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Advanced Deep Learning Framework AquaSense for Comprehensive Marine Pollutant Detection Using Sentinel-2 Multispectral Data

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ABSTRACT

Marine pollution poses a critical threat to aquatic ecosystems and human health, yet its automated detection and monitoring using satellite data remain significant challenges. Existing methods often focus on single pollutants or binary classification tasks, limiting their effectiveness in real-world, operational settings. The research intends to develop a robust, scalable, generalizable automated system for detecting and monitoring marine pollution by deep learning utilizing upscaled multidimensional satellite images. Used extensive testing on the Marine Debris and Oil Spill (MADOS) dataset. To address these limitations, suggested the Aqua-Sense, an innovative deep-learning architecture that offers a comprehensive method for detecting marine pollutants. AquaSense, leverages high-resolution multispectral data from Sentinel-2 satellites, allowing to detect variety of contaminants such as plastics, oil spills, and other contaminants. The framework is built on state-of-the-art semantic segmentation techniques, which have been optimized for processing complex marine environments. Aqua Sense significantly improves the robustness and scalability of marine pollutant monitoring systems. In MATLAB, it can simulate and evaluate various algorithms and techniques using built-in functions, toolboxes, and custom code. This framework leverages recent advancements in state-of-the-art architectural designs and demonstrates superior performance, outperforming all baseline models mean Intersection over Union (mIoU) (%), F1-score (%), precision (%), Overall Accuracy (%), Cohen's Kappa (%) and Recall (%) metrics. AquaSense offers significant advancements over existing marine pollutant detection methods by providing a comprehensive, scalable, and globally generalizable solution.

Keywords: Marine Pollution Detection, Satellite Data, Multispectral Imaging, Deep Learning, AquaSense Framework, Marine Debris and Oil Spill Dataset (MADOS), Image Processing

INTRODUCTION

The field of marine pollution identification addresses the public's increasing awareness of the state of oceans and marine life. The discharge of pollutants has enhanced the growth of industries and urbanization, leading to numerous problems affecting ecological systems and health [1]. All the actions, such as realizing the effects of pollutants, managing their sources and developing plans to minimize the effects, require the identification of pollutants [2]. The different species affect the marine ecosystem and the health of humans. The maritime environment was wide and complicated and had obstacles to pollution detection in the sea, while developing and implementing [3]. The temperature fluctuations and changing depth of oceans cover more than 70% of Earth's surface. The dynamic nature of the water body constitutes the identification and tracking of contaminants in the ocean [4]. Some of the characteristics that are absolutely crucial to a good detection technique are that they have to be strong and flexible. Technologies, inclusive of remote sensing, and enhanced analytical procedures could identify

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and analyze contaminants much more effectively. Self-driving vehicles and sensors provide precise data from the surface, whereas satellite imagery and aerial drones provide pollution patterns and density [5]. The chemical analysis constitutes techniques like spectrophotometry and gas chromatography. Monitoring the effects of pollutants on marine organisms, and related biological values such as bioassay and biomonitoring are increasingly used to assess the environmental effects of pollution [6]. The early detection of oil spills enhances the response time as well as decreased costs and impacts on the environment. Similarly, monitoring plastic pollution enables identifying how it accumulates and the danger to marine creatures [7].

Marine pollution constitutes a global problem and fights against the need for operational public awareness campaigns and educational activities. Human beings and communities could even reduce the overall environmental impact by being more proactive in the process of avoiding the source of pollution and its effects [8]. Moreover, frameworks of regulations and policies were necessary for the prevention of the levels of pollution and ensuring that the businesses complied with environmental standards. The application of such advanced technology to integrate with traditional methods has enhanced the ability to detect marine pollution [9]. The predictive analytics tool to predict potential pollution hotspots and assess the effectiveness of an effective pollution control plan to identify the trends. To attend to the fact that the problem of marine pollution is aglobal issue, for collaboration and sharing of information [10]. The rigorous process which requires techniques and equipment to identify such impurities in the feedstock. Traditional methods were usually associated with taking samples of water, suspended material, or biota and analyzing them in the laboratory. The technology of sensor systems and remote sensing constitutes,analytical techniques discovered and developed in recent years to enable the detection of marine contaminants effectively [11]. Differentiating across identical substances and concurrently identifying several contaminants might be difficult for many sensors to detect marine pollutants. The effectiveness of detecting devices could be impacted by harsh maritime settings, which include variations in salinity, temperature and pressure. This study aims to propose AquaSense, a novel deep learning framework that offers a holistic approach to marine pollutant detection. The research intends to develop a robust, scalable, generalizable automated system for detecting and monitoring marine pollution by deep learning utilizing upscaled multidimensional satellite images.

Contributions of the study

- Initially, datasets were collected from Marine Debris and Oil Spill (MADOS).
- The data was pre-processed using histogram equalization and bilateral filtering for the obtained data.
- The research intends to develop a robust, scalable, generalizable automated system for detecting and monitoring marine pollution by deep learning utilizing upscaled multidimensional satellite images.
- To address these limitations, we suggest AquaSense an innovative deep-learning architecture that offers a comprehensive method for detecting marine pollutants.

The article is divided into the following sections: An overview of the research is given in Section 2, as Related Works; The suggested method's study plan in detail described in Section 3; The evaluation results are summarized in Section 4; The current approach and the suggested method's result are outlined in Section 5 as discussion, while conclusion offers a summary of the research's implications in Section 6.

STATE-OF-ART RESEARCH

Marine ecosystems and fisheries were seriously threatened by oil spills from operating maritime operations, including boats, drilling pads and other structures by pipelines and naturally occurring hydrocarbon water seepage [12]. Faster R-CNN a unique deep learning model constituted for efficient SAR oil spill detection. The experimental outcome demonstrated that the suggested approach exhibits good detection results.

The growing generation of chemicals that negatively impact the aquatic environment [13]. The photochemical reactions of a microalgae species has prevalent groups of phytoplankton in the seas that were utilized to distinguish and detect a variety of developing contaminants. The experimental findings demonstrated that luminescence induction rates offer a useful instrument for assessing environmental toxicology.

The Mask R-CNN approach for image recognition segmentation of instances constructs a unique deep-learning oil spill recognition model [14]. The reliability of SAR images for the identification of maritime oil spills is impacted by

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the visual resemblance between the characteristics of gasoline storms and other materials. The experimental findings showed that Mask R-CNN works better than other techniques in the segmentation and identification of oil spills.

The marine oil spill catastrophe reduction constitutes the possibilities of emerging digital developments in reducing oil leakage cause danger [15]. Remote sensing technology has made it easier to quickly locate and identify the source of oil leakage in water, and the existence of additional biogenic substances that constitute visual characteristics makes it more difficult to quickly detect and make emergency reaction decisions. The result findings showed that catastrophe risk mitigation and management.

The plastic garbage floats across the waters, and it poses a hazard to the marine ecosystem. It was essential to develop instruments and eliminate them from the water [16].

Table 1. Comparing the Literature Survey with Proposed Model

Author	Methodology	Algorithm	Novelty	Achieved	Future Scope
Gucma, M.,et al., 2022 [17]	Using remote sensing techniques to monitor and identify marine pollution	Not specifically mentioned	Evaluating and contrasting several remote sensing techniques to find marine pollution	Analysed the performance of a few chosen remote sensing methods	Adding more extensive datasets to the research and utilizing AI to identify pollution in real time
Zhao, D et al., 2022 [18]	Oil spill detection using hyperspectral and multispectral remote sensing	The technique of Spectral Gene Extraction (SGE)	Created a unique SGE technique to enhance the hyperspectral data-based oil spill detection	Improved precision in tracking maritime oil spills using multispectral and hyperspectral data	Testing the SGE approach with more diverse pollutant types and larger datasets to increase computing efficiency
Yang, J, et.al., 2023	Hyperspectral combined with thermal infrared remote sensing for oil spill identification	Not explicitly stated	Combined hyperspectral and thermal infrared data for marine oil spill identification	Successfully identified oil spills using combined spectral and thermal data	Application of the combined method on other pollutants; further enhancing the resolution of thermal sensors
Lin, Z., 2024	China's use of remote sensing technologies to check maritime pollution	Not specifically mentioned	An overview of how remote sensing technology is being used in China to monitor marine pollution	shown how to employ remote sensing in Chinese seas in an efficient manner.	Establishing more reliable, nation-specific algorithms and distant sensing technologies for monitoring in real-time

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Taggio, N., et al., 2022	Hyperspectral PRISMA data combined with machine learning methods to identify marine plastic waste	fusion of algorithms for machine learning	investigated the use of machine learning methods and PRISMA hyperspectral data to find marine plastic waste.	used machine learning and hyperspectral data to find marine plastic litter	Testing more pollutant categories and refining machine learning algorithms to identify smaller-scale plastic litter
Jang, S., et al., 2023	Techniques for improving images to find thin oil coatings on the ocean's surface	Image enhancement algorithms	Analysed how effectively image enhancing methods work when used to find thin oil coatings.	enhanced the use of image enhancement to identify thin oil deposits on the sea surface	Utilising cutting-edge image processing methods and integrating with real-time monitoring systems
Kikaki, K., et al., 2024	Sentinel-2 imaging and deep learning for the detection of marine contaminants and sea surface features	Deep learning	Sentinel-2 images was analysed using deep learning to find marine contaminants and sea surface characteristics.	Sentinel-2 images and deep learning algorithms were utilised to achieve precise identification of marine contaminants and sea surface characteristics.	broader use of deep learning models using input from several sensors, improving accuracy and lowering false positives
Mohsen, A., Kiss, T. and Kovács, F., 2023	Sentinel-2 imaging and machine learning for the detection and mapping of riverine trash	Machine learning (Random Forest, SVM)	Sentinel-2 images was processed with machine learning to identify and map riverine rubbish.	Using satellite data and machine learning, a precise mapping of riverine trash was accomplished.	Extending the technique to more water body types, enhancing algorithms for expedited processing, and incorporating IoT for real-time surveillance.

METHODOLOGY

In this research, a novel approach was introduced, the AquaSense deep learning framework that offers a holistic approach to marine pollutant detection. Data pre-processing used to pre-process the raw data, here histogram

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equalization and bilateral filtering are used. The marine pollutant detection constitutes multispectral image data. The deep learning used for semantic segmentation region growing. AquaSense leverages high-resolution multispectral data from Sentinel-2 satellites, allowing it to detect a variety of contaminants, such as plastics, oil spills and other contaminants. Figure 1 represents the overall paper flow.

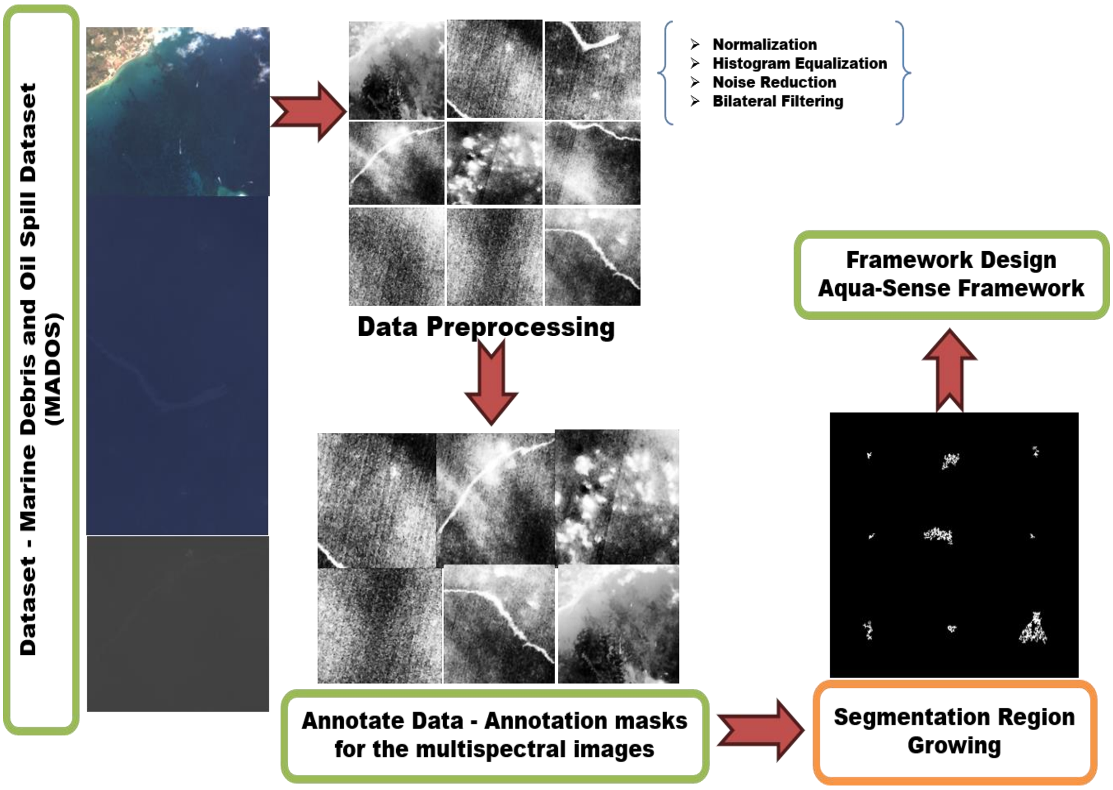

Figure 1: MADOS Working Model Architecture

Dataset

Initially, a dataset was collected from Marine Debris and Oil Spill (MADOS) (*https://zenodo.org/records/10664073*). The MADOS dataset addresses marine trash and oil spills, derived from Sentinel-2 satellite imagery. The consideration of other characteristics on the sea surface constitutes with them or has been proposed to share a spectrum with them. It was difficult at the linguistic segmentation job that MADOS establishes scant annotations. Figure 2 represents the sample images of the dataset.

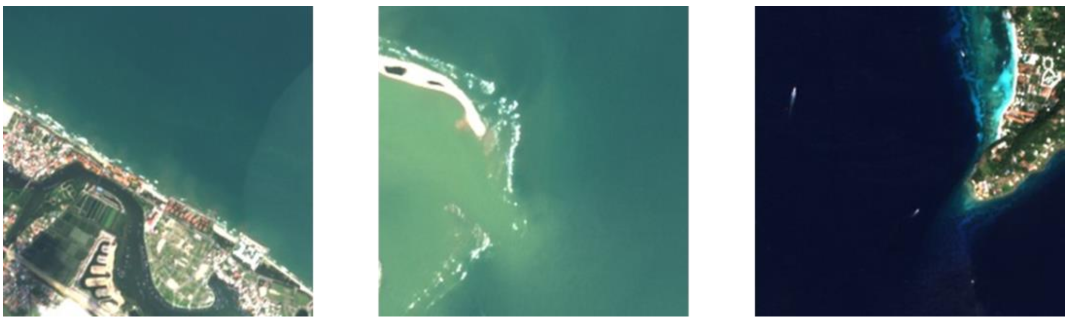

Figure 2: Example images of the MADOS dataset

Data Pre-Processing

Data preprocessing converts raw data into a clear and readable format, an essential stage in data analysis and machine learning. It entails activities that include encoding and categorizing variables, eliminating duplicates, normalizing or scaling data and managing missing values. Enhancing the quality of the data, lowering noise and

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preparing the dataset for precise and effective model training. Preprocessing helps to improve the performance of the model. Pre-processing includes histogram equalization and bilateral filtering.

Histogram Equalization

By improving the contrast of images from coastal habitats, histogram equalization facilitates the identification linked to pollution. It makes variations in intensity and facilitates more accurate detection and measurement of marine pollutants. When analyzing satellite or underwater images, it might be difficult to detect the presence of pollutants. Histogram equalization is a frequently used technique for improving an image's contrast. Histogram equalization constitutes simplicity of implementation and low processing resource requirements. The process involves utilizing the possibility pattern of the source's color levels to determine the image-shaded areas. Its tendency to drastically modify the image brightness, however, possesses primary issues withthe resultant image that becomes saturated with extremely brilliant or dark intensity values expressed in equation (1).

$$r(j) = round\ ((K-1).D(j)) \tag{1}$$

Here, the initial intensity level is depicted as j, and the subsequent intensity level is denoted as $r(j)$. The value of the cumulative distribution function (CDF) for the initial intensity level is represented as $D(j)$. Where K represents the total number of intensities.

Bilateral filtering

Bilateral filtering successfully smooth images while maintaining edges an essential distinction for differentiating contaminants from natural marine features it was appropriate for the identification of marine pollutants. Its capacity to preserve detail while reducing noise improves image quality, which raises the accuracy of pollution identification systems. It facilitates the separation of contaminants from the background by emphasizing both regional and intensity variations. The bilateral filtering constitutes a regressive method, in contrast to traditional linear convolutional algorithms, here the filtering outcome$I$ at j^{th} image represents the average of pixels expressed in equation (2).

$$I_j = \sum_{i\in\Omega} l_{j,i}^{bf}(h_j, h_i)J_i \tag{2}$$

The bilateral filtering core at the j th and ith places denoted as$l_{j,i}^{bf}$, while the filtering inputs and guiding map are represented by j and$h$, respectively. Here, $i$represent as pixel index inside the relevant patch. To be more precise, the kernel uses an exponential spectrum kernel and stochastic physical kernel together, which might be expressed in equation (3) as follows:

$$l_{j,i}^{bf}(h_j, h_i) = \frac{1}{m_j}\omega(j,i)\phi(h_j, h_i) \tag{3}$$

Here m_j serves as the calibrate aspect, the regional stochastic location and range cores at $jth$and ith coordinates, respectively, are denoted by $\omega(j,i)$, and $\phi(h_j, h_i)$expressed on equations (4 and 5).

$$\omega(j,i) = \exp\left(-\frac{||j-i||^2}{\sigma_t^s}\right) \tag{4}$$

$$\phi(h_j, h_i) = \exp\left(\frac{||h_j - h_i||^2}{\sigma_q^2}\right) \tag{5}$$

The standard deviations of spectrum and spatial cores are denoted as $\sigma_t$and σ_q.

Proposed Method AquaSense

In the field of marine pollution identification, AquaSense a revolutionary invention that provides a sophisticated, comprehensive framework that solves many of the drawbacks of previous methods. AquaSense constitutes maritime environmental monitoring due to its innovative integration for pollution identification, deep learning

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models, scalability and tracking abilities. The primary elements of AquaSense apart in this field were provided below:

Comprehensive Pollutant Detection

The AquaSense framework approaches the significant issue of maritime pollution detection by offering a thorough, multi-class solution that can recognize diverse pollutants, including plastics, oil spills, and other contaminants. AquaSense utilizes high-resolution multispectral satellite data from Sentinel-2 and extensive semantic segmentation approaches to identify many pollutant types in intricate marine habitats, in contrast to traditional methods that focus solely on single pollutants or binary classification. This resilient architecture has undergone extensive testing on the Marine Debris and Oil Spill (MADOS) dataset, exhibiting exceptional performance across critical assessment parameters, hence representing a notable development in real-world marine pollution monitoring.

Holistic Approach to Marine Pollution

A significant obstacle in the field of maritime pollution detection has been restricted for conventional techniques. The systems typically identify a particular category of pollutant, such as plastics or oil spills, and utilize fundamental binary categorization tasks. Aqua Sense presented a comprehensive strategy that broadens the scope of pollutants and it can identify obvious substances like oil spills, floating plastics, organic substances and marine debris. For detecting multiple contaminants of pollutants endangering marine ecosystems. Protecting marine ecosystems from variety of challenges, improving the efficiency of pollution monitoring programs and encouraging improved environmental management made possible by AquaSense.

Leveraging Multispectral Data

The Sentinel-2 sensor network delivers high-resolution images across various spectrum bands, including visible, near-infrared and subtropical infrared areas. Through the use of data from many bands, Aqua Sense is able to identify the small forms of contaminants that constitute traditional approaches by using distinct spectral fingerprints to detect them. When comparing oil leakage, floating plastic or organic material, for instance, they reflect light across spectral bands, making it possible for AquaSense to distinguish between them with extreme accuracy. The spectral reflectance across multiple spectrum bands used to detect different pollutants such as oil leaks, floating plastic or organic material expressed in equation (6).

$$Q(\lambda) = \frac{I_{reflected}(\lambda)}{I_{incident}(\lambda)} \tag{6}$$

Where, $Q(\lambda)$represent the wave length reflectance, $I_{reflected}(\lambda)$ indicate the intensity of wavelength reflected and $I_{incident}(\lambda)$ depicts the intensity of wavelength incident.

Advanced Deep Learning Framework

Cutting-Edge Semantic Segmentation

Modern deep learning architecture that has been specially tailored for semantic segmentation is the brains behind AquaSense. Semantic segmentation is perfect for maritime ecosystems where contaminants might change in shape, dimensions and distribution. Since it enables pixel-level categorization. To provide very accurate identification in intricate and crowded marine landscapes, AquaSense's deep learning algorithms properly categorize every pixel in the satellite images as either pollutant or non-pollutant. The AquaSense environmental monitoring were highly precise and the capacity to detect and evaluate marine pollution was greatly improved by utilizing sophisticated algorithms. The identification of smaller-scale contaminants, such as microplastics or isolated oil patches, depends on pixel-level accuracy.

Architectural Innovations Tailored to Marine Environments

The water attenuation, lighting, wave motion and displacing moving objects in marine environments posed a different challenge altogether. In response to these challenges, AquaSense features novel architectural design in neural network architecture. The change in the parameters allows the system to address the characteristics of

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marine images, including the reflection of water bodies and the slow diffusion of pollutants. Aqua Sense is intended to identify and eliminate undesirable components in aqueous systems such as seas, shipping and complex coastal environments. AquaSense supports to preserve the health of marine ecosystems by improving the accuracy and dependability of pollution detection by adjusting the unique characteristics of habitats.

ENHANCED ROBUSTNESS AND SCALABILITY

Robust Performance with High Accuracy

Accuracy constitutes a common problem for traditional models, particularly in varied maritime habitats where toxins take many different forms. The performance parameters like mIoU, F1 score, precision, recall and overall accuracy. These metrics quantify the model's differentiation capability with regard to different types of contaminants, sample its effectiveness in identifying pollutants in different scenario scales and achieve the right balance in terms of precision and recall. Hence, AquaSense was reliable for operational use because of enhanced accuracy, beneficial for near-coastal and off-shore observations.

Scalable to Global Monitoring Needs

The distinctive competencies have enabled AquaSense to grow well in terms of increased data processing capacity and global appeal. The need for systems that were capable of handling large volumes of data constitutes satellite data becoming more accessible and useful. The international satellite systems might be processed using AquaSense’s architecture to monitor large sea areas in real time. The AquaSense might be applied in various locations from the ocean to contaminated coastlines without a loss of accuracy and efficiency. The AquaSense might be used in a variety of settings from marine waters to damaged coastlines effectively and efficiently without compromising accuracy or efficiency. Because of its versatility, AquaSense positioned as essential instrument for international marine monitoring programs, meeting the demand for reliable solutions in ecosystems.

Integration of Tracking Capabilities

Dynamic Tracking of Pollutants

AquaSense has the ability to monitor the contaminants over time, present or absent. Compared with traditional approaches that primarily focus on static detection, possess significant enhancement. The AquaSense enables constant tracking of distribution, interaction with the surrounding conditions and even compartmentalized accumulation of contaminants through movement and dynamic changes. For instance, tracing the path of an oil leakage informs the information reaction teams about containment and cleanup situations, while observing the movement of floating plastics reveals how floating maritime waste patches. By adding tracking functions, AquaSense turns into a single universal tool for observing the dynamics of different marine substances, rather than a measuring tool. The Velocity might be used to simulate how contaminants, like oil spills, spread over time on marine expressed in equation (7).

$$v = \frac{d}{t} \tag{7}$$

Here, v represents the pollutant velocity, d indicated as distance of pollutants travelled and t represent the time taken to spread.

Global Generalization and Broad Applicability

A Generalizable and Adaptable Framework

The existence of functions for a wide variety of conditions and locations represents the challenges of detecting marine pollutants. The AquaSense intended to be universally applicable, it might be utilized to observe numerous marine conditions, including open waters, coastal zones and sensitive environments, such as marshes or coral reefs. The versatility constitutes AquaSense to ensure its inclusion into global marine pollution monitoring efforts, which provides relevant data to environmental agencies, maritime authorities and global bodies involved in the protection of marine health. AquaSense improves the pollution detection efficiency and supports exhaustive efforts to protect marine ecosystems by the distinctive features of various marine environments. Because of its special qualities, it

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can adapt the particulars different marine ecosystems, which makes it essential instrument in the fight against pollution and favor of the sustainable management of Marine resources. AquaSense helps to protect marine biodiversity and guarantee the health of oceans.

Applicability across Various Geographies

Aqua Sense is extremely adaptable due to its capacity to operate in a broad spectrum of geographical areas, including the uncontaminated seas of the Arctic and the contaminated shorelines of industrial areas. To provide constant and dependable pollution detection across continents, independent of environmental circumstances generalizable design was essential. AquaSense's versatility constitutes an invaluable tool for international environmental conservation programs, especially intended at lessening the effects of human activity on marine environments. AquaSense helps international efforts to maintain marine ecosystems and advance environmentally friendly habits by offering reliable statistics and continuous surveillance.

EXPERIMENTAL RESULTS

Using, MATLAB2024a or above version, we can simulate and evaluate various algorithms and techniques using built-in functions, toolboxes, and custom code. The proposed strategy assess and calculate its effectiveness using the following indicators outperforming all baseline models: mIoU (%), F1 score (%), recall (%), Cohen's Kappa (%), precision (%) and overall accuracy (%) metrics. We also present an efficacy comparison between our proposed strategy and other current approaches. The existing methods include Marine Next-generation Exploration and Detection Technology (MariNeXt) [23] and Random Forest (RF) [24].

Performance Evaluation 1st algorithm

The F1 score used to assess a classification model's performance by integrating recall and accuracy into a single. The capacity to recognize all pertinent instances, precision and accuracy of positive predictions have harmonic means. Figure 3and Table 1 illustrates an evaluation of the F1-score in comparison between suggested and conventional methods. Compared to conventional methods MariNeXt has an F1 score of 76.0% and the proposed AquaSense attains an F1-score of 91.06%. The proposed method provided superior results to detect marine pollutants.

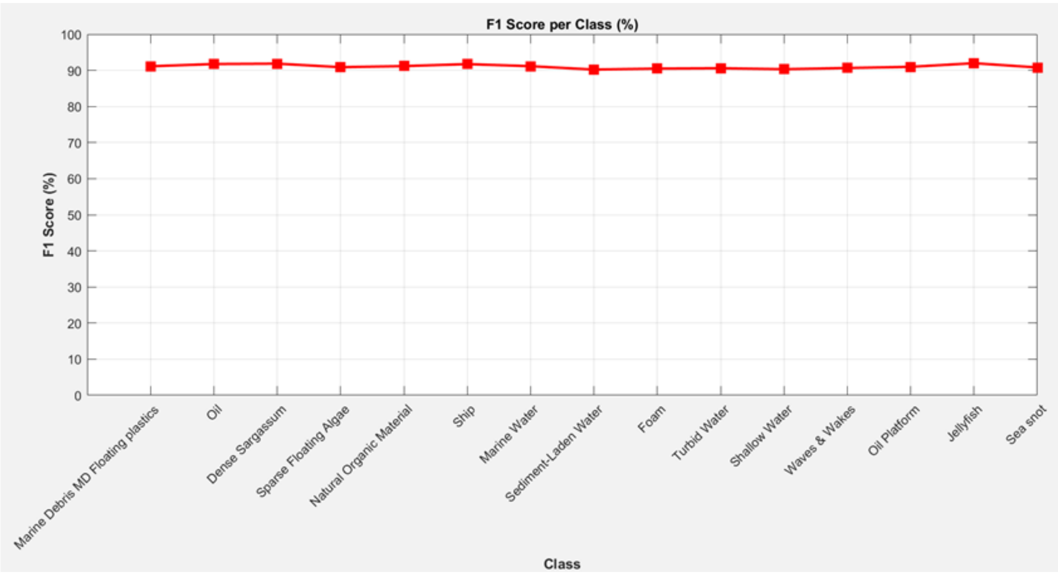

Figure 3: Output graph of F1 Score

The mIoU used to assess segmentation models perform, especially when it comes to tasks like object identification and image segmentation. The intersection surface of the real and anticipated regions divided by the union area of each class yields the IoU. This statistic offers an assessment of how well the model separates objects. Figure 4 and Table 1 illustrate an evaluation of mIoU in comparison between suggested and conventional methods. Compared to

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conventional methods MariNeXt has mIoU of 64.3% and the proposed AquaSense attains a mIoU of 83.52%. The proposed method provided better outcomes for detecting marine pollutants.

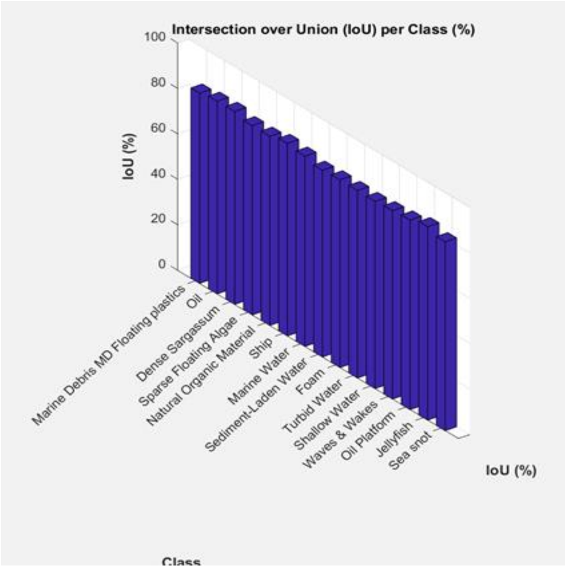

Figure 4: Output graph of mean Intersection over Union

Accuracy provides a strong assessment of the system's effectiveness by evaluating the model's preciseness assessment by computing the ratio of successfully anticipated to the total occurrences. Figure 5 and Table 1 illustrate an evaluation of accuracy in comparison between suggested and conventional methods. Compared to conventional methods like MariNeXt has an accuracy of 89.1% and the proposed AquaSense attains an accuracy level of 91.00%. The proposed method provided superior results to detect marine pollutants.

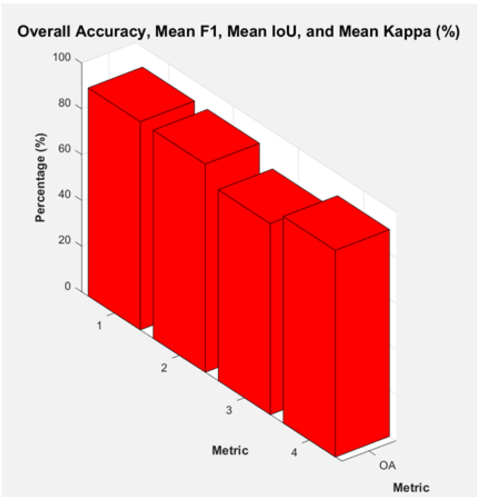

Figure 5: Output graph of overall accuracy

Table 1 Result parameters

Algorithm	Overall Accuracy (%)	Mean Intersection over Union (mIoU) (%)	F1 score (%)
MariNeXt	89.1	64.3	76.0
AquaSense Framework [Proposed]	91.00	83.52	91.05

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A statistical metric called Cohen's Kappa used to evaluate the degree of convergence across two assessors or evaluators while accounting for the risk of agreement. It was computed by contrasting the actual and predicted agreements under the assumption of random chance. Table 2 illustrate an evaluation of accuracy in comparison between suggested and conventional methods. Compared to conventional methods like Random Forest has Cohen's Kappa of 68%, and the proposed AquaSense attain has Cohen's Kappa level of 90.37%. The proposed method provided better results for detecting marine pollutants.

The precision level of a model shows how well it predicted outcomes. The assessment is the ratio of the total expected benefits to the precisely forecasted favorable outcomes. Figure 6 and Table 2 illustrate an evaluation of precision in comparison between suggested and conventional methods. Compared to conventional methods like Random Forest has a precision of 56%, and the proposed AquaSense attains a precision level of 91.01%. The proposed method provided better results for detecting marine pollutants. Recall is a statistic that assesses a model's capacity to locate all pertinent instances of a class. Figure 5 and Table 1 present an evaluation of Recall in comparison between suggested and conventional methods. Compared to conventional methods like Random Forest with a recall of 90%, and the proposed AquaSense attain a recall level of 91.09%. The proposed method provided better outcome for detecting marine pollutants.

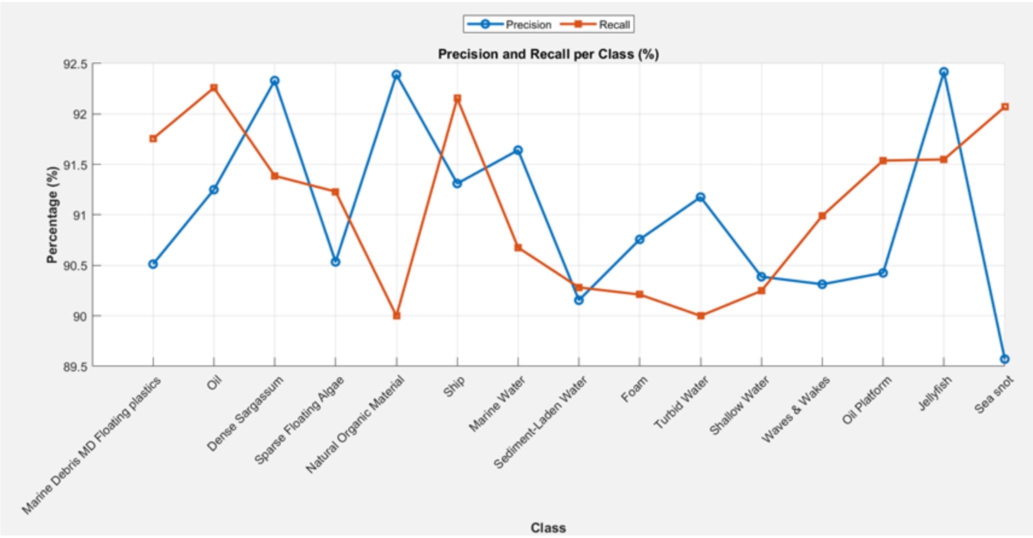

Figure 6: Output graph of Precision and recall

Table 2 Comparison parameters

Algorithm	Recall (%)	Cohen's Kappa (%)	Precision (%)
Random Forest (RF)	90	68	56
AquaSense Framework [Proposed]	91.09	90.37	91.01

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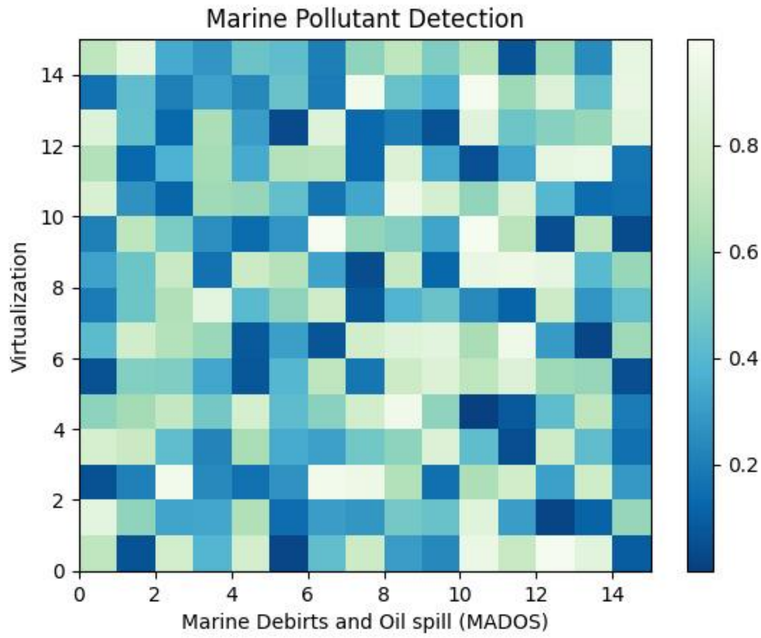

The confusion matrix is employed to assess AquaSense's effectiveness in detecting various marine pollutants. This matrix provides a thorough evaluation of the categorization results generated by the model. By documenting true positives, true negatives, false positives, and false negatives for each pollutant category, it aids in pinpointing areas of misclassification, such as the confusion between oil spills and plastics. Through visual representation of these results, researchers can discern issues such as data imbalances or intricate properties of the contaminants. This comprehensive analysis confirms the robustness and use of AquaSense for scaled, real-world monitoring of marine pollution, supported by metrics like as accuracy, recall, and F1-score.

DISCUSSION

The MariNeXt [23] constitutes cost and scalability issues while providing cutting-edge instruments for the identification of marine pollutants. Accessibility of smaller organizations might be restricted by the high cost of deploying its complex sensors and automated algorithms. Furthermore, due to unstable communication networks, relying on actual time data from distant sites sometimes might be difficult. Certain contaminants calibration might be difficult for the system to detect. Additionally, the high maintenance requirements of equipment used in severe oceanic environments might lead to frequent outages, which compromise continuous monitoring. Random forests have certain limits to handle huge datasets with multiple variables, they were useful for the identification of marine pollutants. Furthermore, random forests might have trouble being interpreted, which makes it difficult to determine how different characteristics affect predictions. The applicability on unknown data with varying distributions might cause worst performance, underscoring the necessity of frequent updates and validation. To overcome this, the proposed method Aqua Sense isan innovative deep-learning architecture that offers a comprehensive method for detecting marine pollutants. AquaSense leverages high-resolution multispectral data from Sentinel-2 satellites, allowing it to detect the variety of contaminants. The framework is built on state-of-the-art semantic segmentation techniques, which have been optimized for processing complex marine environments. AquaSense significantly improves the robustness and scalability of marine pollutant monitoring systems.

CONCLUSIONS

In this study, a novel approach is introduced, the AquaSense deep learning framework that offers a holistic approach to marine pollutant detection. AquaSense leverages high-resolution multispectral data from Sentinel-2 satellites, allowing it to detect a variety of contaminants, such as plastics, oil spills and other contaminants. The research intends to develop a robust, scalable, generalizable robotic system for detecting and monitoring maritime pollution using deep learning utilizing upscaled multidimensional satellite images. Used extensive testing on the Marine Debris and Oil Spill (MADOS) dataset. Data pre-processing is used to preprocess the raw data, here

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histogram equalization and bilateral filtering used to pre-process the data. In MATLAB, simulate and evaluate various algorithms and techniques using built-in functions, toolboxes, and custom code. The experimental result findings demonstrate superior performance, outperforming all baseline models like mIoU (83.52%), f1-score (91.05%), precision (91.01%), recall (91.09%), Cohen's Kappa (90.37%) and overall accuracy (91.00%) metrics. By offering complete, scalable, and globally generalizable solutions, AquaSense delivers notable improvements over current marine pollution detection techniques.

LIMITATIONS AND FUTURE SCOPE

Differentiating across identical substances and concurrently identifying several contaminants might be difficult for many sensors to detect marine pollutants. The effectiveness of detecting devices could be impacted by harsh maritime settings, which include variations in salinity, temperature and pressure. Future scope, moving towards the development of nanoscale sensors to provide increased specificity and sensitivity in the detection of low pollution concentrations.

REFERENCES

[1]. Hasimoto-Beltran, R., Canul-Ku, M., Méndez, G.M.D., Ocampo-Torres, F.J. and Esquivel-Trava, B., 2023. Ocean oil spill detection from SAR images based on multi-channel deep learning semantic segmentation. *Marine Pollution Bulletin*, *188*, p.114651. 10.1016/j.marpolbul.2023.114651

[2]. Gonçalves, G., Andriolo, U., Pinto, L. and Duarte, D., 2020. Mapping marine litter with Unmanned Aerial Systems: A showcase comparison among manual image screening and machine learning techniques. *Marine pollution bulletin*, *155*, p.111158. 10.1016/j.marpolbul.2020.111158

[3]. Yekeen, S.T. and Balogun, A.L., 2020. Advances in remote sensing technology, machine learning and deep learning for marine oil spill detection, prediction and vulnerability assessment. *Remote Sens*, *12*(20), pp.1-31.

[4]. Lin, C., Han, G., Zhang, T., Shah, S.B.H. and Peng, Y., 2022. Smart underwater pollution detection based on graph-based multi-agent reinforcement learning towards AUV-based network ITS. *IEEE Transactions on Intelligent Transportation Systems*, *24*(7), pp.7494-7505. 10.1109/TITS.2022.3162850

[5]. Papakonstantinou, A., Batsaris, M., Spondylidis, S. and Topouzelis, K., 2021. A citizen science unmanned aerial system data acquisition protocol and deep learning techniques for the automatic detection and mapping of marine litter concentrations in the coastal zone. *Drones*, *5*(1), p.6. 10.3390/drones5010006

[6]. Ma, X., Xu, J., Pan, J., Yang, J., Wu, P. and Meng, X., 2023. Detection of marine oil spills from radar satellite images for the coastal ecological risk assessment. Journal of Environmental Management, 325, p.116637. 10.1016/j.jenvman.2022.116637

[7]. Naz, S., Iqbal, M.F., Mahmood, I. and Allam, M., 2021. Marine oil spill detection using synthetic aperture radar over indianocean. *Marine Pollution Bulletin*, *162*, p.111921. 10.1016/j.marpolbul.2020.111921

[8]. Prakash, N., Stahl, F., Mueller, C.L., Ferdinand, O. and Zielinski, O., 2021, September. Intelligent marine pollution analysis on spectral data. In *OCEANS 2021: San Diego–Porto* (pp. 1-6). IEEE. 10.23919/OCEANS44145.2021.9706056

[9]. Waqas, M., Wong, M.S., Stocchino, A., Abbas, S., Hafeez, S. and Zhu, R., 2023. Marine plastic pollution detection and identification by using remote sensing-meta analysis. *Marine Pollution Bulletin*, *197*, p.115746. 10.1016/j.marpolbul.2023.115746

[10]. Le Floch, S. and Muttin, F. eds., 2020. *Remote Detection and Maritime Pollution: Chemical Spill Studies*. John Wiley & Sons.

[11]. Sannigrahi, S., Basu, B., Basu, A.S. and Pilla, F., 2021. Detection of marine floating plastic using Sentinel-2 imagery and machine learning models. *arXiv preprint arXiv:2106.03694*. 10.48550/arXiv.2106.03694

[12]. Huang, X., Zhang, B., Perrie, W., Lu, Y. and Wang, C., 2022. A novel deep learning method for marine oil spill detection from satellite synthetic aperture radar imagery. *Marine Pollution Bulletin*, *179*, p.113666. 10.1016/j.marpolbul.2022.113666

[13]. Rodrigues, N.M., Batista, J.E., Mariano, P., Fonseca, V., Duarte, B. and Silva, S., 2021. Artificial intelligence meets marine ecotoxicology: applying deep learning to bio-optical data from marine diatoms exposed to legacy and emerging contaminants. *Biology*, *10*(9), p.932. 10.3390/biology10090932

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[14]. Yekeen, S.T., Balogun, A.L. and Yusof, K.B.W., 2020. A novel deep learning instance segmentation model for automated marine oil spill detection. *ISPRS Journal of Photogrammetry and Remote Sensing*, *167*, pp.190-200. 10.1016/j.isprsjprs.2020.07.011

[15]. Temitope Yekeen, S. and Balogun, A.L., 2020. Advances in remote sensing technology, machine learning and deep learning for marine oil spill detection, prediction and vulnerability assessment. *Remote Sensing*, *12*(20), p.3416. 10.3390/rs12203416

[16]. Duarte, M.M. and Azevedo, L., 2023. Automatic detection and identification of floating marine debris using multispectral satellite imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *61*, pp.1-15. 10.1109/TGRS.2023.3283607

[17]. Gucma, M. and Deja, A., 2022. Assessment of selected remote sensing methods in detecting and tracking marine pollution. *ZeszytyNaukoweAkademiiMorskiej w Szczecinie*, (71 (143). 10.17402/523

[18]. Zhao, D., Tan, B., Zhang, H. and Deng, R., 2022. Monitoring marine oil spills in hyperspectral and multispectral remote sensing data by the spectral gene extraction (sge) method. *Sustainability*, *14*(20), p.13696. 10.3390/su142013696

[19]. Yang, J., Hu, Y., Zhang, J., Ma, Y., Li, Z. and Jiang, Z., 2023. Identification of marine oil spill pollution using hyperspectral combined with thermal infrared remote sensing. *Frontiers in Marine Science*, *10*, p.1135356. 10.3389/fmars.2023.1135356

[20]. Lin, Z., 2024. Application of Remote Sensing Technology in Chinese Marine Pollution Monitoring. *Highlights in Science, Engineering and Technology*, *83*, pp.770-775. 10.54097/12ecra38

[21]. Taggio, N., Aiello, A., Ceriola, G., Kremezi, M., Kristollari, V., Kolokoussis, P., Karathanassi, V. and Barbone, E., 2022. A Combination of machine learning algorithms for marine plastic litter detection exploiting hyperspectral PRISMA data. *Remote Sensing*, *14*(15), p.3606. 10.3390/rs14153606

[22]. Jang, S., Park, Y., Kwon, J., Lee, S. and Kim, T.H., 2023. Evaluation of Application Possibility for Floating Marine Pollutants Detection Using Image Enhancement Techniques: A Case Study for Thin Oil Film on the Sea Surface. *Korean Journal of Remote Sensing*, *39*(6_1), pp.1353-1369. 10.7780/kjrs.2023.39.6.1.15

[23]. Kikaki, K., Kakogeorgiou, I., Hoteit, I. and Karantzalos, K., 2024. Detecting Marine pollutants and Sea Surface features with Deep learning in Sentinel-2 imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, *210*, pp.39-54.10.1016/j.isprsjprs.2024.02.017

[24]. Mohsen, A., Kiss, T. and Kovács, F., 2023. Machine learning-based detection and mapping of riverine litter utilizing Sentinel-2 imagery. *Environmental Science and Pollution Research*, *30*(25), pp.67742-67757.10.1007/s11356-023-27068-0

List of Abbreviations

Abbreviation	Definition
SAR	Synthetic Aperture Radar
Mask RCNN	Mask Region Convolutional Neural Network
SGE	Spectral Gene Extraction
HSI	Hyper Spectral Images
MSI	Multi Spectral Images
DNA	Deoxyribonucleic Acid
Faster RCNN	Faster Region Convolutional Neural Network

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