype** is built based on the initial design, incorporating essential features that allow users to interact with the system. The prototype then undergoes **initial evaluation**, where stakeholders assess its usability, functionality, and alignment with identified requirements. Feedback obtained at this stage is systematically documented to identify limitations and areas for improvement.

The **prototype refinement** phase involves revising and enhancing the system based on stakeholder feedback. This iterative cycle of evaluation and refinement continues until the prototype satisfies technical standards and user expectations. Finally, once the refined prototype is approved, the study proceeds with **system implementation and maintenance**, ensuring stable deployment, continuous monitoring, and necessary updates to support long-term functionality and relevance (see figure 1).

Study Area

This study was be conducted at the University of Science and Technology of Southern Philippines (USTP) Panaon Campus is situated in Purok 6, Barangay Punta, within the Municipality of Panaon, Misamis Occidental, Philippines, the campus has evolved into a regional hub for fisheries education, marine research, and community extension services. Panaon is a coastal municipality bordered by rich marine ecosystems, including seagrass meadows, coral reefs, and mangrove forests. These habitats are vital to local biodiversity and support the livelihoods of small-scale fishers and aquaculture practitioners. The proximity of the campus to these ecosystems provides direct access for fieldwork, sensor deployment, and underwater imaging, making it a strategic location for real-time habitat monitoring.

Data Analysis

The data analysis focused on evaluating the quality and acceptability of the developed *Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification* using the ISO/IEC 25010:2011 software quality standards. Responses obtained from the respondents were summarized and analyzed using descriptive statistics.

Specifically, the weighted mean was computed to determine the respondents' assessment

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of the system in terms of Functional Suitability, Performance Efficiency, Compatibility, Usability, Reliability, Security, Maintainability, and Portability.

The weighted mean was calculated using the formula:

$$\bar{X} = \frac{\sum fx}{N}$$

where:

- $\bar{X}$= weighted mean
- $\sum fx$= sum of the weighted responses
- N= total number of responses

The computed means were interpreted using a five-point Likert scale to determine the level of acceptability of the developed system. Higher mean scores indicated greater acceptance and satisfaction with the system's quality characteristics. The results served as the basis for evaluating the overall performance and usability of the developed monitoring system.

RESULTS AND DISCUSSION

This chapter presents, analyzes, and discusses the findings of the study entitled ***"An Integrated Machine Learning System for Realtime Water Quality Monitoring for Sea Grass Identification."*** The results were presented according to the specific objectives of the study and focused on the development, implementation, and evaluation of the proposed integrated monitoring system. The chapter particularly examined the effectiveness of the system in collecting real-time physicochemical water quality data, specifically temperature, pH, and dissolved oxygen, through the use of sensor-based technologies integrated with machine learning and image-processing techniques for seagrass identification.

The discussion also described the capability of the developed system to process and transmit environmental data in real time using wireless communication and web-based monitoring platforms. The performance of the notification and alert system was likewise evaluated to determine its effectiveness in informing users whenever unsafe water conditions were detected. In addition, the study examined the efficiency of the image-processing and machine learning components in identifying seagrass species and generating relevant ecological information that could support environmental monitoring and conservation activities.

Furthermore, this chapter presented the researchers made questionnaire evaluation of the developed system based on ISO-standard parameters, particularly in terms of Functional Suitability, Performance Efficiency, Compatibility, Usability, Reliability, Security, Maintainability, Portability and overall acceptability among the respondents and evaluators. The findings provided insights into the practical applicability of integrating Internet of Things (IoT), artificial intelligence, and environmental sensing technologies in coastal and aquatic ecosystem monitoring.

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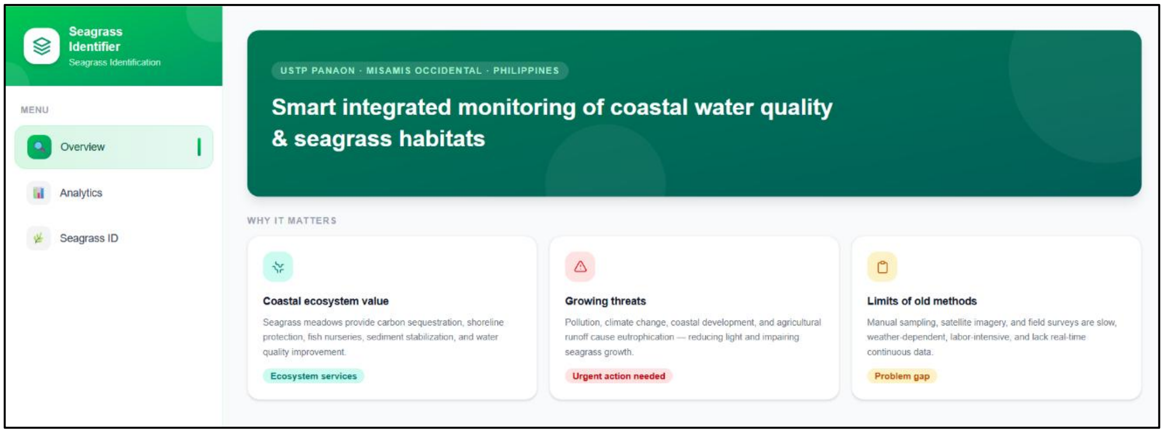
The discussion further emphasized the importance of real-time environmental monitoring in supporting sustainable coastal resource management, improving decision-making among stakeholders, and promoting marine ecosystem conservation. The results obtained from the study were compared and supported with related literature and previous studies on smart water quality monitoring systems, machine learning applications, IoT-based environmental monitoring, and AI-driven seagrass identification technologies.

System Design

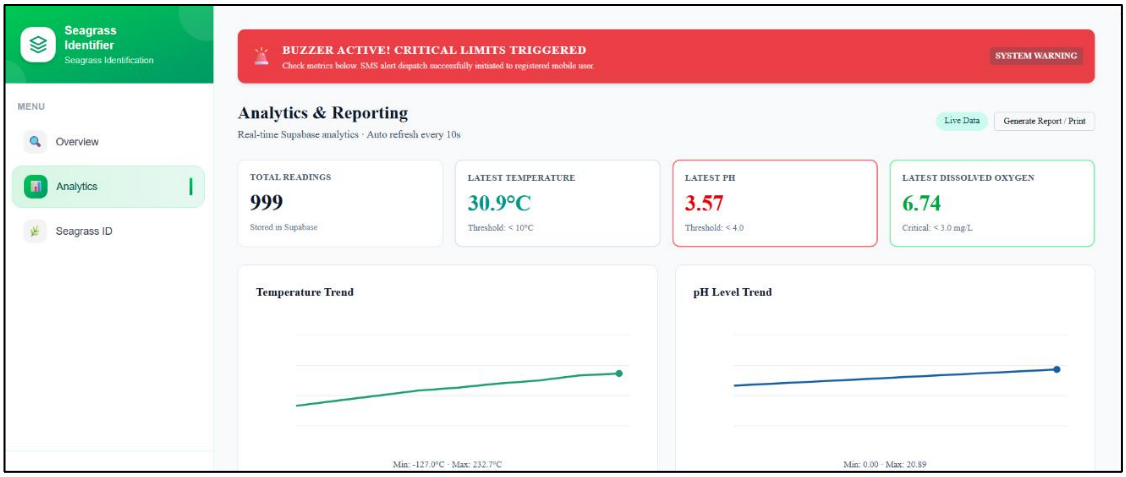
Figure 2

System Dashboard



The developed system dashboard served as the main interface for real-time water quality and seagrass monitoring. It was designed with a simple and user-friendly layout that allowed users to easily access monitoring data, analytics, and seagrass identification features through the Overview, Analytics, and Seagrass ID sections.

The dashboard highlighted the importance of coastal ecosystem monitoring by presenting information about seagrass habitats, environmental threats, and the limitations of traditional monitoring methods. It also improved data visualization and monitoring efficiency by providing an organized and interactive platform for environmental monitoring and coastal resource management (see figure 3).



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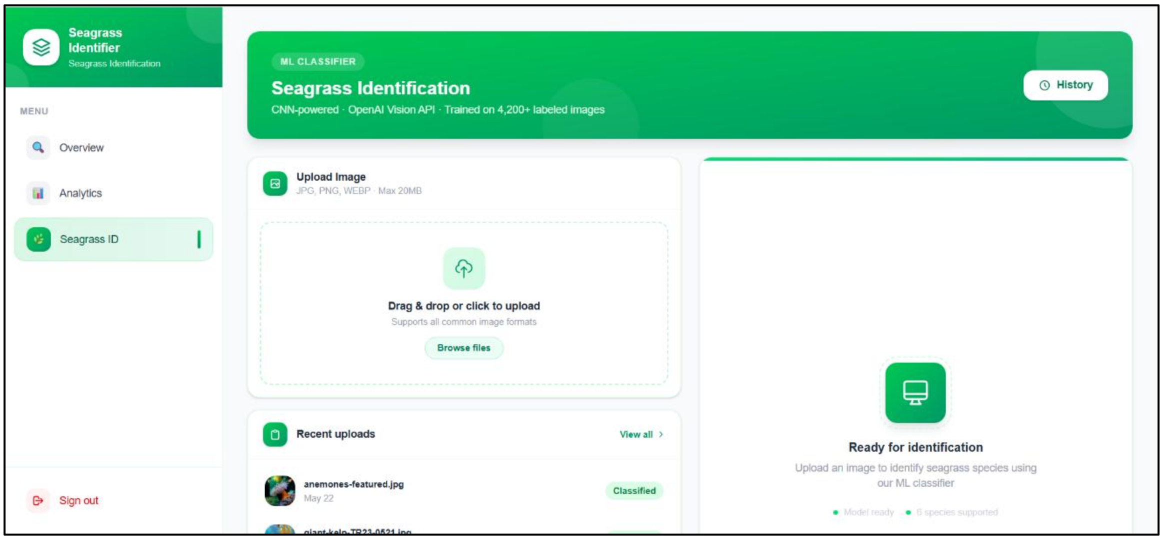
The Analytics and Reporting Dashboard was designed to display real-time water quality readings and system-generated reports in an organized and easy-to-understand format. The dashboard presented important monitoring data such as temperature, pH level, and dissolved oxygen readings, allowing users to quickly assess the current condition of the water environment.

The system also included graphical trend analysis for temperature, pH levels, and Dissolved Oxygen which helped users observe changes and patterns in water quality over time. In addition, the dashboard featured an automatic warning notification and buzzer alert whenever critical water conditions were detected. This feature improved the responsiveness of the monitoring system by providing immediate alerts and supporting timely intervention.



The Seagrass Identification Dashboard was developed to provide an easy and interactive platform for identifying seagrass species using machine learning technology. The dashboard allowed users to upload images in supported formats such as JPG, PNG, and WEBP for automatic seagrass classification and analysis.

The system used an AI-powered classifier to analyze uploaded images and generate identification results efficiently. It also displayed recent uploads and classification history, allowing users to review previously analyzed images and monitoring records. The simple and organized interface improved user accessibility and made the identification process more convenient for students, researchers, and environmental monitoring personnel.

System Evaluation

This section presents the evaluation of the developed *Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification* using a researchers-made questionnaire based on the *ISO/IEC 25010:2011* software quality standards. The evaluation focused on the system's Functional Suitability, Performance Efficiency, Compatibility, Usability, Reliability, Security, Maintainability, Portability, and overall

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performance to determine its acceptability among the respondents. The final evaluation of the system was conducted with seventy (70) participants composed of Marine Biology Students who assessed the overall quality and functionality of the developed system.

Scale	Range	Interpretation
5	4.6 – 5.0	Excellent
4	3.6 – 4.5	Very Satisfactory
3	2.3 – 3.5	Satisfactory
2	1.6 – 2.5	Needs Improvement
1	1.0 – 1.5	Poor

A five-point Likert scale was used in the evaluation, with the following interpretations: 5 – Excellent, 4 – Very Satisfactory, 3 – Satisfactory, 2 – Needs Improvement, and 1 – Poor. The use of this scale allowed the respondents to provide clear feedback regarding their experience in using the developed system. The results of the evaluation helped determine the strengths and possible areas for improvement of the proposed monitoring system.

Overall Mean of Evaluation Criteria
Table 2
Total Weighted Mean

Portability	Mean	Standard Deviation	Interpretation
1. Functional Suitability	4.38	0.73	Very Satisfactory
2. Performance Efficiency	4.23	0.78	Very Satisfactory
3. Compatibility	4.34	0.79	Very Satisfactory
4. Usability	4.35	0.79	Very Satisfactory
5. Reliability	4.33	0.79	Very Satisfactory
6. Security	4.31	0.76	Very Satisfactory
7. Maintainability	4.38	0.73	Very Satisfactory
8. Portability	4.37	0.75	Very Satisfactory
Weighted Mean:	**4.34**	**0.77**	**Very Satisfactory**

Note. Scale: 5 = Excellent, 4 = Very Satisfactory, 3 = Satisfactory, 2 = Needs Improvement, 1 = Poor.

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Table 2 presents the overall evaluation results of the developed *Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification* based on the ISO/IEC 25010:2011 software quality criteria. The results showed that all evaluation categories obtained a verbal interpretation of **Very Satisfactory**, indicating that the respondents were generally satisfied with the overall quality and performance of the developed system.

The overall evaluation obtained a weighted mean of **4.34** with an overall standard deviation of **0.77**, interpreted as **Very Satisfactory**. This result indicates that the developed system was able to meet the expected standards in terms of functionality, efficiency, compatibility, usability, reliability, security, maintainability, and portability.

The findings further suggest that the system effectively performed its intended purpose of providing real-time water quality monitoring and machine learning-based seagrass identification. The evaluation results imply that the developed system is functional, reliable, user-friendly, and suitable for environmental monitoring and coastal ecosystem management applications.

Comparison to existing studies

The comparison shows that while previous studies focused separately on either water quality monitoring, IoT-based aquaculture systems, or AI-driven seagrass identification, the present study uniquely integrates these technologies into a single real-time monitoring platform. The developed system combines machine learning, environmental sensing, underwater image processing, GSM communication, and web-based visualization, making it more comprehensive and applicable for coastal ecosystem monitoring and marine conservation.

Table 3
Comparison Table

Authors/ Year	Title/Focus of Study	Technologies Used	Key Features	Limitations of Existing Study	Contribution of the Present Study
Rogers & Ambili (2024)	Water quality prediction using machine learning algorithms	Machine Learning (Random Forest, SVM, Gradient Boosting)	Predictive analysis of water quality parameters	Focused only on prediction models without real-time hardware integration	The present study integrates real-time IoT sensors, GSM communication, dashboard visualization, and AI-based seagrass identification in one system.
Essamlali et al. (2024)	IoT and machine learning for water	IoT, Machine Learning	Continuous monitoring and anomaly	Mainly conceptual and review-based; lacks	The present study developed an actual working

	quality monitoring		detection	integrated seagrass identification	prototype with real-time monitoring and seagrass classification capabilities.
Tallam et al. (2023)	Deep learning classification of eelgrass from drone imagery	DeepLab v3 Deep Learning Model	High-accuracy eelgrass classification	Focused only on image segmentation without water quality monitoring	The present study combines CNN-based seagrass identification with real-time water quality monitoring.
Perez et al. (2020)	Quantifying seagrass distribution using deep learning	CNN, Deep Capsule Network, Satellite Imagery	Seagrass distribution mapping	Dependent on satellite imagery and remote sensing only	The present study utilizes underwater image analysis combined with IoT sensor monitoring for localized and real-time assessment.
Scarpetta et al. (2022)	Monitoring seagrass meadows using CNN	U-Net CNN, Satellite Images	Large-scale seagrass mapping	Limited to image segmentation and remote sensing applications	The present study integrates environmental sensing, machine learning, GSM communication, and dashboard reporting.
Gleiser and Moro (2023)	IoT-based water quality monitoring for aquaculture	IoT Sensors, ESP32, Blynk App	Remote aquaculture monitoring	No AI-based environmental classification or seagrass identification	The present study expands monitoring capabilities by integrating machine learning and ecological habitat identification.

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Rosaline & Sathyalakshimi (2019)	IoT-based aquaculture monitoring and control system	NodeMCU, Sensors, Ubidots	Monitoring pH, salinity, DO, temperature	Focused only on aquaculture monitoring	The present study supports both aquaculture monitoring and coastal ecosystem conservation through AI-based seagrass identification.
Noman et al. (2023)	AI-based underwater seagrass detection	YOLOv5, EfficientDet-D7	Faster underwater detection	Focused only on object detection accuracy	The present study combines AI detection with real-time environmental monitoring and user notification systems.
Present Study	An Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification	IoT Sensors, Arduino Uno, Raspberry Pi, GSM Module, CNN, OpenCV, Web Dashboard	Real-time monitoring of pH, temperature, dissolved oxygen, AI-based seagrass identification, GSM alerts, web dashboard, machine learning integration	Limited to selected water quality parameters and supported image formats	Provides an integrated, real-time, AI-driven coastal monitoring system designed for environmental monitoring, marine conservation, and sustainable coastal ecosystem management.

CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclusions drawn from the findings of the study entitled ***"An Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification."*** The conclusions were based on the results obtained from the development, implementation, and evaluation of the proposed system using the ISO/IEC 25010:2011 software quality standards. The study focused on integrating Internet of Things (IoT), machine learning, image processing, and real-time environmental monitoring technologies to support coastal ecosystem management and seagrass conservation.

Furthermore, this chapter provides recommendations intended to improve the developed

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system and guide future researchers, environmental practitioners, coastal resource managers, and technology developers in enhancing real-time water quality monitoring and AI-based seagrass identification systems. The recommendations are based on the limitations encountered during the study and the overall evaluation results provided by the respondents. The chapter also emphasizes the importance of continuous technological innovation, sustainable environmental monitoring practices, and the integration of smart systems in supporting marine ecosystem protection and coastal resource sustainability.

Summary and Findings

The study successfully developed an **Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification** that combines Internet of Things (IoT), machine learning, image processing, and real-time environmental monitoring technologies. The system was designed to monitor important water quality parameters such as temperature, pH, and dissolved oxygen using sensor-based hardware connected to a Raspberry Pi and Arduino Uno. It also included GSM communication and buzzer alert features that automatically notify users whenever unsafe water conditions are detected. These features helped improve the efficiency and responsiveness of environmental monitoring activities.

The developed system also provided a user-friendly monitoring dashboard that displayed real-time water quality readings, graphical trend analysis, and seagrass identification results. Users were able to upload underwater images for automatic seagrass classification using artificial intelligence. The dashboard improved accessibility and made environmental monitoring easier for students, researchers, and coastal monitoring personnel by presenting information in a clear and organized manner.

The integration of machine learning and image-processing technologies allowed the system to identify seagrass species more efficiently compared to traditional manual methods. Through the use of a Convolutional Neural Network (CNN), the system was able to analyze underwater images and provide automated seagrass classification results. This helped reduce the limitations of manual field surveys and improved the overall monitoring process for coastal ecosystems and marine habitats.

The developed system was evaluated using a researchers-made questionnaire based on the ISO/IEC 25010:2011 software quality standards. The evaluation involved seventy (70) Marine Biology students who assessed the overall functionality and performance of the system. The findings showed that all evaluation criteria received a verbal interpretation of **Very Satisfactory**, indicating that the respondents were highly satisfied with the developed monitoring system.

Among the evaluation criteria, **Functional Suitability** and **Maintainability** obtained the highest weighted mean of **4.38**, showing that the system effectively performed its intended functions and could easily be improved or modified for future development. **Portability** followed with a weighted mean of **4.37**, while **Usability** obtained **4.35**, indicating that the system was easy to use and adaptable across different devices and platforms. In addition, **Compatibility**

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obtained **4.34**, **Reliability** obtained **4.33**, **Security** obtained **4.31**, and **Performance Efficiency** obtained **4.23**, all interpreted as Very Satisfactory. These results suggest that the system was stable, secure, responsive, and reliable during continuous real-time monitoring operations.

The developed Integrated Machine Learning System obtained a total weighted mean of **4.34** with a standard deviation of **0.77**, verbally interpreted as **Very Satisfactory**. This indicates that the developed system successfully met the expected software quality standards and demonstrated its potential as an effective tool for real-time water quality monitoring, AI-based seagrass identification, and coastal ecosystem management. The findings also highlighted the importance of integrating IoT, machine learning, and environmental sensing technologies in supporting marine conservation, sustainable coastal resource management, and informed environmental decision-making.

Conclusions

The study concluded that the developed Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification successfully achieved the objectives of the research by providing an integrated and automated solution for coastal and aquatic environmental monitoring. The system was able to continuously monitor important water quality parameters such as temperature, pH, and dissolved oxygen through the use of sensor-based technologies integrated with IoT and real-time communication features. This allowed the system to provide immediate environmental data and timely alerts that can support faster decision-making and response to changing water conditions.

The study also concluded that the integration of machine learning and image-processing technologies successfully improved the process of seagrass identification. Through the use of underwater image analysis and artificial intelligence, the system was able to identify seagrass species more efficiently compared to traditional manual methods. This demonstrated the potential of combining environmental sensing and AI technologies in supporting marine habitat monitoring and coastal ecosystem assessment.

Furthermore, the developed system successfully provided a centralized and user-friendly monitoring platform that allowed users to access real-time water quality information, visualize monitoring trends, and generate environmental reports. The integration of GSM communication, web-based monitoring, and automated notifications also improved accessibility and responsiveness, especially in coastal and remote monitoring environments.

The study demonstrated that integrating IoT, machine learning, and environmental monitoring technologies can provide a practical, innovative, and sustainable approach to real-time coastal ecosystem monitoring. The developed system has the potential to support marine conservation efforts, environmental research, coastal resource management, and sustainable monitoring practices by providing accurate, continuous, and accessible environmental information.

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Recommendations

Based on the findings and conclusions of the study, it is recommended that the developed **Integrated Machine Learning System for Realtime Water Quality Monitoring for Seagrass Identification** be continuously improved to further enhance its effectiveness and long-term usability in environmental monitoring. Future enhancements may include additional water quality parameters such as salinity, turbidity, ammonia, and water level monitoring to provide a more comprehensive assessment of aquatic ecosystem conditions.

Further improvement of the machine learning and image-processing components is also recommended by expanding the image dataset and integrating more advanced artificial intelligence models. Conducting additional testing in different coastal environments and varying water conditions may help improve the accuracy, adaptability, and reliability of the seagrass identification process.

To improve accessibility and monitoring efficiency, future development may focus on integrating mobile application support, cloud-based storage, and offline synchronization capabilities. These features can help ensure continuous monitoring and easier access to environmental data, especially in remote coastal areas with unstable internet connectivity.

It is also recommended that the durability and sustainability of the hardware components be enhanced for long-term field deployment. The use of more durable waterproof materials, energy-efficient devices, and improved power management systems may help increase the operational lifespan and reliability of the system under harsh marine environmental conditions.

Lastly, wider adoption of smart environmental monitoring technologies is highly encouraged among coastal communities, academic institutions, environmental agencies, and local government units. The integration of IoT, machine learning, and real-time monitoring systems can greatly contribute to marine conservation, sustainable coastal resource management, and informed environmental decision-making. Strengthening collaboration among stakeholders may also help support the continuous protection and sustainability of marine ecosystems.

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