Using Multispectral UAV Imagery for Marine Debris Detection in Sri Lanka

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***Abstract*—Marine pollution is a significant issue in Sri Lanka, with the country being a major contributor to marine debris. Marine pollution has the potential to adversely impact marine and coastal biodiversity, as well as the fishing and tourism industries. Current methods for monitoring marine debris involve labor-intensive approaches, such as visual surveys conducted from boats or aircraft, beach clean-ups, and underwater transects by divers. However, an emerging trend in many countries is the use of Unmanned Aerial Vehicle (UAV) imagery for monitoring marine debris due to its advantages, including reduced labour requirements, higher spatial resolution, and cost-effectiveness. The work presented in this study utilizes multispectral UAV imagery to monitor marine debris in a coastal area of Ambalangoda, Sri Lanka. For the automated detection of marine debris in captured images, this work replicates the state-of-the-art *CutPaste* method for region detection and utilized the ResNet-18 model with Faster R-CNN for the final classification of marine debris instances. The implemented approach demonstrated a classification accuracy of approximately 60% in automatic marine debris detection, laying the groundwork for potential enhancements in the future.**

***Index Terms*—marine debris monitoring, unmanned aerial vehicles, multispectral camera, self-supervised learning, anomaly detection**

I. Introduction

Marine debris refers to solid materials intentionally or unintentionally discarded into oceans, seas, or coastal areas, which can include manufactured or processed substances [1]. The main categories of marine debris include plastic, metal, textiles, glass, and rubber [2]. It stems from a multitude of sources, including anthropogenic activities such as littering on beaches and improper waste disposal from boats and offshore structures, as well as unintentional waste entry from land through storm drains, canals, rivers, and wind-blown trash from landfills [3]. The impact of marine debris cannot be ignored, given its substantial risks, which include harming marine and coastal wildlife, damaging and degrading habitats, causing economic losses for fishing and maritime industries, undermining the quality of life in coastal communities, and posing threats to human health and safety [4].

Sri Lanka is one of the leading contributors to marine debris [5]. A study conducted in 2020 revealed that the waters around the island are predominantly affected by domestic debris (99%), with only a small fraction resulting from foreign sources (1%) [6]. Packaging materials, consumer products, and waste from fisheries are the main sources of marine debris in Sri Lanka [5]. Current methods to monitor marine debris involve visual surveys conducted from boats or aircraft, beach clean-ups, and underwater transects by divers. Visual surveys suffer from limitations due to weather conditions. Beach clean-ups, while valuable for onshore debris, are labor-intensive and time-consuming and do not address the larger amounts of debris still in the water. Underwater transects are costly, require skilled divers, and may not be feasible in certain oceanic environments.

Due to the aforementioned challenges associated with conventional methods, many countries have transitioned towards the utilization of Unmanned Aerial Vehicle (UAV) imagery for monitoring marine debris. This standardized approach enables the cost-effective acquisition of high-resolution images over wide areas. The reduction in labour expenses and time commitment makes it particularly advantageous [7]. Compared to satellite remote sensing, UAVs offer benefits such as higher image acquisition frequency, greater spatial resolution, low-altitude operation beneath clouds, increased mobility, and suitability for monitoring specific regional areas of interest [8]. Furthermore, many UAVs provide real-time feedback through live video feeds or real-time data transmission, allowing operators to closely monitor the captured imagery. The automation of marine debris detection and classification in acquired UAV images can be achieved by leveraging advanced image processing, and Machine Learning (ML) and Deep Learning

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(DL) techniques.

In the realm of camera sensor integration with UAVs, the RGB cameras have been commonly employed, capturing images in visible light's red, green, and blue wavelengths. However, there is a growing interest in multispectral cameras, especially in fields such as environmental monitoring. Multispectral camera sensors enable the capture of images from both the visible and near-infrared (NIR) regions of the electromagnetic radiation spectrum, utilizing three or more distinct bands [9]. This provides a high level of spectral resolution compared to RGB sensors. Prior studies have revealed that identifying the composition and category of debris from RGB images is frequently challenging, as the utilization of red, green, and blue channels solely permits a chromatic depiction [10]–[13]. Various materials exhibit distinct reflection and absorption patterns at different wavelengths [14]. Thus, multispectral cameras may offer an enhanced portrayal of marine debris due to the broader range of wavelengths encompassed by image acquisition compared to the limited RGB spectrum.

In this study, UAV imagery obtained from a multispectral camera was employed to detect both onshore and floating marine debris within the confines of the Ambalangoda coastal zone in Sri Lanka. What sets this study apart is its embrace of a pioneering training mechanism—a self-supervised learning approach, specifically employing the innovative *CutPaste* method. Inspired by the research outlined in [15], this method involves strategically integrating image segments, achieved by adeptly selecting and placing crops of these segments into different areas of an image, thereby creating entirely new training instances. The driving force behind this approach is to equip the model with a prior understanding of the visual environments it will encounter, effectively enabling it to familiarize itself with the contextual intricacies of these scenes. The underlying aspiration of this training strategy is to cultivate, within the model, an ability to glean insights from its learned environment, thus enriching its capacity to discern complex features. By integrating this state-of-the-art *CutPaste* technique into the methodology, this work embarks on an expedition to unravel intricate patterns within the distribution of marine debris.

This paper is structured as follows. Section II discusses the background of the study and reviews prior research on UAV-based marine debris monitoring. It specifically focuses on cases involving multispectral cameras while identifying existing gaps. Section III outlines the methodology employed for automated marine debris detection in captured images. The evaluation and results are presented in Section IV, followed by the conclusion in Section V. The potential future research directions in this study are finally discussed in Section VI.

II. Background and Related Work

A. Background

1) Multispectral Image Processing: This study utilizes the *MicaSense RedEdge-MX* camera to capture images of onshore and floating marine debris through the deployment of UAVs (see Figure 1). It captures five spectral bands: red, green, blue, red edge and NIR [16]. The red edge band operates within the spectral range of 680–750nm, while the NIR band extends from 750–1400nm—both diverging from the conventional visible RGB spectrum of 400–700nm [16]. A single capture produces five distinct images, facilitating the formation of an RGB orthophoto via the combination of the red, green, and blue bands, as well as a multispectral orthophoto by employing all five bands.

(a)

(b)

Fig. 1: The hardware equipment for image acquisition: (a) MicaSense RedEdge-MX camera, DLS 2 GPS, and the Calibrated Reflectance Panel (CRP); (b) the equipment mounted on the drone platform.

2) Self-Supervised Anomaly Detection: Anomaly detection is the identification of data instances or events that deviate from anticipated patterns of behaviour [17]. Identification of marine debris within collected UAV images represents an anomaly detection task in this context, as it entails discerning and classifying elements that deviate from the expected visual characteristics of the marine environment. Self-supervised learning has gained significant attention as a viable approach for anomaly detection in images due to its inherent capability to effectively leverage large amounts of unlabelled data, allowing the acquisition of meaningful and informative representations. This is particularly advantageous in cases of sparsely labelled anomaly data and when anomalies display unique attributes not comprehensively reflected in the training data [18].

B. Related Work

While marine debris monitoring utilizing UAVs remains relatively unexplored in Sri Lanka, multiple work in other countries have successfully employed this approach. Recent advancements have led those work to adopt the use of multispectral cameras. Thus, the literature review conducted primarily concentrated on studies that employ multispectral UAV imagery for marine debris monitoring, aiming to identify existing approaches in this domain.

Cortesi et al., in their study [20], compared the performance of Random Forests (RF) and Support Vector Machine (SVM) classifiers in detecting macro plastic within flowing water in a fluvial habitat using a handheld multispectral camera with nine bands (i.e. red, green, blue, violet, red edge 1, red edge 2, NIR 1, NIR 2, NIR 3). They utilized connected region detection to pinpoint plastic areas while disregarding small, isolated regions as likely errors. With 98% accuracy attained in binary classification using RF, the approach, however, exhibited an undesirably high rate of false positives; concurrently, employing the SVM classifier resulted in comparatively less satisfactory outcomes. Challenges such as identifying white rocks, sea foam, and sun glint remained unresolved, highlighting the need for refining the approach.

In another work by Cortesi et al. [21], an approach was introduced for automated plastic detection based on UAV images captured along the Arno River in Italy, utilizing a multispectral proximity sensor camera with the same nine spectral bands used in the previous work. Their detection methodology centred around pixel-based classification, effectively discerning plastic materials from other substances using a cascade of two random classifiers. The study emphasized multispectral sensors' potential over traditional imagery, attributed to the additional infrared bands improving plastic detection in challenging conditions, such as making plastic more distinguishable from sun glint. While achieving over 98% accuracy and recall for plastic detection, precision and quality were lower, with performance varying based on UAV altitude and being less optimal at higher altitudes.

Gonçalves and Andriolo conducted a study utilizing a UAV-mounted multispectral camera with five distinct bands (i.e. red, green, blue, red edge, and near infrared), focusing on the classification of litter types and materials within a Portuguese beach-dune system [22]. The study underscored the efficacy of multispectral imagery in advancing remote litter classification, which is crucial for identifying pollution sources. The researchers adopted the Sample Angle Mapper (SAM) technique for automated litter material and type categorization using multispectral orthophotos formed by combining all five bands. SAM, a physically-based classification method reliant on comparing image spectra with reference spectra, yielded a F-score of 64%. However, before the classification, the identification of litter items necessitated manual marking on the RGB orthophotos, which is a constraint in their study.

Jakovljević et al. utilized high-resolution UAV multispectral images and a U-Net architecture-based deep learning algorithm to detect and classify floating plastic in water ecosystems [23]. They employed a UAV equipped with a 5-band multispectral camera to capture images in Lake Balkana, Republic of Srpska and Bosnia and Herzegovina, highlighting a knowledge gap in understanding the spectral signatures of floating plastic. Their analysis of spectral signatures revealed the suitability of the NIR channel for detecting floating plastics due to its higher reflectance compared to water, while the visible spectrum was preferable for submerged plastic. However, the algorithm had limitations in detecting all plastic pixels; nevertheless, it exhibited high accuracy in cases where detection occurred, indicating its reliability.

III. Methodology

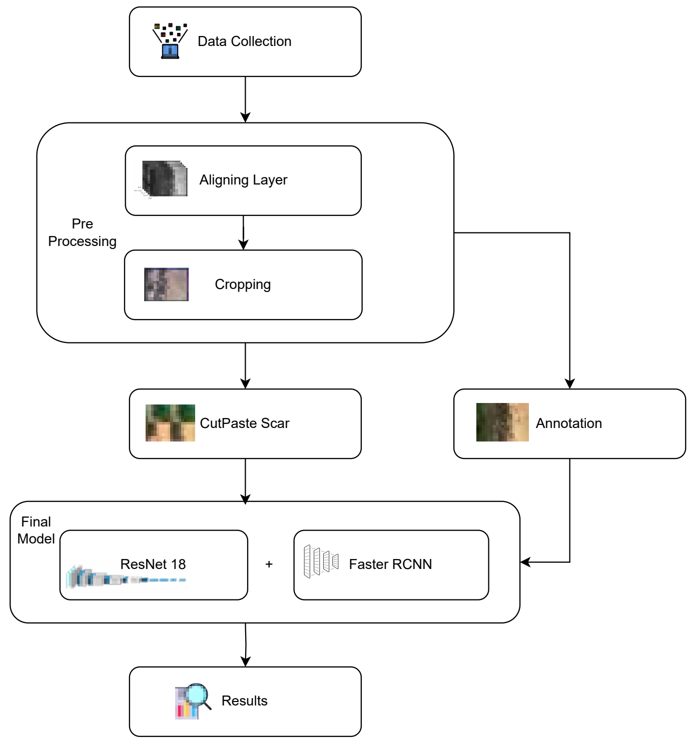


Fig. 2: High-level overview of the methodology.

A. Data Collection

A dataset was generated through the utilization of a *MicaSense RedEdge-MX* multispectral camera, which was mounted to a *DJI Phantom 4* drone. At an altitude of 30 meters above ground level, it captured a diverse array of 84 images that collectively cover a coastal stretch within the vicinity of Ambalangoda, Sri Lanka. The collection of images encompassed various aspects, including the coastal landscape, and captured both onshore and floating marine debris that existed in the area prior to data collection, as well as additional debris that was deliberately placed for the purposes of the study.

B. Data Preprocessing

As outlined in Subsection II-A1, a single acquisition by the multispectral camera yields five distinct images representing the red, green, blue, red edge, and NIR spectral bands. To facilitate the image processing and machine learning tasks, these images underwent a conversion process, culminating in the formation of RGB orthophotos and multispectral orthophotos. This transformation was achieved by combining the relevant spectral bands, and it necessitated a meticulous alignment of each band with the other bands. It is not possible to simply overlay the multispectral images to create orthophotos because the five sensors in the camera capture images from slightly different angles for each band. Therefore, some additional work is required to align each image with the others.

The alignment process encompassed three main steps. Initially, the images were unwarped using MicaSense's built-in lens calibration functionality. Subsequently, a transformation was applied to align each individual band with a standardized reference band. Finally, the aligned images were combined and cropped to eliminate pixels that lacked overlapping presence across all bands.

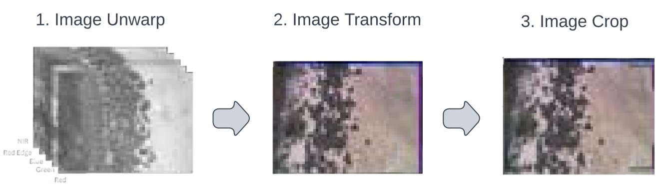


Fig. 3: Steps for image alignment.

C. Image Annotation

The preprocessed images were labeled manually using the *labelImg* utility [19]. Each image was inspected for the presence of marine debris and a bounding box was created around the debris. When two or more pieces of trash are in close proximity to each other, they are treated as a single entity. Only the ones that are having trash in the image have been selected for annotation. Once the annotation part is done, the annotated images and label files are been broken into tiles to increase the number of the training data for the *Faster Region-Based Convolutional Neural Network (Faster R-CNN)* object detection module.

D. Training CutPaste Model

In the domain of marine remote sensing imagery, the challenge arises from the detection of minute debris, often spanning mere tens of pixels. Consequently, the most intricate aspect revolves around establishing effective representations for these minuscule targets. Given the inherent scarcity of pixel information encapsulating the debris, contemporary state-of-the-art detection algorithms struggle to discern the subtle variations within these objects. This poses a formidable obstacle for object detection algorithms, such as Faster R-CNN, particularly when tasked with autonomously capturing these diminutive objects during the training process. To mitigate premature exposure of the model, specifically Faster R-CNN, to images, we leverage the *CutPaste* self-supervised learning technique—serving as a pretext task—by incorporating it into the core of the Faster R-CNN network. This strategic integration facilitates a nuanced comprehension of the background textures inherent to the images, effectively enhancing the model's capability to discern intricate environmental nuances.

Given the distinctive attributes associated with diminutive target objects within remote sensing images, this work introduces a novel approach for detecting marine debris. This approach centers around an enhanced CutPaste self-supervised strategy. Illustrated in Figure 2, the model comprises two integral modules: the self-supervised learning module and the object detection module. The self-supervised learning module harnesses the Resnet-18 architecture, which is trained on a specially designed CutPaste auxiliary task. The primary objective of this module is to acquire effective representations from unlabeled remote sensing images that lack detected objects. The module dedicated to object detection is responsible for both classification and identification of objects. This module operates on the foundation of a customized Faster R-CNN network, wherein the Feature Pyramid Network (FPN) has undergone adaptations to incorporate our self-supervised learning module.

Figure 2 illustrates the comprehensive training process flow. Initially, the gathered data from the drone, acquired through the multispectral camera, undergoes a preprocessing stage. In this step, the individual 5-band spectral TIFF files are amalgamated to facilitate training. As a preliminary phase of our experiment focuses on RGB images, these TIFF files need to be converted into a 3-channel band stack configuration, incorporating the bands alignment and bands adjustment phases.

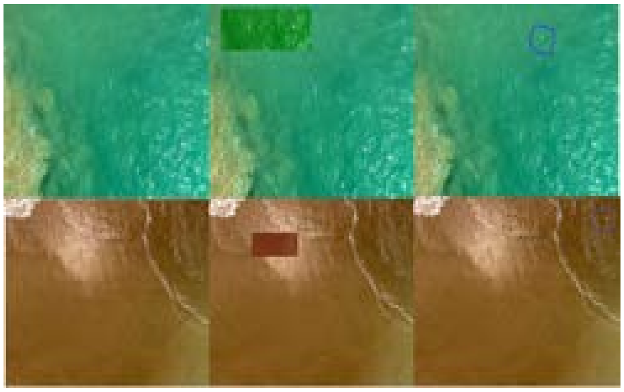
After the images have undergone the preprocessing stage, the initial phase of training commences. This first training phase employs the CutPaste self-supervised learning strategy, which has been elaborated upon in the preceding subsection. The entire dataset is subjected to the CutPaste augmentation technique, resulting in augmented images that are fed into the utilized encoder network. The CutPaste augmentation involves cropping (i.e., copying) random sections from non-trash image samples and subsequently pasting (using a scaled-down version of the crop) them onto another random location within the same image. Notably, this augmentation technique operates within a single image. The augmentation samples are depicted in Figure 4.

The encoder network is tasked with predicting three classes during the self-supervised learning phase: the original image, cutpaste, and cutpaste-scar. Once the encoder network has been fully trained using the Self-Supervised Learning (SSL) method, it is replaced with the Faster R-CNN backbone network. Figure 4 illustrates the preprocessing part in two distinct stages: first, the entire dataset undergoes image alignment and adjustment, followed by isolating the instances of trash within the images for annotation. This annotated data is subsequently used to train the Faster R-CNN network. During the annotation process, images containing debris are labeled as 'trash.' Upon setting the Faster R-CNN object detection module for training, the network's backbone is frozen, and the remaining layers are fine-tuned in the training process.

IV. Evaluation and Results

A. Experimental Setup

To facilitate the training of the self-supervised learning module, a set of 60 images devoid of any trash instances is randomly curated. In order to assess the object detection model's performance, particularly in contexts where labeled



(a) *CutPaste* Module.

(b) *CutPaste Scar* Module.

Fig. 4: The two *CutPaste* modules that were used in the study.

images are scarce, augmentation techniques such as rotations and flips are employed to expand the training dataset. The training process is conducted utilizing the Stochastic Gradient Descent (SGD) optimizer, with a designated batch size of 8. The learning rate is meticulously set at 0.0001. Notably, the chosen backbone architecture for this task is ResNet-18[1].

The stride values for the anchor boxes are configured as 4, 8, and 16, respectively. For the anchor box's aspect ratio, a randomized selection is made from the options 0.5, 1.0, and 2.0. An anchor box is classified as a foreground region of interest when the computed Intersection over Union (IoU) metric between the anchor box and the ground-truth box surpasses the threshold of 0.6. Conversely, if the IoU metric falls below 0.3, the anchor box is categorized as an unrelated background region.

B. Experimental Results

In the self-supervised learning module, a multi-faceted CutPaste task has been meticulously crafted, enabling the concurrent execution of 3-way, cutpaste scar, and cutpaste operations within a single image. Furthermore, the experiment was evaluated by conducting tests on distinct individual single cutpaste tasks, followed by a comparative analysis between the outcomes of the different approaches. A selection of 60 images devoid of any trash instances — consequently unlabeled — was expanded to a comprehensive pool of 480 images through the application of augmentation techniques, such as flips and rotations. The resulting accuracies and validation losses of the self-supervised learning task are detailed in Table I.

Table I presents a noteworthy observation: the 3-way task exhibits superior detection accuracy in contrast to the other self-supervised learning tasks. Specifically, the mean Average Precision (mAP) metric reflects a substantial performance boost of approximately 10.7 percent, ascending from 0.566 to 0.622. This enhancement is particularly pronounced when the integration of blocks and scars is selectively applied rather than ubiquitously. As the training epochs unfold, the network's detection capabilities, as depicted in Figure 5, progressively refine. Remarkably, as depicted in Figure 6, the training loss exhibits a consistent pattern throughout this process.

[1]An 18-layer deep convolutional neural network.

TABLE I: The results of various *CutPaste* task modules

***CutPaste* Task**	**Metric**		
	Accuracy	***Validation Loss***	***Mean Avg. Precision***
more-way	63.45%	0.572	0.5662
3-way	68.32%	0.4883	0.6220
CutPaste (Block)	58.24%	0.5732	0.5321

V. Conclusion

The issue of marine pollution is a pressing concern in Sri Lanka, necessitating a more efficient approach to monitoring marine debris. Current manual methods, such as beach clean-ups and visual surveys from boats and aircraft, are labour-intensive and time-consuming. This study represents a significant step towards improving marine debris monitoring in Sri Lanka by utilizing UAV imagery. We employ the CutPaste method for precise region detection and a ResNet-18 model with faster R-CNN for classification, reducing analysis time while achieving an initial accuracy of around 60%. This research not only addresses a critical environmental challenge but also contributes to global efforts to preserve marine ecosystems.

VI. Future Work

The current study is limited to using images solely from the red, green, and blue bands of the multispectral camera. However, there's significant potential for enhancing the results by fully utilizing all five available bands, including the red edge and NIR bands, which offer a higher level of spectral resolution. This expanded spectral information can facilitate a more precise classification of the diverse material types such as plastic, metal, and polythene present in the detected marine debris. Additionally, our current dataset is relatively small in scale, and we have the opportunity to improve our results by either increasing the dataset size through the acquisition of more images or by diversifying it through data augmentation techniques. By taking these steps, we can substantially enhance the reliability and robustness of our research findings, thereby elevating the overall quality and impact of our study.

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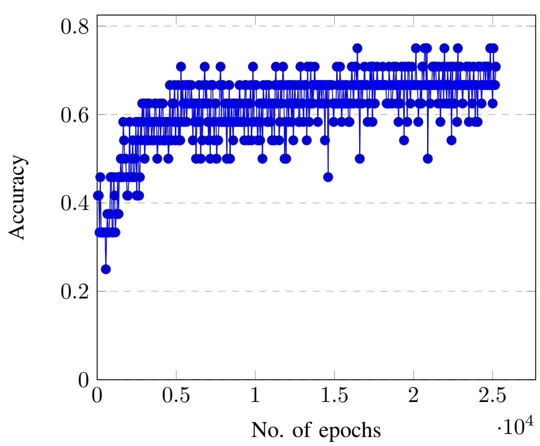

Fig. 5: The change of accuracy with the number of epochs.

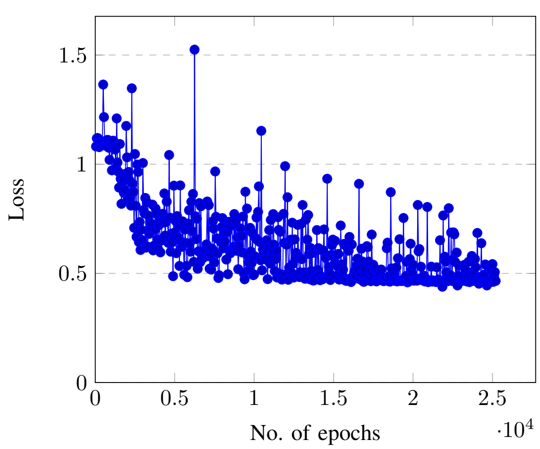

Fig. 6: The change of loss with the number of epochs.

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