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ADVANCES IN MACHINE LEARNING AND DEEP LEARNING APPROACHES FOR PLASTIC LITTER DETECTION IN MARINE ENVIRONMENTS

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ABSTRACT

A serious threat to the environment is plastic pollution in marine ecosystems, and thus an effective detection of litter plastics is needed for proper management. This review critically assesses recent studies that use CNNs and other machine learning approaches to detect and measure plastic debris in various water bodies. The study delves into the models, datasets, and evaluation measures used in these studies factoring in persistent challenges associated with detecting small objects and variability of environmental conditions. In addition, the study offers future perspectives highlighting the need for complete data gathering, utilization of various sources of imagery, and development of real-time monitoring mechanisms to combat plastic pollution. Through the integration of these findings, this review attempts to assist researchers, decision-makers, and stakeholders in designing creative approaches for minimizing the destructive consequences of plastic pollution on marine environments.

Keywords: *Machine Learning, Deep Learning, Object Detection, Remote Sensing, Monitoring*

1. INTRODUCTION

The rise of plastic pollution has become one of the most pressing and complex environmental challenges of our time. Plastic was invented as a practical, hygienic, and affordable material with almost infinite possibilities, and progressively replaced paper, glass, wood, and metal in a variety of applications, from food packaging to furniture and automobiles [1]. According to a report from the Organization for Economic Co-operation and Development (OECD) from February 2022, production increased between 2000 and 2019 from 234 to 460 million tonnes [2]. Unfortunately, only 9% of the total amount of plastic ever produced has been recycled. The vast majority, 79%, is piling up in plastic litter landfills or spreading into nature in the form of litter [3]. At some point, most of them will inevitably end up in our oceans, a kind of the last container [4]. Plastics are resistant to degradation, but over time, macroplastics fragment into smaller microplastics, which can cause marine organisms to become entangled or ingested, causing severe damage and even death. Overall, the presence of plastic litter in oceans and rivers is a global problem with significant environmental, public health, and economic consequences [5]. Current studies estimate that around 8 million tonnes of plastic are dumped into the oceans every year, and it is predicted that by 2050, the amount of plastic in the oceans will surpass that of fish [5]. However, the problem does not stop there. Plastic undergoes degradation through prolonged exposure to sunlight, water, and air, transforming into microplastics. Fish, other marine mammals, and birds then ingest these microplastics. Every year, between 12,000 and 24,000 tonnes of plastic are absorbed by fish in the North Pacific, causing intestinal damage, mortality, and transmission of plastic up the food chain to larger fish, marine mammals, and, ultimately, seafood consumers. In addition, when microplastics eventually degrade - a process that can take up to 400 years - they release harmful toxins, further contributing to ocean pollution [6]. Although traditional observer-based methods offer many advantages for the detection of floating plastic debris (e.g. accurate target identification, no constraints related to camera battery charge time or storage space), there are

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disadvantages to consider. One of the main drawbacks is the limitation of the observer's visual range, making it difficult to monitor large bodies of water. In addition, these methods are often dependent on weather conditions, lighting, and visibility, which can lead to a reduction in detection efficiency [7]. In addition, human observers can be prone to fatigue and human error, which can compromise the reliability of results. Therefore, while these methods have their merits, it is essential to complement them with more advanced technologies to optimize the detection of plastic debris in the ocean. Among these advanced technologies, over the past decade, machine-learning models have made enormous strides in the analysis of environmental processes. In particular, deep learning models using convolutional neural networks (CNNs) have been widely used due to their remarkable ability to identify and understand features and patterns present in large image or video datasets [8]. These technological advances have been put to good use in the detection and classification of floating plastic debris using drones and automated monitoring systems. This approach has proved particularly promising for monitoring and combating plastic pollution in our oceans, offering an effective and scalable solution to this global environmental problem. This review contributes to the existing literature by providing a comprehensive overview of the state-of-the-art in plastic debris detection using machine learning and deep learning approaches. By analyzing recent studies, we highlight the advancements in detection methods, technologies, and challenges associated with identifying and monitoring floating plastic debris in marine environments. The synthesis of these findings aims to provide a solid foundation for assessing the progress of research in this evolving field while emphasizing the significance of this research for environmental protection and global health.

The remaining of this paper evolves as follows:

- ✓ The second section is devoted to an in-depth examination of the terminology specific to this field while contextualizing the technologies employed.
- ✓ In the third section, we provide a detailed analysis of the methodology we have adopted for our literature review.
- ✓ Finally, the fourth section, before concluding, will present the relevant research succinctly.

2. SCOPE AND FOCUS

The scope of this paper focuses on a comprehensive review of detection methods and technologies used for the identification and monitoring of floating plastic debris in marine environments. To provide a contemporary perspective, our review primarily encompasses studies conducted in recent years to ensure that the selected literature reflects the latest advances in the field.

We will explore several aspects of detection, covering, in particular, the following elements:

Techniques and technologies: We will discuss various detection methods, including color (RGB), hyperspectral and multispectral detection. Each of these methods represents a distinct approach to identifying and quantifying floating plastic debris. Our focus will cover the technologies and tools that facilitate the implementation of these detection techniques, including deep learning algorithms and the datasets used in this field.

Challenges: We will also address the challenges inherent in the detection of floating plastic debris, including issues related to measurement accuracy, method scalability, and data interpretation. In addition, we will explore the environmental and logistical challenges encountered during field surveys and data collection efforts. By defining the scope in terms of both temporal range and specific aspects of detection, this paper aims to provide a comprehensive and up-to-date overview of state-of-the-art techniques, technologies, and challenges associated with the detection. Of floating plastic debris in marine ecosystems.

3. BACKGROUND

3.1. Plastic Debris

Plastic debris, also known as plastic litter, refers to plastic fragments, pieces, particles, or objects that have become detached, fragmented, or unwanted in the environment. This waste is the result of the degradation, fragmentation, and dispersion of plastic products, whether from human consumption, industrial production, or other sources [9]. Plastic debris can vary in size, from tiny microplastics almost invisible to the naked eye to large plastic objects such as bottles, bags, and packaging. The most commonly used method divides pieces of plastic into three main categories: microplastics (1 to 5 mm), mesoplastics (5 to 25

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mm), and macroplastics (over 25 mm) [10], as shown in Figure (1).

They can be found in a variety of environments, including oceans, rivers, soils, landfills, urban areas, and natural ecosystems.

The widespread presence of plastic debris in the environment has given rise to considerable concern due to its harmful effects on fauna, flora, and human health. This waste can persist in the environment for many years, contributing to the contamination of ecosystems and the degradation of water, air, and soil quality.

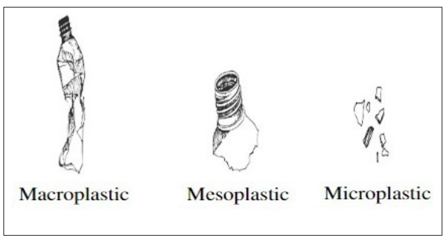

Figure 1 : Distribution and classification of plastic debris.

3.2. Video camera technology for plastic litter detection

Video camera technology is used to automate the process of detecting floating plastic debris. This technology is based on the use of video cameras, which can be deployed for a variety of monitoring purposes, including the monitoring of plastic debris in oceans, rivers, lakes, and other aquatic areas. The idea is to use these cameras to capture images or video of water areas, and then analyze this visual data to locate and track floating plastic debris [11].

3.2.1. Satellite

Satellite cameras are cameras mounted on satellites orbiting the Earth. They offer several important advantages for the detection of floating plastic litter [12].

- ✓ **Global coverage:** Satellites can provide global coverage of the Earth's surface, which means they can monitor vast expanses of water, including remote and hard-to-reach areas.
- ✓ **Regular passage frequency:** Satellites follow predefined orbits and regularly pass over the same areas. This enables continuous monitoring and the possibility of detecting plastic debris at different times and seasons.
- ✓ **High-resolution imaging:** Modern satellite cameras are capable of capturing high-resolution images, making it easier to detect plastic debris even on a small scale.

3.2.2. Drone

Drones are unmanned aerial vehicles equipped with video cameras. They are also used for monitoring and detecting floating plastic debris, and offer several advantages [13]:

- ✓ **Maneuverability and flexibility:** UAVs can be deployed in a targeted manner in specific areas for close-up surveillance. They can move easily to different altitudes and positions to capture detailed images.
- ✓ **Reactivity:** UAVs can be rapidly deployed to meet specific surveillance needs, for example, when a specific area is known to accumulate plastic debris.
- ✓ **Limited human intervention:** UAVs can be programmed to fly autonomously, limiting the need for constant human intervention.

3.2.3. RGB cameras

RGB (Red, Green, and Blue) cameras are the standard cameras commonly found in cell phones, digital cameras, and camcorders. They capture images using three-color channels: red, green, and blue, to produce true-color images that are similar to what the human eye sees. Each pixel in the image is associated with a color value in each of these channels, enabling a wide range of colors to be reproduced.

3.2.4. Multispectral cameras

Multispectral cameras are designed to capture images in several spectral bands, unlike RGB cameras, which capture only three. Multispectral cameras can be used to detect specific information about an object or scene using narrow, predefined spectral bands [14]. They are commonly used in agriculture to monitor crop health, in remote sensing to map soil and vegetation composition, and in other scientific and industrial fields for specialized applications [15].

3.2.5. Multispectral cameras

Hyperspectral cameras go even further, capturing images in hundreds or even thousands of narrow spectral bands, covering a wide range of the electromagnetic spectrum. This enables detailed characterization of the spectral properties of the objects or surfaces captured [16]. Hyperspectral cameras are often used in scientific research, environmental monitoring, geological mapping, chemical detection, and other applications where the spectral composition of objects is crucial to analysis [17].

3.3. Deep Neural Networks

Deep learning, also known as deep neural networks, is a powerful class of machine learning algorithms inspired by the workings of the human brain. They have revolutionized many areas of artificial intelligence [18], enabling machines to learn from data and solve complex tasks. These networks are composed of multiple layers of artificial neurons, each transforming information through mathematical operations to extract increasingly abstract features from the input data. Deep learning has seen spectacular growth thanks to architectures such as convolutional neural networks (CNNs) for computer vision [19], recurrent neural networks (RNNs) for sequence processing, and transformers for natural language processing [20]. These networks have been responsible for numerous breakthroughs in fields such as image recognition, machine translation, natural language understanding, and many others, making a significant contribution to the advancement of artificial intelligence [21]. The general equation of an artificial neuron in a neural network can be expressed as follows:

$$Z = f\left(\sum_{i=1}^{n} (x_i w_i) + b\right) \quad (1)$$

Z: represents the output of the neuron.
n: is the number of inputs (or connections).
x_i: are the input values.
w_i: are the weights associated with each input x_i.
b: is the bias (a constant term added to adjust the output).
f: is the activation function, which can be, for example, the sigmoid function, the ReLU (Rectified Linear Unit) function, the hyperbolic tangent function (tanh), or other activation functions.

This equation (1) calculates the weighted sum of the inputs and then adds a bias, which is often followed by an activation function to produce the neuron's output.

3.4. Computer Vision

Advances in deep learning have dramatically improved the efficiency of computer vision (CV) tasks in the contemporary world. In particular, the introduction of convolutional neural networks (CNNs) has revolutionized the applicability of CV in industrial contexts [22]. CV aims to give computers the ability to identify, classify, and categorize visual information present in images or video streams, in the same way that human beings use their eyes [23]. In computer vision, image analysis refers to the extraction of critical information from images, as opposed to image processing, which focuses on manipulating an image and then creating a new image with enhanced features. Within image analysis, three main categories emerge:

- ✓ **Image classification:** assigning a class to an image [24]. This class can be binary (for example, dog or cat) or multiclass (for example, dog, cat, car, and person). Image classification is a global task, meaning that it deals with the image as a whole. This can be problematic if the image contains several objects, or if the object of interest is small or difficult to distinguish. To solve these problems, image segmentation can be used.
- ✓ **Image segmentation**: involves cutting an image into segments, each representing an object or part of an object. The segments can then be classified individually [25].
- ✓ **Object localization:** an extension of image classification. In addition to assigning a class to an image, object localization also identifies the location of the object within the image. This can be done by surrounding the object with a bounding box [26].
- ✓ **Object detection:** does that by returning a class label along with a bounding box for each detection. We can visualize the bounding box by drawing rectangles over the original image [27].

4. DEEP LEARNING FOR PLASTIC LITTER DETECTION

Deep learning models have revolutionized the ability to overcome complex problems such as plastic litter detection [28]. By using deep neural networks, these models can extract discriminating features from images, making it possible to efficiently spot plastic litter in a variety of environments. Convolutional neural networks (CNNs) are particularly well suited to this task, as they can analyze complex visual patterns in images, such as the shape, color, and texture of plastic litter. These deep learning models have also proved

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adaptable to different situations and environments. For example, they can be used in drones or autonomous robots for real-time detection of plastic litter in hard-to-reach areas. In addition, transfer learning enables pre-trained models to be exploited on large datasets, reducing the need for annotated data specific to plastic litter detection [29]. By final result, thus avoiding classification errors.

- ✓ **Results display :** The detected waste is then highlighted in the image. An output image is generated showing the location of all identified waste, together with its respective classification.

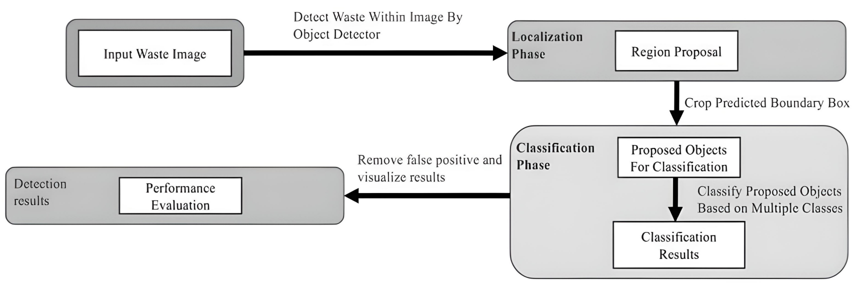

Figure 2 : Block diagram illustrating a typical object detection model for plastic litter detection.

using these deep learning models, plastic litter detection can become more accurate, rapid, and automated, contributing to the global effort to reduce plastic pollution and preserve our environment. Figure (2) illustrates the characteristic block diagram model for plastic debris detection.

The process of waste detection using deep learning models can be described in several comprehensive steps:

- ✓ **Search and Localization:** First, the object detector analyzes the input image to identify potential regions where waste might be present. It does this by carefully examining each part of the image for visual features that correspond to garbage, such as particular shapes, colors or textures.
- ✓ **Creating Bounding Boxes:** Once the detector spots these potential areas, it creates bounding boxes around each of them. These boxes precisely demarcate the regions where waste could be found.
- ✓ **Extraction of Bounding Boxes:** The bounding boxes thus generated are then extracted from the image, and this data is passed on to the classifier. The classifier is responsible for determining the type of waste present in each box.
- ✓ **Removal of False Predictions:** To improve detection accuracy, steps are taken to eliminate false positive predictions. This means that regions that do not contain waste are removed from the
- ✓ **Performance evaluation:** Finally, the section concludes with an evaluation of the performance of the detection models. This can include the use of evaluation metrics such as precision, recall, F-measure, etc., to measure how good the model is at detecting and classifying waste.

This detailed approach demonstrates how deep learning models are deployed to solve the problem of garbage detection, going through each stage from the initial search for garbage to the presentation of results and evaluation of model performance.

In the next section, we will take a close look at several research studies on the use of deep learning for the detection of plastic waste.

5. METHODOLOGY

The conceptualization phase of this study is fundamental to establishing a solid framework. Research questions play an essential role in defining the direction of this research and achieving its objectives. This investigation focuses on three fundamental questions: *i) how are deep learning methods implemented for the detection of floating plastic litter? ii) What are the advantages and limitations of using data collected by drones for the detection of such plastic litter compared to that obtained by satellites?* Moreover, *iii) How deep learning methods contribute to improving the accuracy of the classification of the various categories of plastic litter?*

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Once the research questions have been formulated, the next step involves implementing the search strategy. This study uses several databases, including Science Direct, MDPI, Springer, arxiv, The International Archives of the Photogrammetry, International Society for Photogrammetry and Remote Sensing, Remote Sensing and Spatial Information Sciences, and Iopscience. The first keyword chosen from these databases is *"plastics detection deep learning"* with a range of articles covering five years from 2019 to 2023. The choice of these five years is explained by the appearance of advanced real-time detection methods during this period. However, as the first keyword did not give satisfactory results in the databases, other keywords were used, including *"plastics debris detection", "plastic litter detection"* and *"plastic detection marine deep learning"*.

The final step involves establishing inclusion and exclusion criteria, a crucial step in ensuring the relevance of the articles chosen for this study. We included only scientific articles written in English. Given that our objective is not strictly limited to the detection of plastic waste, but also extends to the detection of general waste that may contain plastic, we have restricted our selection to research articles dealing with these areas. Articles not related to plastic or general waste detection were not considered in this study.

6. FINDINGS

In this section, we will explore the key findings from the literature review on plastic debris detection. Technological advances and innovative approaches in this field have led to the development of increasingly effective and sensitive detection methods. Our in-depth analysis of the selected articles will highlight the different techniques, devices, methodologies, and results obtained, to provide a comprehensive overview of the state-of-the-art in plastic debris detection. We will also examine the limitations and gaps in current research, identifying opportunities for future studies and the potential for improving existing detection techniques.

The findings presented in this section will serve as a solid basis for assessing the progress of research in this ever-evolving field while highlighting persistent challenges that require further attention. These findings will help to enlighten the reader on current advances in plastic debris detection while underlining the importance of this research for the protection of our environment and global health.

Table (2) refers to our literature review; we summarize different research related to plastic debris detection using deep learning detection approaches. Each line corresponds to a separate study, including its specific objective, the deep learning model used, and the results obtained. Together, these studies provide us with valuable information on the current state of the art in plastic waste detection.

These results illustrate the progress and variety of deep machine learning techniques employed in plastic debris detection, encompassing a diversity of models and measurement criteria to address this critical environmental problem. The following section will go into more detail on the materials used in these studies.

6.1. Materials Research

To provide a better understanding of the differences and similarities between these approaches, we have drawn up the comparison table below. Table (2) highlights three significant studies in this field, focusing on key aspects such as the title of the article, the dataset used (including the name of the dataset and the number of images), the type of camera employed (drone or Sentinel-2) and the camera color (RGB or multispectral). This comparison will enable us to examine how these factors influence the performance of plastic waste detection models and to identify emerging trends in this research.

7. LIMITATIONS OF THE STUDY AND FUTURE WORK

This review offers an in-depth perspective on the multiple deep learning approaches to plastic waste detection. Although these studies have made considerable progress in solving this critical environmental problem, it is crucial to recognize their limitations and suggest avenues for future research.

Among the limitations identified is data diversity, as many studies are based on specific sets collected in restricted geographical and environmental conditions, hindering the generalization of models to real-world scenarios. Detection of small objects is also a challenge, requiring improved model efficiency to accurately identify and classify these elements. The predominant use of RGB images limits the ability of models to distinguish certain materials, suggesting that multispectral imaging could

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improve detection accuracy. In addition, the limited availability of ground-truth data on plastic waste makes it difficult to validate and adjust detection models.

For the future, improved collection of diversified datasets should be a priority, covering varied regions, environments, and types of plastic waste. Merging data from multiple sources, such as drones and satellites, could offer a more comprehensive view of plastic waste in oceans and coastal areas. Exploring advanced spectral analysis methods, such as hyperspectral or thermal imaging, is essential to differentiate materials more effectively. Adopting active learning strategies could help overcome ground truth limitations by enabling models to select the most informative samples for annotation. In addition, research should focus on the development of real-time monitoring systems for the rapid identification of plastic waste, with major implications for pollution reduction. Finally, the integration of detection systems with political initiatives and clean-up efforts should be considered for an effective response to areas at risk from plastic waste. It is imperative to resolve these limitations and pursue these research directions to advance plastic waste detection and contribute to more effective environmental conservation.

8. CONCLUSION

Detecting plastic waste in our aquatic environments has become a major concern in the preservation of our planet. In this article, we have conducted a comprehensive review of deep learning-based approaches to plastic debris detection. The results of these studies testify to the impressive progress made in the field of plastic debris detection, highlighting the power of deep learning techniques to solve crucial environmental problems.

Our analysis has identified several promising trends. The studies presented demonstrated that models based on convolutional neural networks (CNNs) can achieve high levels of accuracy in detecting plastic debris, with results regularly exceeding 85% accuracy.

However, it is crucial to recognize the current limitations of these approaches, particularly concerning data diversity, the size of detectable objects, and the impact of camera color. Detecting small pieces of plastic waste remains a challenge, requiring future developments to improve the sensitivity and specificity of the models.

The future of plastic waste detection relies on key initiatives, including collecting more diverse and comprehensive data, integrating multiple imaging sources, exploring new spectral technologies, and engaging in the search for real-time solutions for plastic waste monitoring.

Ultimately, this work demonstrates the crucial importance of plastic waste detection research to our environment and society. By collaborating on these challenges, continually improving detection approaches, and integrating these solutions into concrete waste management actions, we can look forward to a cleaner, more sustainable future for our planet and future generations.

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Table 1: Summary of plastic litter detection approaches, including titles, models used in each study, and results.

Paper	Study	Model	Results
[30]	Identifying floating plastic marine debris using a deep learning approach	VGG16 CNN architecture, pre-trained on ImageNet	Accuracy: 86%
[31]	Machine learning for aquatic plastic litter detection, classification, and quantification (APLASTIC-Q)	CNN-based algorithm for plastic debris detection	Precision: 77%, Recall: 77%, F1 score: 77%
[32]	Deep Learning Model for Automatic Plastic Mapping Using UAV Data	Semantic segmentation with ResUNet50	Precision: 82%, Recall: 75%, F1 score: 78%
[33]	Towards detecting floating objects on a global scale with learned spatial features using sentinel 2	CNN (U-Net)	Accuracy: 84.28%, F1 score: 81%
[34]	Automatic detection and quantification of floating marine macro-litter in aerial images	Deep learning approach based on a CNN architecture	RF Accuracy: 88%, SVM Accuracy: 84%, GAN-RF Accuracy: 96%
[35]	A Cloud-Based Framework for Large-Scale Monitoring of Ocean Plastics Using Multi-Spectral Satellite Imagery and Generative Adversarial Network	Random forest (RF), support vector machine (SVM), generative adversarial network-random forest (GAN-RF)	Accuracy: 85%, Precision: 79%, Recall: 94%, F1-score: 86%
[36]	A Deep Learning Model for Automatic Plastic Waste Monitoring Using Unmanned Aerial Vehicle (UAV) Data	EfficientNet classification algorithm and Yolov5 target detection algorithm	mAP: 91%
[37]	Targeting Plastics: Machine Learning Applied to Litter Detection in Aerial Multispectral Images	Machine learning algorithm based on Random Forest approaches	F1 score: 93%
[38]	Improved YOLOv7 for Small Object Detection Algorithm Based on Attention and Dynamic Convolution	YOLOv7-CA dynamic network model	mAP: 81%, F1 score:79%
[39]	Large-scale Detection of Marine Debris in Coastal Areas with Sentinel-2	UNet; UNet++	UNet Accuracy: 90%, UNet++ Accuracy: 93%

Table 2: Summary of Datasets and Imaging Specifications.

Paper	Dataset	Camera Type	Camera Color
[30]	Dataset unspecified (4000 images)	Drone	RGB
[31]	PLD-CNN and PLQ-CNN. PLD-CNN was established from eight of the 16 RGB true color images, while seven images were used to create the dataset for PLQ-CNN	Drone	RGB
[32]	Captured	Drone	RGB
[33]	Collected from Google Earth Engine (GEE)	Sentinel-2	RGB
[34]	Captured (3900 images)	Drone	RGB
[35]	PLP2019 dataset [40]	Sentinel-2	RGB
[36]	UAV data monitoring plastic waste dataset [41]	Drone	RGB
[37]	Captured by MicaSense [42]	Drone	Multispectral
[38]	FloW-Img [43]	Unmanned boat	RGB
[39]	MARIDA [44]	Sentinel-2	RGB

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