Advanced Classification of Marine Pollutants Using Sentinel-2 Multispectral Thermal Imaging and Vision Transformer for Enhanced Water Quality Assessment

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Abstract

Marine pollution introduces harmful substances into the ocean, affecting ecosystems, marine life, coastal communities, and the global economy. Classifying these pollutants is essential for identifying their sources and assessing their ecological impact. Computer vision techniques are used to automate analysis and enhance the accuracy of detecting and classifying marine pollutants as visual identification results in underreporting of pollutants. Sentinel-2 Multispectral images have very low visibility of pollutants. The proposed method uses (i)High quality Sentinel-2 multispectral thermal images generated by Stable Diffusion Thermal Image Generator highlights temperature variations for better classification (ii) Transverse Dyadic Wavelet Transform (TxDyWT) to pre-process the thermal images as it retains structural details for classifying pollutants.(iii) Denoising Convolutional Neural Network (DnCNN) optimized with Hippopotamus Optimization Algorithm enhances images and Vision transformer (ViT) is employed to classify as microplastics, sediments and oil spills by identifying subtle patterns in pollutants. The proposed methodology identifies fragments of microplastics as small as 0.5 mm, large-scale oil spills, and hydrogenous sediments. The detection accuracy for microplastics, oil spills, and sediments is approximately 95%.

Keywords: Marine pollution, Water Test, Microplastics, Oil Spills, Sediments.

1. Introduction

Ocean pollution is an environmental issue and it is caused by the addition of harmful substances into the ocean. Ocean Pollution also known as marine pollution occurs in various forms like chemicals, plastic substances, organic waste. It affects the marine ecosystem and human health. Around 80% of ocean pollutants are land-based sources like sewage, industrial waste that enters the ocean through rivers and storm water [1]. Plastics like bags and bottles dumped into ocean creates ocean pollution and chemicals like fertilizers, pesticides and heavy metals also cause ocean contamination. Oil spills from marine transportation and marine activities such as deep-sea mining and fishing also cause pollution and has a huge impact on marine ecosystem [2].

Marine ecosystem is affected by various types of pollutions. Marine animals die and get injured because of the ingestion of plastic debris caused by Plastic pollution. It also leads to accumulation of toxins affecting the food web. Nutrient pollution causes toxic algal blooms affecting the growth and overall health of marine life. Coral reefs struggle to survive as they depend on clean water for reproduction, and this creates loss in biodiversity. Marine species are affected by diseases caused by pathogens and pollution changes the temperature, salinity and pH affecting the survival of marine species. [3]. Pollution in the marine ecosystem also affects the human health.

Ocean pollution is a threat to the health and well-being of humans. Consumption of contaminated seafood causes the marine pollutants to enter to human food chain. Humans are exposed to harmful mercury pollution, microplastics and chemicals present in the seafood. The Pollutants like mercury causes autism, dementia. Chemical mixtures damage the nervous system, cardiovascular and metabolic disease and even cause death to human beings. Effect of microplastics on human health needs to be explored more and it can be done by improved monitoring of ocean pollution. Studies on the effect of ocean pollutants on human health is required [4] and the first step is to detect.

Detection of ocean pollution is required to protect human health, maintain marine ecosystem and to manage the sustainable resources. Monitoring ocean pollution helps to identify and reduce exposure to contaminated seafood as the mercury and algal bloom contains toxins that affect the human health. Public health policies can be implemented by understanding the correlation between ocean pollution and occurrence of diseases. It can be done by monitoring the ocean pollution and it also helps in finding the sources and impacts caused by pollution. Sustainable development Goals to conserve marine resources can be achieved by tracking pollution levels. Overfishing can be avoided and detecting and taking preventive measures to reduce pollution provides clean water, enhancing tourism and supporting local economies [5].

Smaller plastic particles are called as microplastics. Microplastics are formed due to the degradation of larger plastic items. Microplastics disrupt the marine ecosystems. They are ingested by many organisms due to smaller size and it results in bioaccumulation and toxicity. Microplastics increase the effect of other pollutants and the toxicity in marine ecosystem intensifies. They resist to degrade and undergo transformation that enhances their toxicity [6]. Marine species needs to be protected from microplastics and other pollutant

Marine life should be protected to support biodiversity and to maintain ecosystem. Healthy marine ecosystem is essential for human well-being, climate regulation and clean water supply. Protecting marine life also ensures sustainable fisheries and tourism creating source of income and employment. Overfishing and pollution can be reduced by establishing Marine Protected Areas (MPAs). Biodiversity hotspots are protected by restricting human activities in the particular zone. Sustainable fisheries management can be implemented to set catch limits and to promote fishing methods to reduce bycatch. Effective management strategies like restoration projects and global collaboration can improve ecosystem [7]. Marine life is linked with human health and it shows the need to protect ocean ecosystem.

Humans are exposed to microplastics by ingestion, inhalation and through direct contact. Ingestion occurs through contaminated seafood, salt and water. Airborne microplastics enters the human body through inhalation and direct contact with products containing microplastics leads to exposure. Microplastics affect the human metabolism and immune system causing stress and DNA damage. Chronic pulmonary diseases and respiratory complications are caused by inhalation of microplastics and they also affect gastrointestinal tract leading to various digestive issues. Chemicals released from microplastics can cause cancer with their carcinogenic properties [8]. Continuous monitoring and research can reduce their impact on human health.

Sediments carry pollutants and affect the water quality and marine ecosystems. Sediments affect aquatic life, damages food webs and biodiversity. Run off from agricultural land, urban development, and natural erosion are the sources of sediments. Sediment impact can be reduced by the implementation of certain management practices. Pollutants can be filtered before entering the marine systems by establishing buffer zones. It reduces sediment run off. Wetlands can be created and restored to improve water quality. Conservation techniques can be used to reduce soil erosion and prevent their addition to water bodies [9].

Sediments contribute to the ecosystem through various ecological processes like nutrient cycling, water filtration and providing habitat to various organisms. Sediments help in food production through nutrient delivery and also helps in flood regulation. Accumulation of sediments determines the tree density and forest structure. Sediments deposited from storm surges recovers eroded areas and support ecosystem recovery. Regular sediment supply from rivers maintains healthy coastal areas. Health monitoring systems and policies can be developed to assess sediments [10].

Oil spills affect marine ecosystem, disrupts habitats and endangers various species. International agreement called MARPOL (Marine Pollution) convention regulates ship operations to reduce spills. Improvement in ship design, increased surveillance and strict enforcement of regulations can minimize oil spills [11]. Skimmers recover oil from water surface minimizing its impact on marine life. Wildlife rehabilitation centers can be established to treat animals affected by oil spills. Biodiversity recovery can be achieved by implementing projects to rehabilitate affected ecosystems like coral reefs and mangroves [12].

Oil spills affect the aquatic life and coastal habitats with the consequences like contamination of water, soil. Better governance framework regarding oil extraction, environmental protection and community welfare needs to be implemented. Integrated Coastal Zone Management should be implemented to protect the coastal communities. Strict enforcement of regulation should be done to mitigate the impact of oil spills on coastal and marine ecosystems. Compensation and benefit -sharing is essential to address the social and economic impacts of oil activities on coastal communities [13].

Detection of oil spills is essential for timely responsive measures. Recent developments in image processing techniques particularly in Computer Vision Approaches, Synthetic Aperture Radar (SAR) and Machine Learning Techniques have improved the ability to detect oil spills. DeepLAb3+ is used to enhance accuracy in noisy SAR images. Deep learning method is used as it enhances detection accuracy and handles complex SAR images. It is suitable for small and large oil spills and it has efficient detection with no human intervention [14].

Unarmed Vehicle and IR camera are used to detect oil spills. Convolutional Neural Network is used as it automatically extracts features from Thermal infrared images and classifies. Machine learning technique is used as the process of oil spill detection is automated and it increases the detection rate and reduces cost to clean oil spill. It has higher accuracy and can process large infrared images in real-time, adapts to other data sources [15].

Automated detection of oil spills and estimation of oil concentration from satellite images is done by using Machine Learning approach. Synthetic Aperture Radar (SAR) imagery is used as it can capture images in different weather conditions and lighting. Optical and multispectral imagery is used to obtain additional information about oil spell for estimating concentration. Various machine learning algorithms are used to classify and detect oil spills. Automated detection minimizes environmental damage, cost effective and can be used to monitor other pollutions [16]. The author has used Canny edge detection Algorithm to determine the size, shape and type of microplastics [17]. In [18] Crude oil spills are detected by using Convolutional Neural Network(CNN) from the images obtained unmanned areal vehicles (UAV) and a thermal infrared (IR) camera images.

1.2 Research Gap

Microplastics presence in the surface and subsurface waters are detected using Polarised Light Microscopy, Ramn Spectrometry and Micro-Fourier Transform Infrared Spectrometry [19]. Microplastics in other layers of ocean were not considered and the existing FTIR method analyses only larger particles of sample, visual identification leads to underreporting of pollutants present. Oil spills on the sea surface are detected by Bilateral Segmentation Network (BiSeNet), Convolutional Neural Network and Synthetic Data Generation [20]. Complexity of the BiSeNet network affects the overall accuracy and the network's performance is sensitive to variations in input leading to inconsistent detection. Oil spills on the shorelines and sediments need to be detected. Sediments are captured using UAV and are classified using U-Net Architecture [21]. Inaccuracy in boundaries are caused by over-lap strategy used in U-Net architecture and the sediment types maybe be classified accurately without trained datasets. Figure 1 shows the presence of microplastics, oil spills and sediments on ocean.

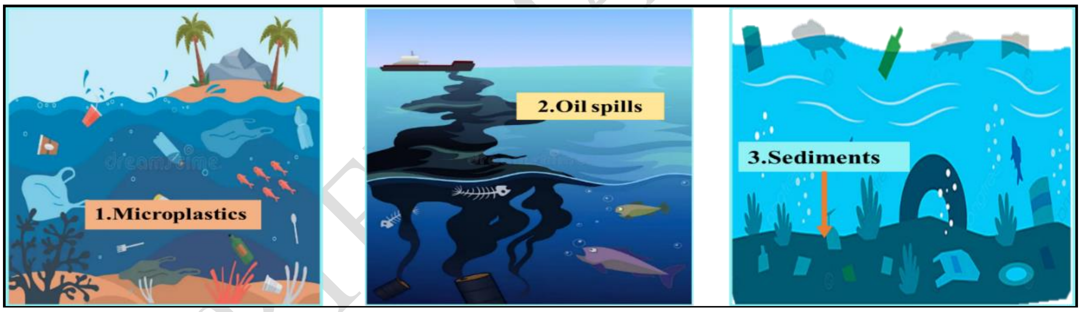


Figure 1 Microplastics, Oil spills, Sediments in Ocean

1.3 Contribution

The study focuses on an advanced methodology for generating and processing thermal images to classify marine pollutants with high accuracy. Sentinel-2 multispectral thermal images, highlighting temperature variations, are generated using a Stable Diffusion Thermal Image Generator. This model enhances contrast and emphasizes spatial and channel-wise features, ensuring precise pollutant representation for classification. Pre-processing employs the Transverse Dyadic Wavelet Transform (TxDyWT), which utilizes multi-resolution decomposition to preserve structural details such as edges and corners. This enables the accurate identification of pollutants of varying sizes, shapes, and distributions.

Noise removal and image quality enhancement are achieved using the DnCNN technique, optimized by the Hippopotamus Optimization Algorithm (DnCNN-HOA). The HOA fine-tunes DnCNN parameters to address diverse image noise conditions, producing cleaner images suitable for classification. The Vision Transformer (ViT) is employed for pollutant classification, leveraging its self-attention mechanism to identify subtle patterns and distinguish complex pollutant types. Section 2 of this paper provides a comprehensive literature survey. Section 3 outlines the detailed methodology, while Section 4 presents the results and discussion. This systematic approach ensures effective classification of marine pollutants and contributes to environmental monitoring advancements

2. Literature Survey

Author has discussed the presence of microplastics in ocean [22]. Fourier transform Infrared Microscopy is used to detect the microplastics present in the halo and thermoclines region of the ocean. It was observed that water column has more microplastics but there are limitations in sampling and uncertainty in measurements. In [23] author presents Statistical models with regression analysis to detect the oil spills and microplastics in the ocean surface. However varying environmental conditions, different sized microplastics are not considered. Microplastics in the subsurface water are detected using micro–Fourier Transform Infrared method [24]. But, microplastics of smaller size are not studied and filtering process affects the nature of microplastics. In [25] microplastics present in the surface, middle region, bottom of seawater column and sediments were detected. Fourier Transform Infrared Spectroscopy was used but the research has not included the variations in distribution of microplastics due to seasonal change and depth stratification. Author has detected the presence of microplastics in surface water, middle water, bottom water, sea bottom sediment and intertidal sediment [26]. FTIR and μ-FTIR methods are used. However, the sampling sites are limited and microplastics of small size are not focused.

Author has identified the contamination of sea food by sensory and chemical analysis caused by the oil spills in ocean [27]. Sea food contamination in particular area is alone considered and other effects of oil spills in the marine ecosystem are not studied. In [28] author identifies the oil spills in the surface water and coast using advanced technique called SisMOM. Source of the oil spills are found in the surface of water and coastal areas is tracked. Short-term data is used for analysis and a particular region is focused. Effects of oil spills on other areas are not studied. Fingerprinting method is used by the author to identify oil spills in ocean [29]. Oil spills are found in the shoreline and research is done to find the source of it. Spill trajectory model used to track the source uses limited data and it affects the accuracy of detection. Field collection, sampling and taxonomic survey are done by the author to detect the oil spills in ocean [30].

Oil spills are found on the surface water and the research is done in limited region and is not applied in environment with different weather conditions. The methods used are simple and is not suitable for the complex original conditions. In [31] author detects the oil spills in coastal areas by Synthetic aperture radar and image processing techniques. Detection accuracy is affected by the environmental factors and needs more processing time which is a drawback when used in real time applications. Bubble curtain method is used to detect the oil spills in surface water of ocean [32]. Bubble curtains prevent the spread of oil and its interaction with marine organisms. This method cannot be used in marine environment with strong waves and it not applicable to large scale oil spills.

In [33] author detects the presence of microplastics in water surface by using a tidal tank setup and statistical analysis. Microplastics of different size and shape are not included in the study. Varying tidal conditions are not considered making it difficult to be applied in real time detection. Author detects the microplastics present in floating and sinking sea ice [34]. Microcosm setup, micro-Raman and fluorescence microscopy is used. Controlled environment is used in the research and results may vary in real time. Testing was done with the sample of high concentration than the real microplastic. In [35] author uses deep learning methods to detect the microplastics present in beach sediment. The results depend on the training dataset which may vary in real time and differentiating the microplastics by this method is complex. Microplastics in the surface water and sediments are detected by the author in [36]. Photoacoustic imaging and deep learning methods are used. However, implementation is complex and models are not trained for different environmental conditions[37].

3. Methodology

Here, table 1 shows the existing methodology its drawbacks in detecting marine pollutants such as microplastics, oil spills and sediments in ocean.

Table.1 Comparison of Existing methods in detecting marine pollutants using image processing techniques.

Ref.No	Pollutant	Method	Distribution of pollutants	Drawback
[22]	Microplastics	Fourier Transform Infrared (FTIR)	1.Halo and thermoclines 2.water column has more microplastics	Limitations in sampling and uncertainty in measurements
[23]	Microplastics and oil spills (MOADs)	Statistical models with regression analysis	surface	Oil spills in varying environmental conditions are not considered. Effect of different sized microplastics is not discussed.
[24]	Microplastics	μ-FT-IR	Subsurface water	Smaller size microplastics were not considered. Filtering can affect the microplastics.
[25]	Microplastics	Fourier transform Infrared Spectroscopy	Seawater column (surface, middle, bottom), sediment	Variations in distribution of microplastics due to seasonal change and depth stratification is not considered.
[26]	Microplastics	FTIR and μ-FTIR	surface water (SW), middle water (MW), bottom water (BW), sea bottom sediment	Limited sampling sites. Smaller particles are not focused.

			(SS), and intertidal sediment (IS).	
[27]	Oil Spills	Sensory and Chemical analysis	Seafood	Limited regions are studied. Other effects of oil spill are not studied.
[28]	Oil spills	SisMOM	Surface water, coast	Study is done with short-term data, focuses on specific region not considering other areas with oil spills
[29]	Oil spills	Fingerprinting	Shoreline	Spill trajectory models use limited data.
[30]	Oil spills	Field collection, sampling, Taxonomic survey	Surface water	Limited region coverage and use of simple models
[31]	Oil spills	Synthetic Aperture Radar, image processing techniques	Coastal areas	Detection accuracy is affected by environmental factors. Requires more processing time.
[32]	Oil spills	Bubble curtain	Surface water	Cannot be used in environment with strong waves and can't be used in large scale oil spills.
[33]	Microplastics	Tidal tank setup, statistical analyses	Water surface	Various range of microplastics and varying tidal conditions were not considered.
[34]	Microplastics	Microcosm setup, μ-Raman and fluorescence microscopy	Sea ice-floating, sinking	Results may vary in real time as controlled environment is used to study. High concentration of microplastics is used than real sample.
[35]	Microplastics	Deep learning methods R-CNN	Beach sediment	Results depend on the training dataset, differentiating microplastics is complex.
[36]	Microplastics	Photoacoustic imaging and deep learning	Surface water, sediments	Implementation is complex. Models are not trained for different conditions.
Proposed	Microplastics,	Thermal Images,	Surface layer,	

method	Oil spills and sediments	DAGAN, TxDyWT, DNCNN-HOA, ViT	midwater layer, deep-sea and deep sea	

Overall architecture of the proposed methodology is shown in figure 2. Microplastics, oil spills and sediments are present in the ocean because of various human activities and natural processes. Multispectral images of sediments, oil spills and microplastics present in the ocean layers are converted to thermal image with stable Diffusion Thermal image generator due to the low visibility of pollutants.

Underwater images are colour distorted and are processed with Discrete Wavelet Transform (DWT) and Transverse Dyadic Wavelet Transform to differentiate from background. Thermal images of microplastics, oil spills, sediments are denoised using Deep Convolutional Neural Networks (DnCNN). Vision Transformer model is used to detect and identify the pollutants in ocean water. Microplastics, oil spills and sediments are classified based on the analysis of model. Process involved in the proposed methodology is explained in the flowchart given in figure 3.

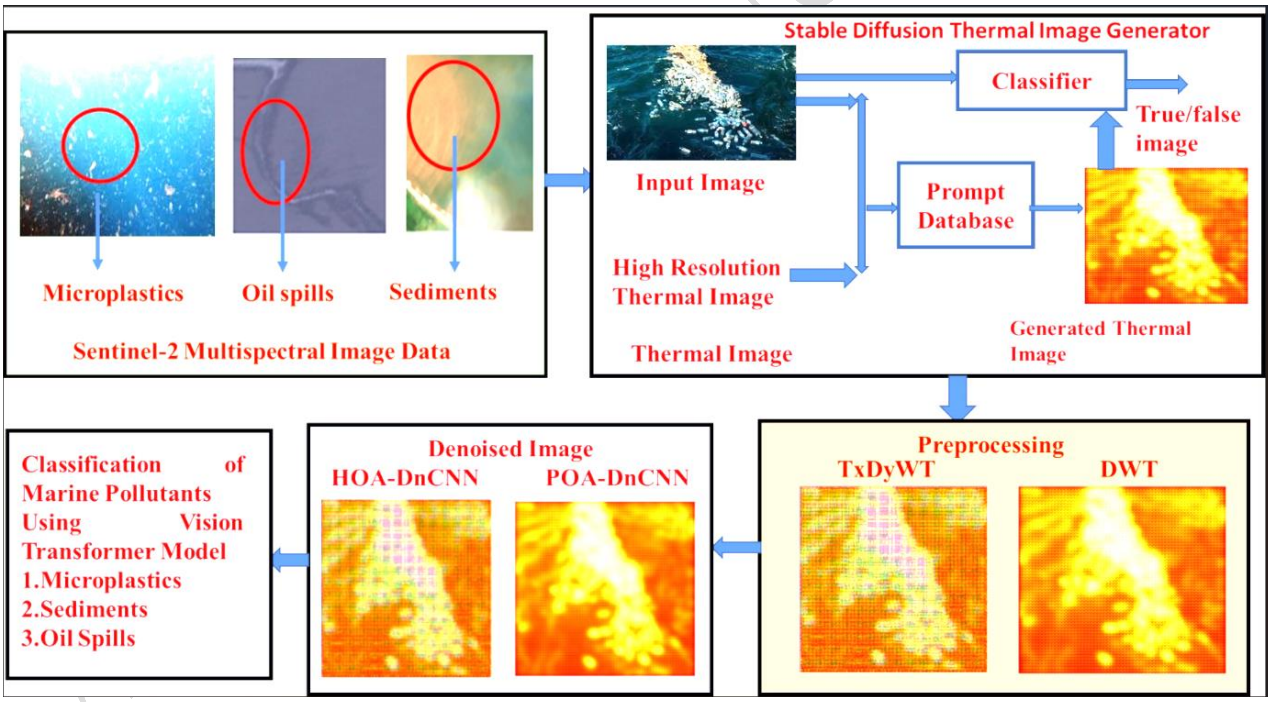


Figure 2 Block diagram of overall methodology

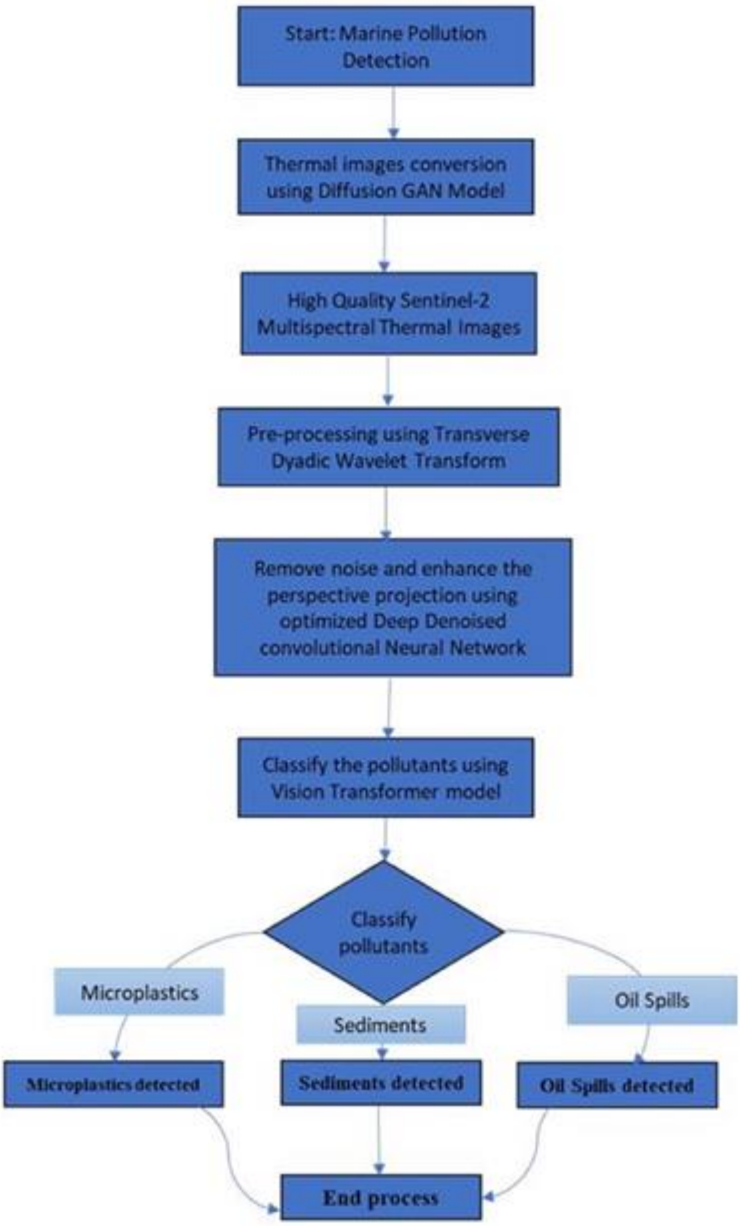


Figure 3. Workflow of overall methodology

3.1Sentinel-2 Multispectral Image Data

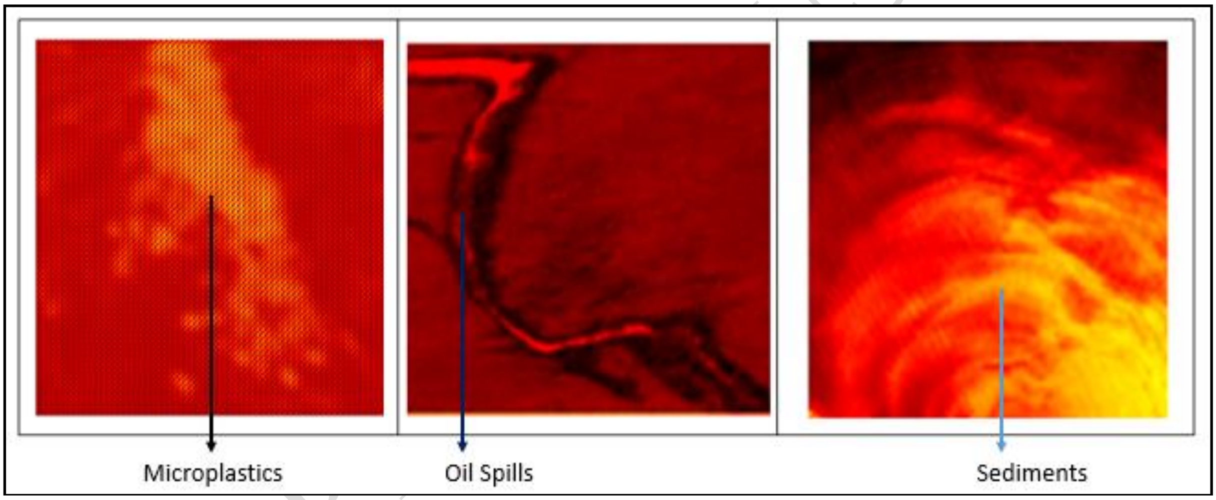
Microplastics are present in the ocean because of domestic run off and improper waste disposal. Oil spills into the ocean by accidents in tankers, pipelines and storage facilities. Sediments are formed due to the deposit of insoluble materials in the ocean. A sentinel-2 satellite with Multispectral Instrument (MSI) captures the sediments, oil spills and microplastics present in various ocean layers. The images are of high-resolution imagery across 13 spectral bands covering the visible, near-infrared and shortwave infrared regions. Spatial resolution of microplastics, oil spills, sediments images present in various layers of ocean varies from 10 to 60 meters allowing detailed analysis. Short wave Infrared (SWIR) and Near Infrared (NIR) effectively highlights the characteristics of pollutants. Visibility of smaller microplastics, thin oil slicks are low in sentinel-2 multispectral image and are converted to thermal image with Stable diffusion image generator.

3.2 Stable Diffusion Image Generator

The stable diffusion generator model converts the sentinel-2 multispectral color image into thermal image through guided text generation and sentinel-2 multispectral color image. The conversion of sentinel-2 multispectral color image to thermal image is shown in the equation (1).

$$\begin{aligned} Predicted\ Thermal\ image(y) &= RGB\ image \\ &+ w(predicted\ thermal\ image\ based\ on\ prompt\ conditioning \\ &- RGB\ image) \end{aligned} \qquad (1).$$

In equation (1), w is the guidance factor, which provides the balance between sentinel 2 multispectral colour images and generated thermal image. Therefore 'w' provides classifier free guidance for converting sentinel-2 multispectral colour image into thermal image. Hence, the stable diffusion thermal image generator model generates the thermal image from the text and sentinel-2 multispectral colour image. The classifier model acts as an image classifier and classifies the generated samples based on desired input text such as "High Resolution Thermal Image". Figure 4 shows the generated images of microplastics, oil spills, sediments.



(a) Microplastics (b) Oil Spills (c) Sediments

Figure 4 Generated images of Microplastics, Oil spills and sediments using Stable Diffusion Image Generator model

3.3 Perspective Projection

Thermal images of microplastics, oil-spills, sediments are pre-processed with DWT and TxDyWT techniques as the underwater images are low contrast, colour distorted and with noise due to the scattering and absorption of light.

3.3.1 Discrete Wavelet Transform (DWT)

DWT is used for the identification of smaller particles in complex backgrounds and it helps to distinguish microplastics from natural substances. Images are decomposed into various frequency bands for feature analysis in DWT, large oil spills and smaller microplastics are detected using this technique. DWT enhances edges and boundaries within the images which segments extent of oil spills and the boundaries of sediment layers. DWT

extracts texture information from images, this helps to identify different types of sediments, texture variation in oil slicks and physical properties of materials present in sediments.
Images of microplastics, oil spills, sediments obtained from ocean are processed through Continuous Wavelet Transform (CWT) using the formula

$$W_f\ (a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\varphi(t-b|a)\, dt \qquad (2)$$

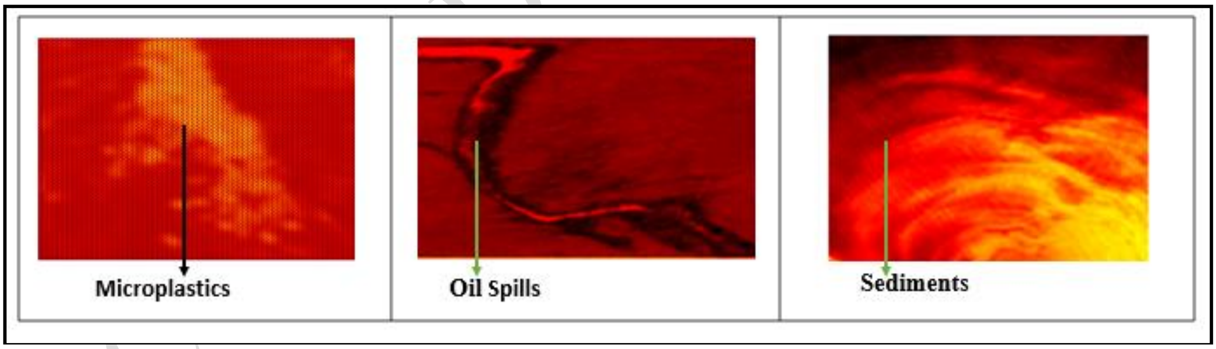
Where,

$W_f(a,b)$ are the wavelet coefficients,
a is the scale parameter,
b is the translation parameter,
$\psi(t)$ is the wavelet function.

The wavelet coefficients W_f (a, b) identifies and isolates microplastics from background and other contaminants. The wavelet function $\varphi(t-\frac{b}{a})$ highlights the boundaries and spreading patterns of oil slicks and it helps to assess the extent, behaviour oil spills. Normalization factor $\frac{1}{\sqrt{a}}$ reduces noise in the processed images of microplastics, oil spills, sediments by maintaining consistent energy at different scales.
Images are reconstructed from wavelet coefficients $W_f(a_j, b_k)$ by inverse transform using the equation given below

$$f(t) = \sum_j \sum_k W_f\ (a_j, b_k)\varphi_{j,k}(t) \qquad (3)$$

Where $\varphi_{j,k}(t)$ are the scaled and translated versions of wavelet function. Reconstruction is used for visualizing and assessing the level of contamination caused by microplastics, sediments, oil spills in ocean. Figure 5 shows the reconstructed image of microplastics, oil spills, sediments using DWT.



(a) Microplastics (b) Oil Spills (c) Sediments

Figure 5 Reconstructed images of pollutants using DWT.

Underwater images of microplastics, sediments, oil spills with high noise cannot be processed with DWT. Energy from noise distorts and masks the features of pollutants leading to poor identification of smaller size, irregular shaped microplastics and variations in oil slicks. High noise in images creates loss of important information like texture, boundaries required for analysis. High noise levels decrease Signal-to-Noise Ratio (SNR), lowering the effectiveness of DWT. It leads to inaccurate reconstruction of images. Transverse Dyadic Wavelet Transform (TxDyWT) technique is used in pre-processing of underwater images to overcome the drawbacks of DWT.

3.3.2Transverse Dyadic Wavelet Transform (TxDyWT)

Transverse Dyadic Wavelet Transform (TxDyWT) is used to pre-process thermal images of marine pollutants. Images of microplastics, oil spill, sediments are decomposed into different frequency components by TxDyWT improving the visibility and enabling the differentiation of pollutants from background noise and other sediment materials. TxDyWT extracts features like size, shape and distribution patterns of microplastics to determine the quantity of microplastics present in ocean sediments. TxDyWT analyses the texture of oil spills to differentiate oil spills and water surface to assess the extent of contamination. Thermal images of pollutants are analysed in multiple resolution to monitor changes over time. TxDyWT analyses the frequency components of sediment images and identifies different sediment types and their composition. TxDyWT estimates the abundance and distribution of pollutants by processing the sediment images.

$$W_f(j,k) = \sum_n f[n].\varphi_{j,k}[n] \tag{4}$$

where:

$W_f\,(j,k)$ are the wavelet coefficients,

$f[n]$ is the input signal or image,

$\psi_{j,k}[n]$ are the wavelet basis functions at scale j and position k.

Thermal images of marine pollutants are represented as signal by f[n] and the signal is decomposed into different frequency components by TxDyWT to isolate specific features of microplastics, oil spills, sediments.

Wavelet coefficients W_f (j, k) identifies distinct patterns corresponding to pollutants to differentiate from natural sediment backgrounds.

TxDyWT provides edge detection through multi-resolution analysis to highlight the boundaries of oil slicks in water surface.

Formula for image pre-processing is given below

$$I_{(x,y)} = A + D_H + D_V + D_D \tag{5}$$

Where,

A is the approximation,

D_H, D_V, D_D are the horizontal, vertical, and diagonal detail coefficients respectively.Constant A corrects the background noise and light variations in thermal images of sediments. The directional derivatives D_H, D_V, D_D enhances the edges and contours of microplastics in the sediment images.

Images are reconstructed from wavelet coefficents with inverse TxDyWT, and the equation is given below

$$I_{(x,y)} = \sum_{j,k} W_f(j,k).\varphi_{j,k}[\mathrm{n}] \tag{6}$$

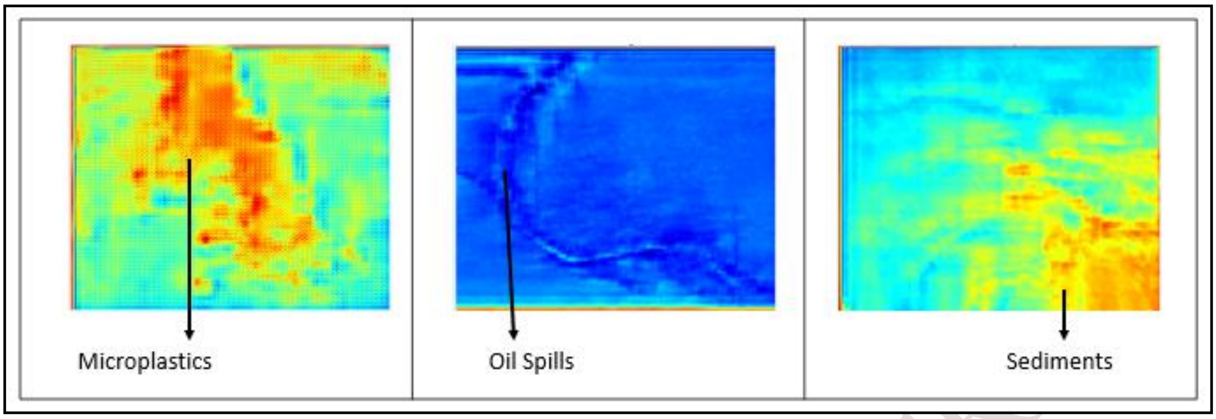
Where,

$I_{(x,y)}$ represents processed image intensity at pixel coordinates(x,y),

W_f(j,k) are wavelet coefficients,

$\Phi_{j,k}$[n] are wavelet basis functions.

The wavelet coefficients W_f (j,k) captures the essential features of microplastics, oil spills, sediments within the thermal images. The coefficients are summed and multiplied by their corresponding wavelet basis functions $\varphi_{j,k}$ [n] and the images are reconstructed. Figure 6 shows the reconstructed images of microplastics, oil spills, sediments by using TxDyWT. Comparison of Pre-processing of images using CWT, MODWT, DWT and proposed TxDyWT is shown in table 2.



(a)Microplastics (b) Oil spills (c) Sediments

Figure 6 Reconstructed images of (a) microplastics, (b) oil spills, (c) sediments using TxDyWT.

Table 2 Comparison of Pre-processing of images using CWT, MODWT, DWT and proposed TxDyWT

Performance Metrics	CWT	MODWT	DWT	TxDyWT
Mean	0.05	0.04	0.763	6.281
Standard deviation	0.10	0.09	0.39	2.11
Entropy	0.15	0.14	2.23	8.87
Energy	0.02	0.01	6.778	2.926
Contrast	0.03	0.02	0.152	4.462

Comparison of Pre-processing of images using CWT, MODWT, DWT and proposed TxDyWT in table 2 shows TxDyWT with a higher mean indicating brighter images, enhancing the differentiation between microplastics, sediments and oil spills. TxDyWT has higher standard deviation indicating more variability which enables the identification of regions with various pollutants, aiding accurate classification. DWT has lower value which indicates uniform area. Higher entropy in TxDyWT shows the presence of various types of contaminants enabling their classification. TxDyWT has higher contrast value which enables to identify boundaries for accurate classification of pollutants. Figure 7 Shows the comparison of DWT and TxDyWT based on performance metrics. Pre-processed images are denoised using DnCNN techniques. DWT and TxDyWT are chosen to transform multicolour pixel data of microplastics, oil spills and sediments into low pixel colour space to retain their essential characteristics. By applying DWT and TxDyWT microplastic distribution, behaviour of oil spill, sediments over time can be distinguished. DWT and TxDyWT are used for preprocessing microplastics, oil spills, and sediments for the multi-resolution analysis, noise reduction, data compression, and enhanced feature extraction.

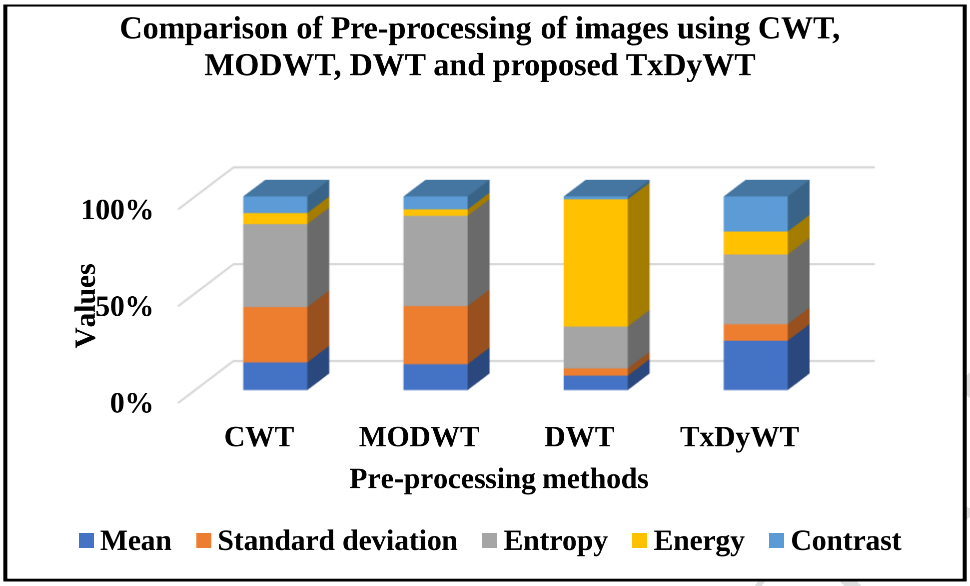


Figure 7 Comparison of Pre-processing of images using CWT, MODWT, DWT and proposed TxDyWT

3.4 Denoising

Thermal images of microplastics, oil spills, sediments are noisy due to various factors like sample preparation and imaging conditions. It is important to denoise the images for accurate detection and segmentation of marine pollutants.

3.4.1 Denoising Convolutional Neural Network - DnCNN

DnCNN uses deep learning techniques to denoise image. DnCNN enhances the quality of thermal images for better detection and classification of marine debris and pollutants. DnCNN preserves important features of marine pollutants when reducing noise.DnCNN enhances the visibility of small particles against complex backgrounds providing clear images as clear images are required to assess the type and concentration of pollutants in ocean. Denoised images of oil spills help to understand the distribution and behaviour of oil-mineral aggregates in marine environments. DnCNN is integrated with Pelican Optimization Algorithm to enhance its denoising capabilities by optimizing parameters.

3.4.2 Pelican Optimization Algorithm (POA)

Pelican Optimization Algorithm is a nature-inspired optimization algorithm that is based on the hunting behaviour of pelicans. POA operates through two main phases exploration and exploitation phase allowing the algorithm to explore potential solutions and to refine the search on solutions to find optimal outcome.

Pelican Optimization Algorithm is used with DnCNN technique to minimize noise in the images of microplastics, oil spills, and sediments. POA optimizes hyper parameters of the DnCNN model to achieve optimal denoising. Exploration and exploitation phases of POA are used to optimize the Peak-Signal to Noise Ratio (PSNR) parameter, which is used as evaluation metric to assess the quality of denoised images.

POA is used to optimize the parameters of DnCNN as it is essential to achieve better denoising improving the accuracy and efficiency of the model. Dynamic nature of POA adaptively adjust the learning rates resulting in faster convergence and improved denoising. Pelican optimization algorithm maintains a balance between exploration – searching new areas of solution space and exploitation -refining good solutions finding new configurations for DnCNN and enhancing its ability to handle different types of noise in the images. POA as a meta-optimizer improves the denoising capabilities of DnCNN with extensive manual tuning.

Pseudo-code of POA

Start POA

1. *Input the noisy image. (microplastics, sediments, oil spills)*
2. *Determine POA population size (N) and number of iterations (T).*
3. *Initialize positions of pelicans (denoising parameters).*
4. *For t = 1:T*
5. *Generate random position of the prey (ideal denoised image).*
6. *For I = 1:N*
7. *// Phase 1: Moving towards prey (exploration phase)*
8. *For j = 1:m // m = number of parameters/dimensions*
9. *// Calculate new status of the jth dimension (denoising parameter) using the given equation* $y_{u,v}^{P1} = \begin{cases} y_{u,v} + rand.\left(p_v - I.\, y_{u,v}\right), & O_p < O_u, \\ y_{u,v} + rand.\left(p_v - I.\, y_{u,v}\right), & else, \end{cases}$ (7)
10. *NewParameter[j] = CurrentParameter[j] + RandomAdjustment*
11. *End.*
12. *// Apply DnCNN or other denoising method with updated parameters*
13. *DenoisedImage = ApplyDenoisingMethod(NoisyImage, NewParameter)*
14. *// Calculate objective function value (PSNR)*
15. *ObjectiveValue = CalculateObjectiveFunction(DenoisedImage, ReferenceImage)*
16. *End.*
17. *End*

Output best candidate solution based on lowest objective function value.

End Exploration Phase.

POA integrated with DnCNN results in increased computational demands leading to longer training times, making it difficult to be used in real-time applications. POA complicates and adds complexity to the training process of DnCNN. Managing two distinct algorithms introduces challenges in maintaining the system. Hippopotamus Optimization Algorithm is used to overcome the mentioned drawbacks.

3.4.3 Hippopotamus Optimization Algorithm (HOA)

Hippopotamus optimization algorithm is a trinary-phase model reflecting the natural behaviour of hippopotamuses, focusing on their aquatic movement and social interactions. HO balances exploration (searching new areas) and exploitation (refining known good solutions) to solve complex optimization problems. It incorporates mathematical formulation that simulate the behaviours to update positions of candidate solutions in optimization space.

HOA is integrated with DnCNN to optimize the parameters of model to improve denoising. HOA trains DnCNN on a dataset with the images of microplastics, oil spills and sediments with noise to enhance the convergence speed and accuracy of the model. HOA adjusts the hyperparameter Peak Signal-to-Noise Ratio (PSNR) during training and the performance of the integrated model is evaluated after training to access the effectiveness of denoising. The combined approach removes noise and preserves important details in the images. Integration adapts to different types of noise.

Algorithm 2 Pseudocode of HOA

Start Image Denoising HO Algorithm

1. *Define an image denoising optimization problem*
2. *Set the maximum number of iterations (T) and number of candidate solutions (N)*
3. *Generate the initial population of candidate solutions (images) based on equation*
   $I_u : i_{uv} = lb_v + r \,.\, (hb_v - lb_v), u = 1,2, \ldots N, v = 1,2, \ldots . m$ *(8)*
   and evaluate their quality using an objective function Peak Signal- to- Noise Ratio (PSNR)
4. *For t= 1 to T*
5. *Update dominant candidate solution based on objective function value criterion*
6. *Phase :1 Candidate solution update in the image domain (Exploration phase)*
7. *For i= 1 to N*
8. *Apply Gaussian filter to the i-th candidate image:*
   -Let G be the Gaussian kernel
   -Denoised_Image[i]= Convolve (Candidate_ Image[i], G)
9. *Evaluate the quality of the denoised image using the objective function*
10. *End for*
11. *Save the best denoised image found so far*
12. *End for*
13. *Output the best denoised image solution found by IDO*
    End Image Denoising HO Algorithm

Candidate solutions are updated through Gaussian filtering approach. In step 8, each candidate image is convolved with a Gaussian kernel to reduce noise. Each denoised image's quality is evaluated after applying the filter enabling comparison and selection of best result. Comparison of DnCNN optimized by Pelican Optimization Algorithm and Hippopotamus optimization algorithm is given in table 3.

Table 3 Comparison of Denoising methods using DnCNN and Optimized DnCNN

Metrics	**DnCNN**	**DnCNN-POA**	**DnCNN-HOA**
PSNR	25	31	35.2
Convergence Time(s)	150	120	90
Training epochs	60	50	40
Robustness score	0.60	0.75	0.85
No. of layers	30	20	17

The Deep Denoised Convolutional Neural Network (DnCNN) has 20 convolutional layers that are used to remove thermal noise patterns from Sentinel-2 marine pollutant images and enhance the perspective projection of fragmented pixel regions of microplastics, sediments, and oil spills. However, the large number of convolutional layers reduces the convergence of DnCNN. To improve the convergence speed of DnCNN, the number of convolutional layers is optimized through the HOA and POA optimization algorithms. From Table 3, HOA optimization has a higher PSNR (Peak Signal-to-Noise Ratio) value, which indicates better image quality. The convergence rate of DnCNN-HOA is lower compared to DnCNN-POA due to the exploration and exploitation capabilities of the Hippopotamus Optimizer compared to the Pelican Optimizer. Thus, DnCNN-HOA reduces computational complexity with an optimum number of convolutional layers set at 17. Figure 8 Shows the comparison of performance metrics of DnCNN optimized by HOA And POA and Convergence analysis of POA and HOA is shown in figure 9.

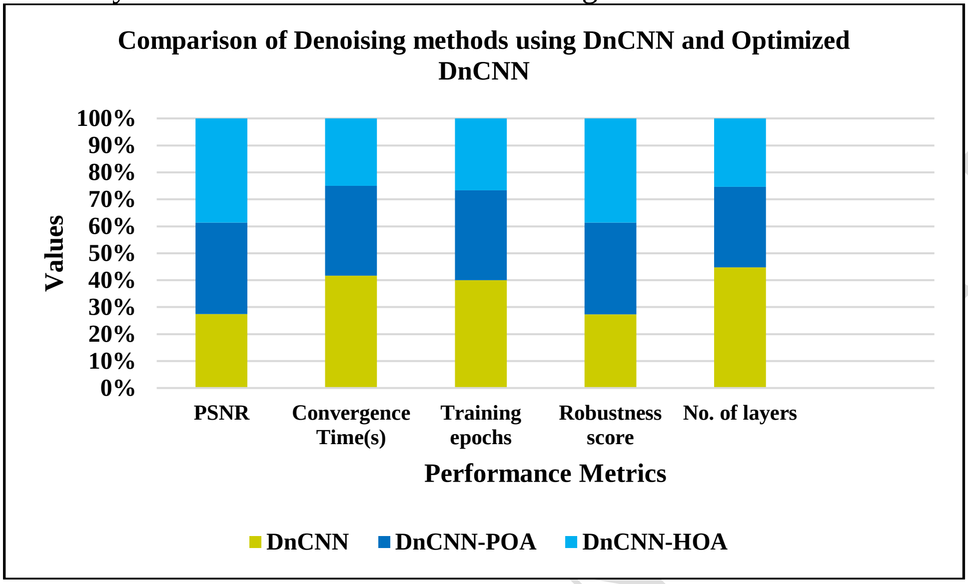


Figure 8 Comparison of performance metrics of DnCNN optimized with POA and HOA

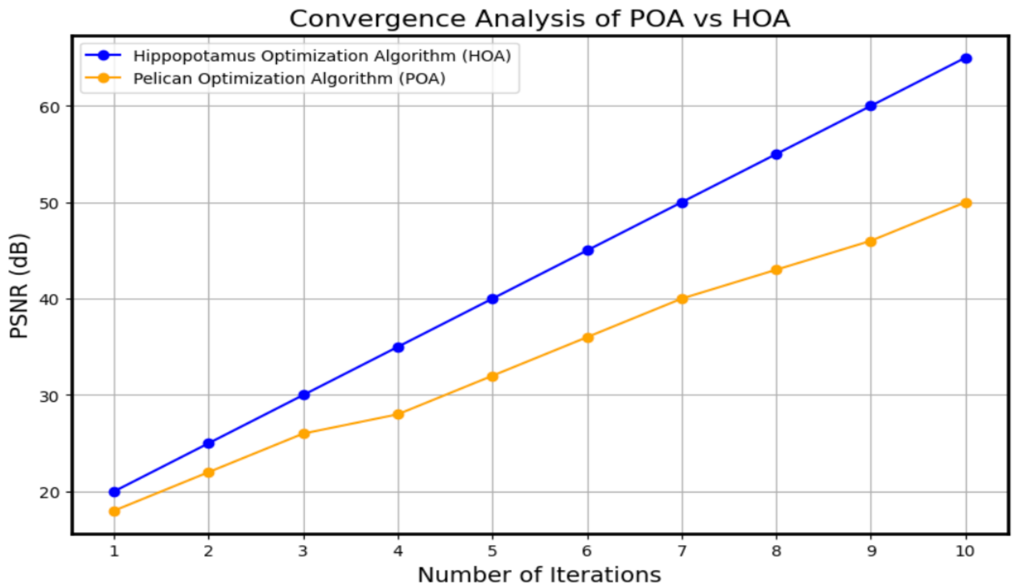


Figure 9 Convergence Analysis of DnCNN optimization techniques POA and HOA

Convergence analysis of POA and HOA is shown in figure 8. Hippopotamus Optimization Algorithm has higher values across all iterations. Both the algorithms show an increasing trend but POA converges to higher PSNR values more rapidly than HOA, indicating it is more efficient in optimizing solutions for pollutant detection.

3.4.4 Vision Transformer Model (ViT)

Vision Transformer Model is a neural network that applies principles from transformer model. ViT uses self-attention mechanism to differentiate various types of pollutants. Architecture of Vision Transformer Model is given in below in Figure 10.

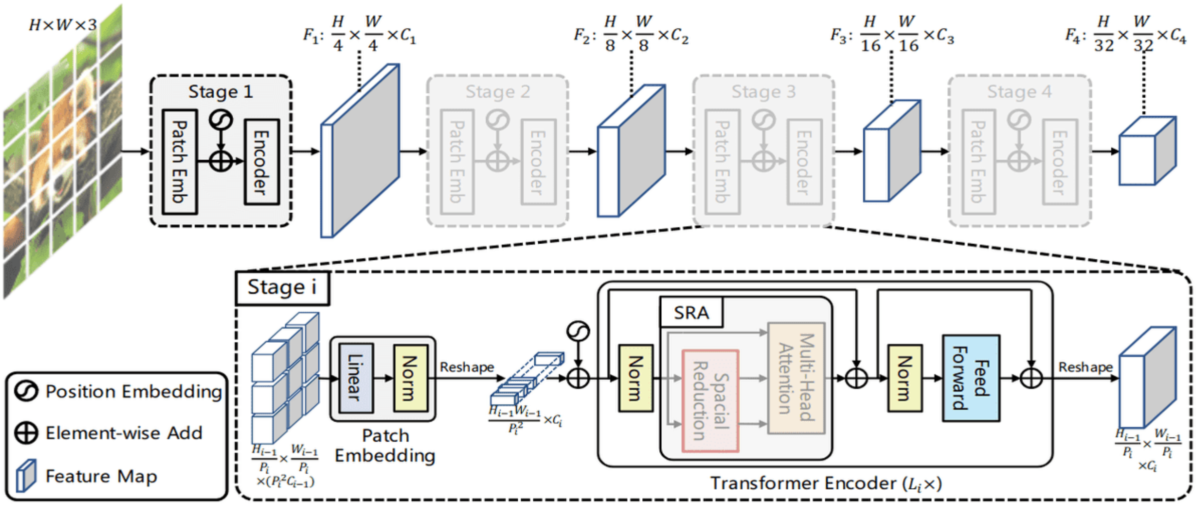
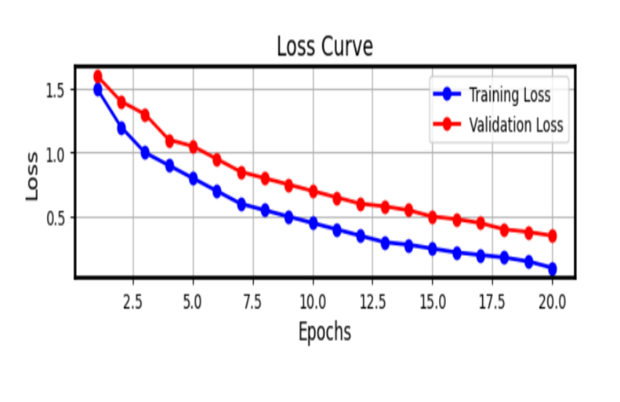


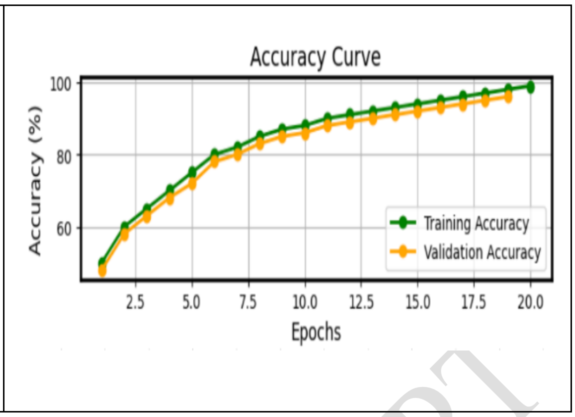
Figure 10 Architecture of Vison Transformer (reference: [38])

Vit architecture alters the processing of images by treating them as sequence of patches. Processing involves input Images of microplastics, oil spills and sediments are divided into fixed-size patches in image patching. Each patch is flattened into one - dimensional vector in flattening, enabling the model to process the pixel values linearly. Flattened patches are projected into a higher-dimensional space through a linear transformation, creating embeddings for each patch. The embeddings capture essential features of the patches. Positional encoding is added to each patch to retain spatial information lost during flattening and to understand the relative positions of patches in the original images of microplastics, sediments and oil spills.

Sequence of patch embedding is fed into a standard transformer encoder. ViT base architecture has of 12 transformer layers, each layer contains layer normalization stabilizes training before attention mechanism. Multi-Head Self-Attention weighs the importance of each patch and generates attention scores to focus on relevant areas within the image to identify the features of microplastics, sediments and oil spills. Feed-Forward Neural Network is a multi-layer perceptron (MLP) with two linear transformations and a non-linear activation function to process the output.

Self-attention mechanism computes attention weights for each patch relating to other patches. It helps the model to differentiate subtle sediment types and dispersed microplastics. Classification head process the output corresponding to classification head after passing through all the transformer layers. It generates class predictions based on the based on the transformer encoder. SoftMax activation function converts the predictions into probabilities for each class microplastics, sediments and oil spills. ViT model is pre-trained with large datasets to learn general image features before being fine-tuned on specific datasets that include examples of microplastics, oil spills and sediments. Fine tuning adjusts the model's weights to improve its accuracy in classifying microplastics, sediments and oil spills. Figure 11 shows the Loss and Accuracy curves of proposed ViT.





(a) Loss Curve (b) Accuracy Curve

Figure 11 (a) Loss Curve (b) Accuracy Curve of proposed vision transformer Model

Accuracy and Loss curves of Vision Transformer used to classify the microplastics, sediments and oil spills is shown in Figure 11. The curves show the performance of Vision transformer in classifying the pollutants. Steady decrease in training and validation loss curve shows effective learning. Training and Validation Accuracy curve increases indicating ViT's improved classification performance.

4. Results and Discussion

4.1 MADOS dataset

Sentinel-2 Multispectral Image Data forms the MADOS dataset [39]. The Remote sensing data focuses on marine litter and spills. Images from 174 scenes and 47 tiles each corresponding to a unique Sentinel-2(S2) scene are present in the dataset and the data are annotated. The images are of different spatial resolution 10m,20m and 60m. 80% of the data is used for training and 20% is used for testing. The study was conducted in Amazon River in South America, Arabian sea in Asia, Mediterranean Sea in Europe-Sentinel images.

Thermal images of microplastics, oil spills and sediments pre-processed with Discrete Wavelet transform and denoised with DnCNN optimized using pelican optimization algorithm. Vision transformer is used to classify the images. Performance metrics the methods used are measured using the given formulas.

$$Recall = \frac{True\ positives}{True\ Positives + False\ Negatives} \tag{9}$$

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \tag{10}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ positives} \tag{11}$$

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Population} \tag{12}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (13)$$

Table 4 shows the comparison of performance metrics of Sentinel-2 thermal image, DWT pre-processing technique, DnCNN optimized with POA and Vision Transformer model in the classification of pollutants.

Comparison of performance metrics of Sentinel-2 Thermal image, DWT, DnCNN-POA and ViT is shown in table 4. Low sensitivity affects the detection of microplastics, oil and sediments. Low specificity leads to the incorrect identification of clean areas as contaminated. Comparison of performance metrics of Sentinel-2 thermal image, DWT, DnCNN optimized with POA and Vision Transformer is shown in figure 12.

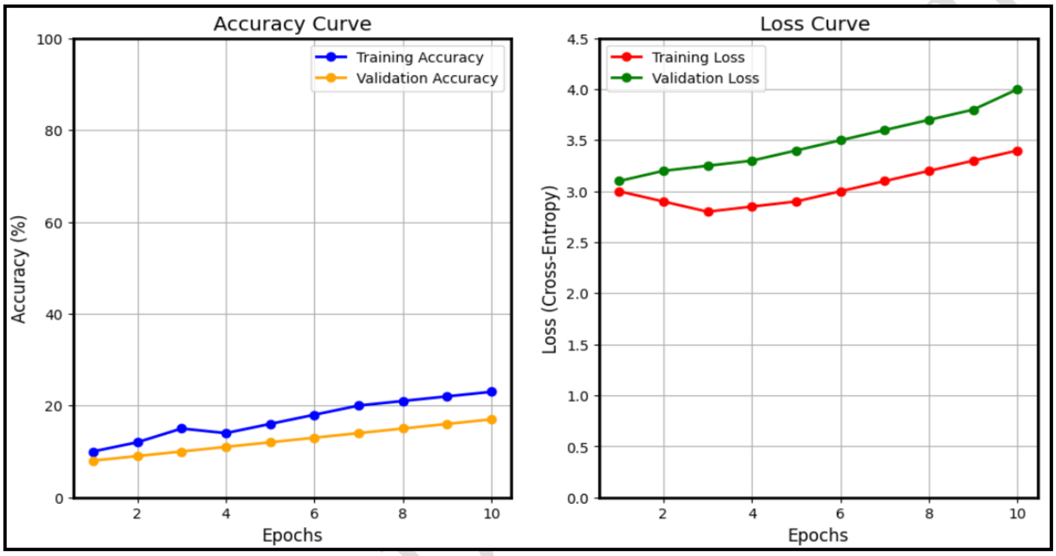


Figure 12 Comparison of Sentinel-2 Thermal image, DWT, DnCNN-POA, ViT performance metrics.

Table 4 Comparison of performance metrics of Sentinel-2 Thermal image, DWT, DnCNN-POA and ViT.

Performance metrics	Sensitivity	Specificity	Precision	Accuracy	F1 Score	AUC
Microplastics	0.10	0.15	0.12	0.13	0.11	0.20
Oil spills	0.08	0.18	0.10	0.12	0.09	0.15
Sediments	0.05	0.20	0.07	0.09	0.06	0.10

Training accuracy values ranging from 10-23 shows the low performance of the model in studying the underlying patterns of the data. Validation loss curve with high values indicates low prediction of the model. The model fails to capture the patterns required to classify pollutants. DnCNN optimized with Hippopotamus Optimization Algorithm is used to improve the performance of the model and the performance metrics are analysed. Table 5 Shows the comparison of metrics of Sentinel -2 thermal image, Discrete Wavelet Transform, DnCNN optimized using HOA and Vision Transformer Model.

Table 5 Comparison of performance metrics of Sentinel-2 Thermal image, DWT, DnCNN optimized with HOA and ViT

Environmental Issue	**Sensitivity**	**Specificity**	**Precision**	**Accuracy**	**F1 Score**	**AUC**
Microplastics	0.4	0.5	0.45	0.48	0.42	0.55
Oil Spills	0.35	0.55	0.4	0.45	0.37	0.52
Sediments	0.3	0.6	0.35	0.4	0.32	0.5

Comparison of performance metrics of Sentinel-2 Thermal image, DWT, DnCNN optimized with HOA and ViT is shown in table 5. Values of specificity, precision, recall, accuracy and F1 Score are low indicating low performance in the classification of pollutants. Low precision shows that the prediction of system is incorrect and leads to poor decision making. Low accuracy reflects the combined effects of sensitivity and specificity issues. Low accuracy also indicates the poor performance of overall system in classifying microplastics, sediments and oil spills. Figure 13 shows the comparison of performance metrics of Sentinel-2 thermal image, DWT, DnCNN optimized by HOA, Vision Transformer.

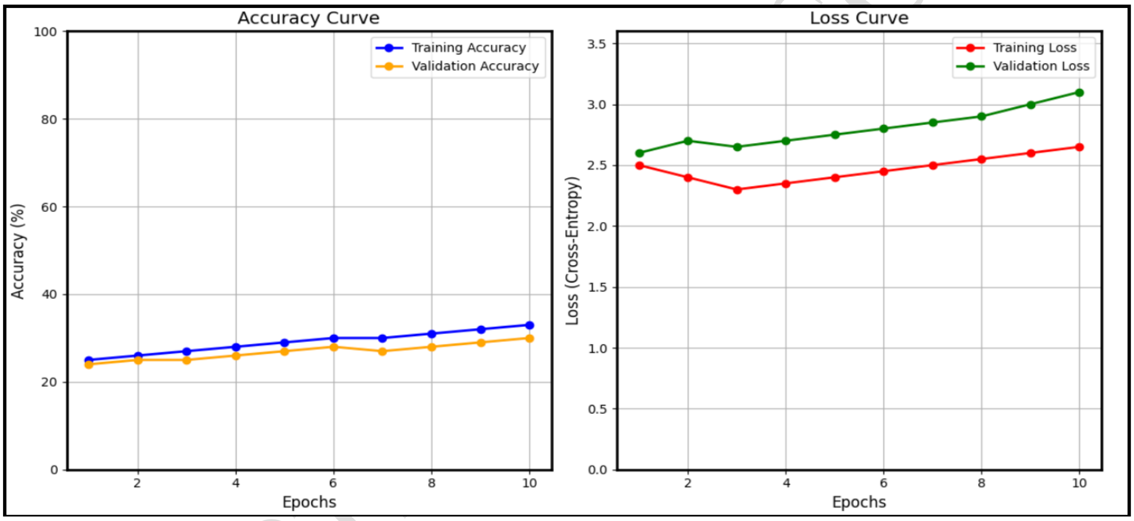


Figure 13 Comparison of performance metrics of Sentinel-2 Thermal image, DWT, DnCNN and Vision Transformer.

Comparison of performance metrics of Sentinel-2 Thermal image, DWT, DnCNN and Vision Transformer in figure 13 shows validation low accuracy and high validation loss. Values indicate low performance of the model in the classification of pollutants. Transverse Dyadic Wavelet Transform is used to improve the pre-processing of microplastics, sediments and oil spills images. Comparison of performance metrics of Sentinel-2 thermal image, TxDyWT, DnCNN-POA, ViT is shown in table 6.

Table 6 Comparison of performance metrics of Sentinel-2 thermal image, TxDyWT, DnCNN-POA, ViT.

Performance Metrics	**Sensitivity**	**Specificity**	**Precision**	**Accuracy**	**F1 Score**	**AUC**
Microplastics	0.85	0.8	0.82	0.83	0.83	0.9
Oil Spills	0.78	0.85	0.8	0.82	0.79	0.88
Sediments	0.75	0.82	0.76	0.78	0.75	0.85

Performance metrics of methods shown in table 6 has low specificity indicating that the model incorrectly classifies clean areas as contaminated. Low precision shows the incorrect identification of pollutants. Microplastics, oil spills and sediments can remain undetected with low recall. Low accuracy reflects the misclassification of pollutants. Values of the performance metrics are low and the comparison of performance metrics of Sentinel-2 thermal image, TxDyWT pre-processing technique, DnCNN-HOA and Vision Transformer is given in figure 14.

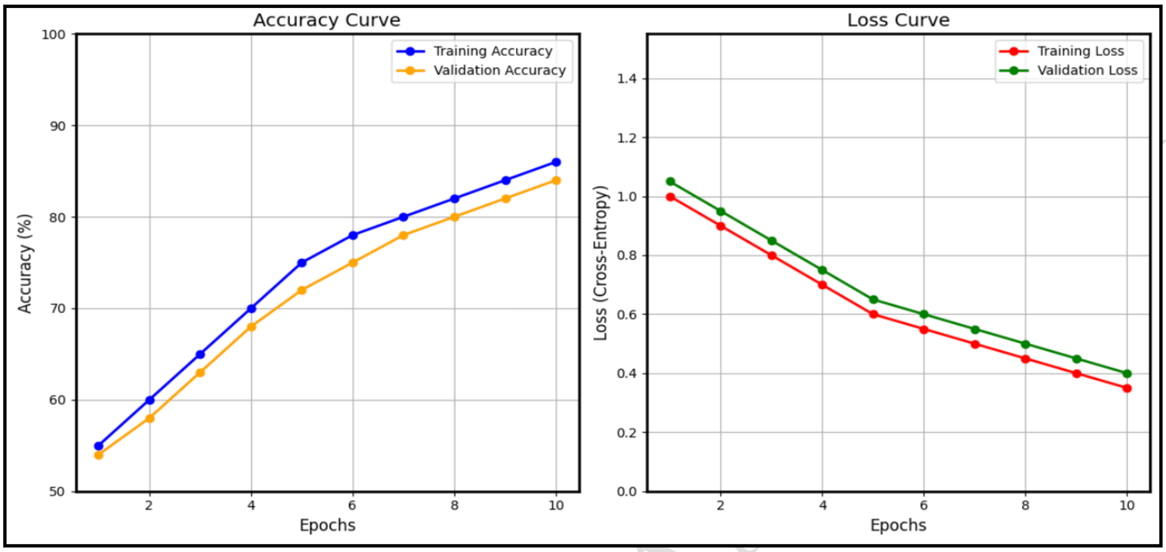


Figure 14 Comparison of performance metrices of Sentinel-2 Thermal image, TxDyWT, DnCNN-HOA and Vision Transformer.

Comparison of performance metrices of Sentinel-2 Thermal image, TxDyWT, DnCNN-HOA and Vision Transformer in figure 13 shows higher accuracy reflecting effectiveness in classifying pollutants and low loss values indicates a well-functioning model. Thermal images are pre-processed with Transverse Dyadic Wavelet Transform and denoised with DNCNN optimized with HOA to improve the performance of the system. Table 7 shows the comparison of performance metrics of Sentinel-2 Thermal image, TxDyWt pre-processing technique, DnCNN optimized by HOA and Vision transformer.

Table 7 Comparison of performance metrics of Sentinel-2 thermal image, TxDyWT, DnCNN-HOA, Vision transformer.

Performance Metrics	Sensitivity	Specificity	Precision	Accuracy	F1 Score	AUC
Microplastics	0.9	0.85	0.88	0.89	0.89	0.95
Oil Spills	0.85	0.9	0.87	0.88	0.86	0.93
Sediments	0.8	0.88	0.82	0.84	0.81	0.91

High specificity indicates the effectiveness of model in correctly identifying the polluted areas. High precision shows that system's detection of microplastics, oil spills and sediments are accurate. Pollutants are correctly identified by the model with high recall. High accuracy indicates that the overall performance of the system is reliable with correct classifications.

Figure 15 shows the comparison of performance metrics of Sentinel-2 thermal image pre-processed with TxDyWT, denoised using DnCNN optimized with HOA and images classified using Vision Transformer.

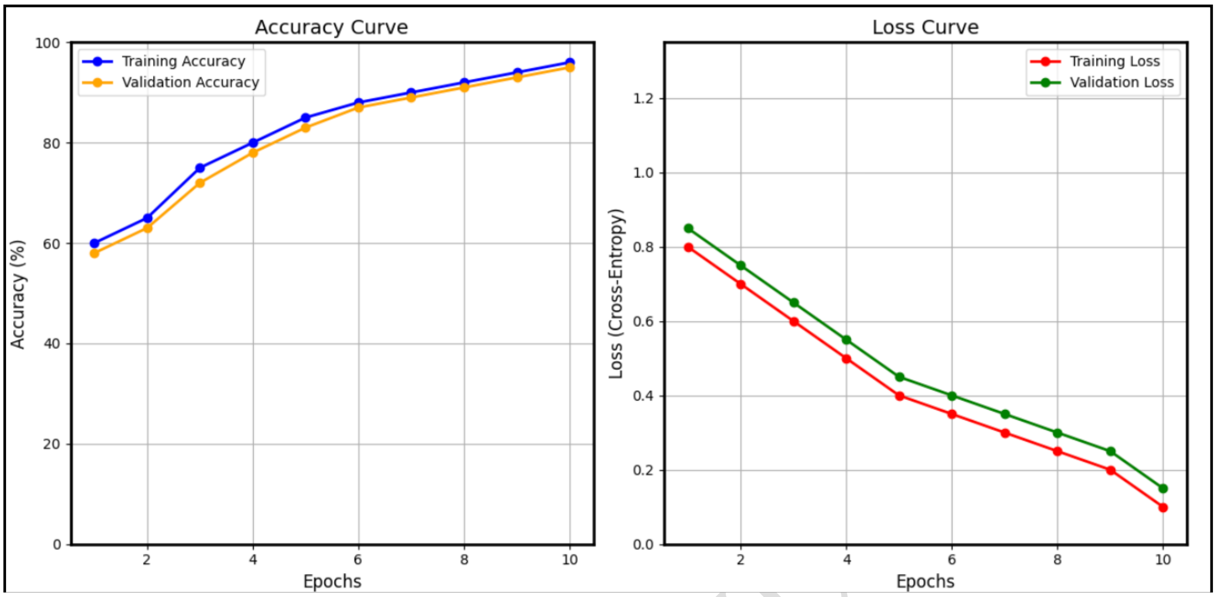


Figure 15 Comparison of Performance Metrics of Sentinel-2 thermal image, TxDyWT pre-processing technique, DnCNN optimized by HOA and Vision transformer.

Comparison of Performance Metrics of Sentinel-2 thermal image, TxDyWT pre-processing technique, DnCNN optimized by HOA and Vision transformer in figure 14 shows high accuracy and low loss values indicating effective differentiation of microplastics, oil spills and sediments.

4.2 Seawater test bed for Microplastics, Oil spill and Sediment detection

Methods used to pre-process, denoise and classify the thermal images of microplastics, sediments and oil spills are tested with the image of sea water with pollutants. Image sea water with pollutants in a tank is pre-processed with Transverse Dyadic Wavelet Transform and DnCNN optimized with HOA is used to denoise the image. Figure 16 Shows the thermal image of seawater test bed pre-processed with DWT and TxDyWT.

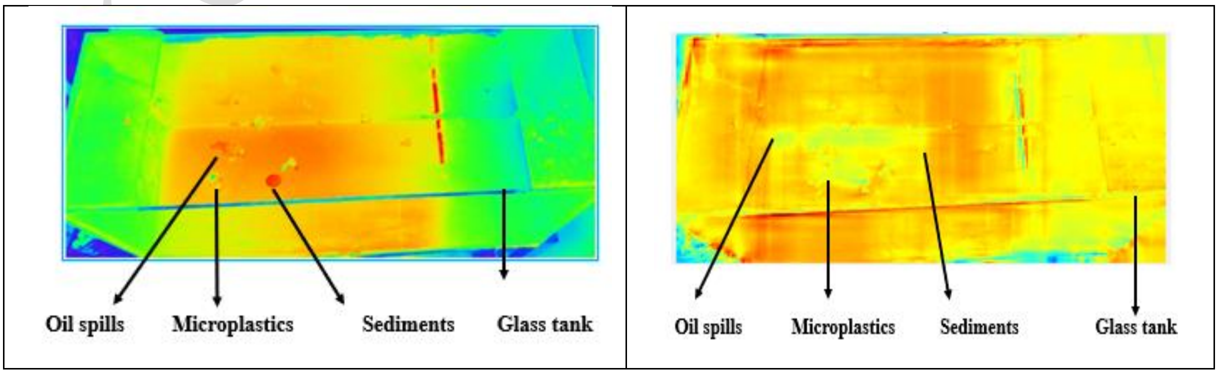


Figure 16 Thermal Image of seawater test bed pre-processed with DWT and TxDyWT.

Performance analysis on classification of Marine pollutants using optimized DnCNN with Vision Transformer model and existing methods is shown in table 8 and figure 17 shows Comparison of Performance Metrics of existing classification methods with proposed ViT

Table 8 Performance analysis- Classification of Marine pollutants using optimized DnCNN with Vision Transformer model and existing methods

Metrics	[40] Microplastics	[41] Oil Spills	[42] Sediments	Proposed Method
Specificity	0.65	0.70	0.60	0.98
Precision	0.70	0.65	0.75	0.93
Recall	0.60	0.75	0.55	0.92
Accuracy	0.68	0.70	0.65	0.95
F1Score	0.65	0.70	0.64	0.93
AUC	0.75	0.78	0.77	0.90

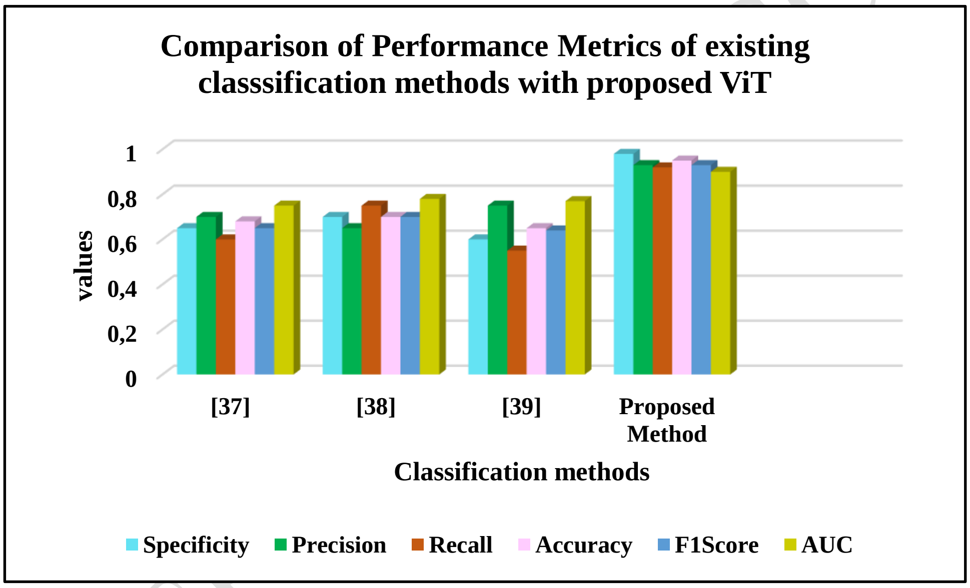
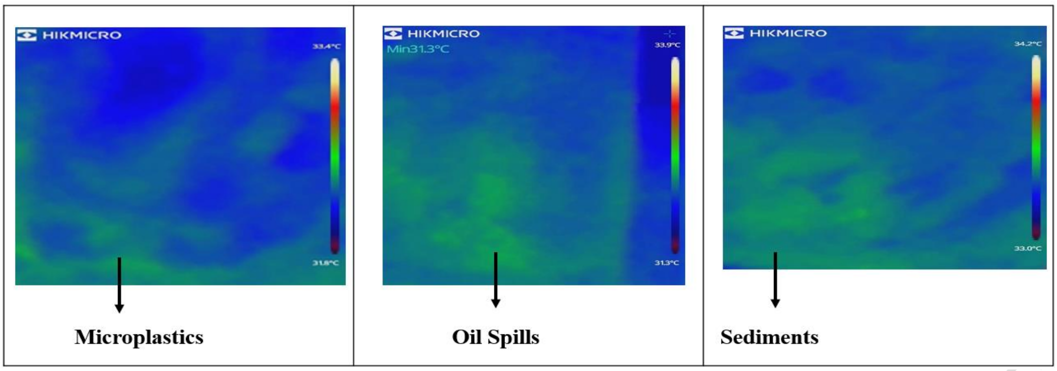


Figure 17 Comparison of Performance Metrics of existing classification methods with proposed ViT

Comparison of Performance Metrics of existing classification methods with proposed method shown in figure 17 has high values of specificity indicate the effectiveness of model in correctly identifying clean areas. Correct prediction of pollution by the model is shown by high precision. High recall indicates successful identification of majority of pollutants with the model. Reliability of the model is enhanced by high accuracy reflecting the correct prediction of the model. F1 score reflects the balance between precision and recall indicating the effectiveness of the model in detecting pollutants. Figure 18 shows the images of microplastics, oil spills and sediments present in the seawater tested.



(a) Microplastics (b) Oil Spills (c) Sediments

Figure 18 (a) Microplastics (b) Sediments (c) Oil Spills in Seawater testbed

4.3 Ablation Study

Denoising technique plays an important role in increasing the accuracy and to enhance the classification of pollutants. Effective denoising is essential for distinguishing pollutants and is validated with the findings of proposed work on MODAS dataset. Table 9 shows the metrics values for MODAS Dataset with Sentinel-2RGB image pre-processed with Discrete Wavelet Transform (DWR), denoised with DnCNN without optimization algorithm and with HOA, POA. The integrated methods have low accuracy of 79%and low PSNR values. Sentinel-2 thermal images pre-processed with Transverse Dyadic Wavelet Transform (TxDyWT) and denoised DnCNN optimized with Pelican Optimization Algorithm has the accuracy values of 81% and are subjected to Vision Transformer (ViT) for classification. DnCNN optimized with Hippopotamus Optimization algorithm denoising the sentinel-2 thermal images pre-processed with Transverse Dyadic Wavelet Transform (TxDyWT)has the accuracy of 95%. Vision Transformers are used to classify the images. The proposed method is superior in terms of accuracy, recall, specificity, precision, F1 score and PSNR (db). DnCNN optimized with HOA is overall superior compared to DnCNN and DnCNN-POA.

Table 9 Ablation Study

Methodology	PSNR(dB)	Recall	Specificity	Precision	Accuracy	F1 Score
Sentinel-2RGB image,DWT, DnCNN(Without optimization algorithm)ViT	**20.50**	**0.78**	**0.80**	**0.79**	**0.79**	**0.785**
Sentinel-2 Thermal image, TxDyWT,DnCNN-POA,ViT (reduced computational cost, overfitting)	**30.85**	**0.80**	**0.83**	**0.81**	**0.81**	**0.805**
Sentinel-2 Thermal Image, TxDyWT,DnCNN-HOA, ViT (High PSNR, faster convergence)	**34.00**	**0.88**	**0.95**	**0.93**	**0.95**	**0.925**

4.4 Discussion

Harmful substances are introduced into marine environment due to human activities and natural processes. The substance introduced in the ocean harms ecosystems, disrupts biodiversity and affects the health of marine organisms and the human beings who depend on marine ecosystems. It is important to classify the pollutants to trace back to their origin like industrial waste, agricultural runoff and marine activities. Classification of pollutants enables targeted action to reduce pollution at its source. Thermal images are used for the classification of pollutants as the temperature variations helps to identify various substances. Thermal images enhance detection and improve classification. Stable Diffusion Thermal Image Generator is used to generate high-quality thermal images. The stable diffusion generator model converts the sentinel-2 multispectral color image into thermal image through guided text generation and sentinel-2 multispectral color image. It generates images with realistic thermal texture and accurate temperature distribution making it easier for classification.

Transverse Dyadic Wavelet Transform (TxDyWT) is used to pre-process the images of pollutants. TxDyWT adapts dyadic structure enabling finer analysis of the image by capturing subtle variations and detecting edges. It captures detailed spatial, frequency and directional information enhancing the classification process. Denoising Convolutional Neural Network (DnCNN) is used to remove noise from the images, enhancing image quality for better classification. DnCNN is optimized with Hippopotamus Optimization Algorithm to achieve higher denoising accuracy and improved PSNR metrics in denoised images. HO Algorithm optimizes DnCNN to handle various noise levels and types and leads to faster convergence.

Vision Transformers (ViT) is used to classify the marine pollutants. ViT identifies the pollutants dispersed in larger area by capturing long-range dependencies and global context within the images. Self-attention mechanism weighs importance of various parts of an image to classify the pollutants. Vision transformers handle images with varying dimensions unlike other CNN techniques and demonstrate superior performance in classification task. TxDyWT, DnCNN-HOA, Vision transformers are integrated classify the pollutants. Table 10 shows the advantages of using proposed Sentinel-2 image based Vision Transformer model.

Table 10. Advantages of using proposed Sentinel-2 image based Vision Transformer model

Methods	Characteristics	Comparison
Pre-processing: DWT	Retains structural details of microplastics, oil spills and sediments essential for pollutant classification.	TxDyWT is an advanced version of DWT that provides better results.
Pre-processing: TxDyWT	Provides improved frequency localization and better handling of noise, enhancing image quality of Microplastics, oil spills and sediments.	TxDyWT outperforms DWT by maintaining more relevant details for classifying microplastics, oil spills and sediments.
Denoising: DnCNN	Reduces noise in images of microplastics, oil spills and sediments, improving the clarity and quality of data for further analysis.	Accurate classification of subtle pollutant patterns.
Denoising: Optimized by POA	Provides efficient optimization, leading to faster convergence and better	POA is effective but not as robust as HOA in certain scenarios

	performance in denoising images of microplastics, oil spills and sediments.	
Denoising: Optimized by HOA	Achieves superior optimization results, leading to enhanced denoising capabilities	HOA is considered the best optimization algorithm due to its adaptability and efficiency.
Classification: Vision Transformer	Captures intricate patterns in microplastics, oil spills,sediments making it ideal for classifying complex pollutants.	ViT's architecture allows for better performance compared to traditional CNNs in recognizing subtle differences among pollutants.

5. Conclusion

The proposed methodology integrates advanced techniques to effectively classify microplastics, sediments, and oil spills. It combines Stable , Transverse Dyadic Wavelet Transform (TxDyWT), and Denoising Convolutional Neural Network (DnCNN) optimized using the Hippopotamus Optimization Algorithm, along with a Vision Transformer for pollutant classification. The evaluation of this approach utilizes the MADOS dataset, which is derived from remote sensing data. In the pre-processing phase, TxDyWT demonstrates superior performance compared to the traditional Discrete Wavelet Transform (DWT). During the denoising stage, the DnCNN optimized by the Hippopotamus Optimization Algorithm shows enhanced effectiveness. Finally, the Vision Transformer successfully classifies the various pollutants. The practical application of this method was tested in a controlled environment using a Seawater test bed containing pollutants, achieved an accuracy of 95%. Future research will focus on applying this method to diverse datasets and exploring strategies to reduce further ocean contamination caused by microplastics, oil spills, and sediments.

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