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Data Article

RGB and RGNIR image dataset for machine learning in plastic waste detection

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The increasing volume of plastic waste is an environmental issue that demands effective sorting methods for different types of plastic. While spectral imaging offers a promising solution, it has several drawbacks, such as complexity, high cost, and limited spatial resolution. Machine learning has emerged as a potential solution for plastic waste due to its ability to analyse and interpret large volumes of data using algorithms. However, developing an efficient machine learning model requires a comprehensive dataset with information on the size, shape, colour, texture, and other features of plastic waste. Moreover, incorporating near-infrared (NIR) spectral data into machine learning models can reveal crucial information about plastic waste composition and structure that remains invisible in standard RGB images. Despite this potential, no publicly available dataset currently combines RGB with NIR spectral information for plastic waste detection. To address this research gap, we introduce a comprehensive dataset of plastic waste images captured onshore using both standard RGB and RGNIR (red, green, near-infrared) channels. Each of the two-colour space datasets include 405 images that were taken along riverbanks and beaches. Both datasets underwent further pre-processing to ensure proper labelling and annotations to prepare them for training machine learning models. In total, there are 1,344 plastic waste objects that have been annotated. The proposed dataset offers a unique resource for researchers to train machine learning models for plastic waste detection. While there are existing datasets on plastic waste, the proposed dataset aims to set itself apart by offering a more comprehensive dataset with unique spectral information in the near-infrared region. It is hopeful that these datasets will contribute to the advancement of the field of plastic waste detection and encourage further research in this area.

Specifications Table

Subject	Computer Science
Specific subject area	Machine Learning. Data Science
Type of data	Raw Numeric Figure Table
Data collection	Plastic waste data was collected from three public locations in Kota Kinabalu, Sabah, Malaysia: Penampang Moyog Riverbank, Tanjung Lipat Beach, and Tanjung Aru Beach. These locations were selected due to their proximity to water bodies and significant human activity, making them key areas for plastic waste accumulation. Waste from land-based sources often enters oceans and rivers through these pathways, making them ideal for observing plastic waste patterns. Additionally, beaches and riverbanks provide diverse backgrounds and lighting conditions, which are crucial for image analysis and the development of machine learning algorithms. Plastic waste images were captured using two

(*continued on next page*)

	types of cameras: an iPhone 12 and a Mapir Survey 3W camera. The iPhone 12 was used to collect RGB images of plastic waste, providing high-resolution color data. In contrast, the Mapir Survey 3W, a compact and affordable multi-spectral camera equipped with a wide-angle lens and high sensitivity to near-infrared (NIR) light, was used to create RGNIR images. This dual-camera approach enabled the collection of both standard RGB and RGNIR datasets, allowing for comprehensive analysis of plastic waste in natural environments under various spectral conditions.
Data source location	State: Sabah Country: Malaysia
Data accessibility	Repository name: RGB-and-RGNIR-Plastic-Waste-Database Data identification number: https://doi.org/10.5281/zenodo.13827422 Direct URL to data: https://github.com/plastic-waste-database/RGB-and-RGNIR-Plastic-Waste-Database Instructions for accessing these data: Direct access to the link
Related research article	Tamin, O., Moung, E.G., Dargham, J.A., Yahya, F., Farzamnia, A., Sia, F., Naim, N.F.M. and Angeline, L., 2023. On-Shore Plastic Waste Detection with YOLOv5 and RGB-Near-Infrared Fusion: A State-of-the-Art Solution for Accurate and Efficient Environmental Monitoring. *Big Data and Cognitive Computing*, *7*(2), p.103. https://doi.org/10.3390/bdcc7020103

1. Value of the Data

- The dataset introduces near-infrared (NIR) spectral information, which is currently unavailable in other public datasets for plastic waste detection. This added spectral data could enhance machine-learning models by providing insights into the material properties of plastic waste that are not visible in standard RGB images.
- By providing comprehensive information on plastic waste characteristics, including size, shape, color, texture, and NIR data, the dataset enables researchers to develop more robust and efficient machine learning models for plastic waste detection and classification.
- The dataset provides an opportunity for interdisciplinary collaboration between fields like computer vision, environmental science, and waste management. It encourages further exploration of integrating spectral imaging with machine learning for innovative plastic waste detection solutions.
- The availability of this dataset could drive future research aimed at improving the accuracy, efficiency, and scalability of plastic waste detection methods, contributing to advancements in environmental monitoring and sustainability initiatives.

2. Background

Plastic waste is one of the most critical environmental challenges, with millions of tons generated globally each year, and the amount is expected to rise significantly in the future [1]. Accurate sorting methods are crucial for effective recycling, and while spectral imaging offers promise, it faces challenges such as high cost, complexity, and limited resolution [2,3]. Machine learning presents an efficient and cost-effective alternative for addressing this issue, as it has proven valuable in image-based tasks, including plastic waste detection [4,5].

A comprehensive dataset is vital for training ML models to recognize and classify plastic waste accurately [6]. While several plastic waste datasets exist, they often lack critical features, such as NIR spectral data, which can reveal material properties not visible in RGB images. This paper addresses this gap by introducing a dataset that includes both RGB and RGNIR images of plastic waste collected from onshore environments. The dataset provides researchers with the necessary resources to develop more robust machine-learning models for plastic waste detection

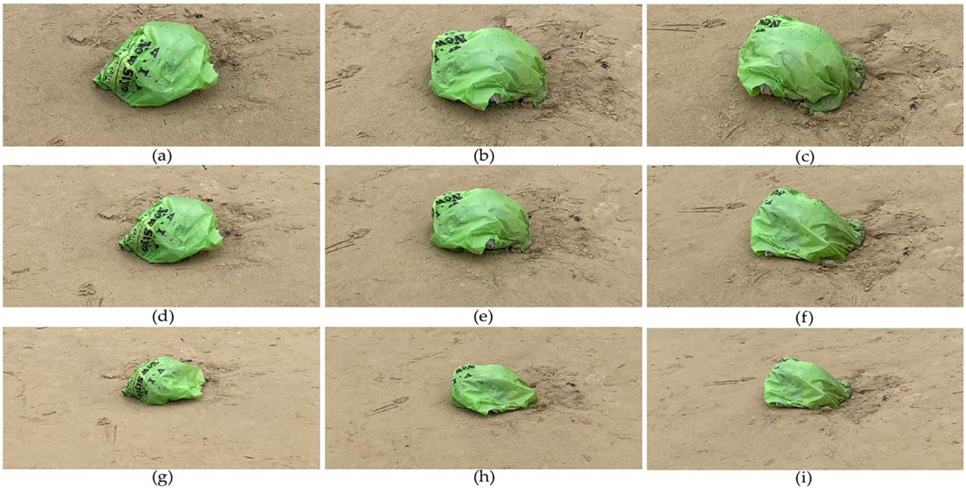

Fig. 1. A sample of nine unique images of the plastic object from the RGB dataset; (a) 1.0 m and 30° left, (b) 1.0 m and center, (c) 1.0 m and 30° right, (d) 1.5 m and 30° left, (e) 1.5 m and center, (f) 1.5 m and 30° right, (g) 2.0 m and 30° left, (h) 2.0 m and center, (i) 2.0 m and 30° right.

and automatic sorting. It is a valuable contribution to the field, offering a foundation for future research and the development of advanced waste management solutions.

3. Data Description

The dataset was developed using images captured from three selected public locations in Kota Kinabalu, Sabah, Malaysia: Penampang Moyog Riverbank (5°53′08.3"N 116°05′55.4"E), Tanjung Lipat Beach (6.004142° N, 116.109792° E), and Tanjung Aru Beach (5.947682° N, 116.046424° E). The geographical coordinates of the three locations were obtained using Google Maps [7]. These sites were chosen for their proximity to water sources and high human activity, making them ideal for understanding plastic waste entry into marine environments. The dataset consists of images captured using two types of cameras: an iPhone 12 for RGB images and a Mapir Survey 3W for RGNIR images. The Mapir Survey 3W camera is noted for its multi-spectral capabilities and high sensitivity in the near-infrared range.

Each plastic waste object was captured from nine unique positions, comprising three distances—1.0 m, 1.5 m, and 2.0 m—and three angles—centre, 30° to the left, and 30° to the right. These three distances were chosen to provide an optimal balance between coverage and visibility, ensuring that the entire object is captured within the frame while maintaining sufficient detail for accurate detection. In total, 405 images were collected, covering 45 distinct plastic waste scenes, with each scene including nine images taken at various angles and distances, as illustrated in Figs. 1 and 2. Images were systematically named to facilitate organization and management, employing a coding scheme that includes the order number, camera type, distance, angle, and filters used. The dataset repository is organized into folders based on different image capture distances and conditions. Each folder contains subfolders that categorize images by specific attributes, such as distance from the plastic waste object and spectrum (e.g., RGB or RGNIR). This structure allows users to easily navigate through the dataset and select images according to their experimental requirements. The naming conventions in each folder facilitate quick identification of image types and capture parameters. Detailed descriptions of each folder's contents can be found in the dataset's metadata.

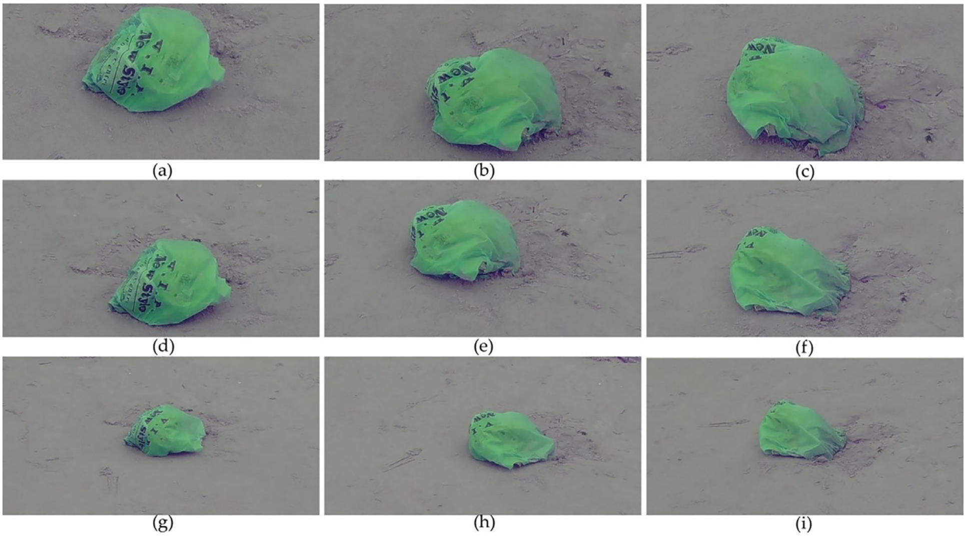

Fig. 2. A sample of nine unique images of the plastic object from the RGNIR dataset; (a) 1.0 m and 30° left, (b) 1.0 m and center, (c) 1.0 m and 30° right, (d) 1.5 m and 30° left, (e) 1.5 m and center, (f) 1.5 m and 30° right, (g) 2.0 m and 30° left, (h) 2.0 m and center, (i) 2.0 m and 30° right.

Table 1
Camera information of iPhone 12 and Mapir Survey 3W.

Camera	Focal length	Aperture	Sensor size	Resolution	Spectral band	Frame per second	Sensor
iPhone 12	Wide: 26 mm Ultrawide: 13 mm	Wide: f/1.6 Ultrawide: f/2.4	1/3.6 inch	12 MP	Not applicable	Up to 240 fps	LiDAR scanner
Mapir Survey 3W	19 mm	Not applicable	Not applicable	8 and 12 MP	Red: 550 nm Green: 650 nm NIR: 850 nm	24 to 240 fps	Sony Exmor R IMX117

4. Experimental Design, Materials and Methods

The experimental setup involved the careful positioning of cameras on heavy-duty tripod stands to ensure stability during image capture. The details of both cameras are shown in Table 1. Cameras were set at distances of 1.0, 1.5, and 2.0 meters, with angles adjusted to the centre of each object and at 30-degree increments to the left and right, illustrated in Fig. 3. This approach aimed to optimize the dataset by capturing a variety of perspectives that the object detection model may encounter in real-world conditions.

After image acquisition, pre-processing techniques were applied to enhance data quality and standardize the dataset for downstream tasks. Images were initially named automatically using the cameras' default naming convention, consisting of a base filename and an incremented number. For clarity and efficient management, images were renamed manually using a structured coding scheme:

P01_**M**_**D**1_**A**1_**F**1.jpg

P01_**I**_**D**1_**A**1.jpg

where each letter represents its specific properties, such as

P	-	the order number of the plastic object;
M/I	-	the devices used to capture the image;
D	-	the distance of the object from the camera;
A	-	angle of the object;
F	-	filters set in Mapir camera.

The use of alphabet characters for naming the parameter and digits as the parameter values are introduced for better image management for users. The established values of defined parameters are presented in Table 2. After the images were named, a cropping process was conducted to remove irrelevant backgrounds. This step ensures that the dataset remains focused on the target objects while eliminating noise that may interfere with model training. All images were then resized to 416 × 416 pixels to ensure uniformity and compatibility with deep learning frame-

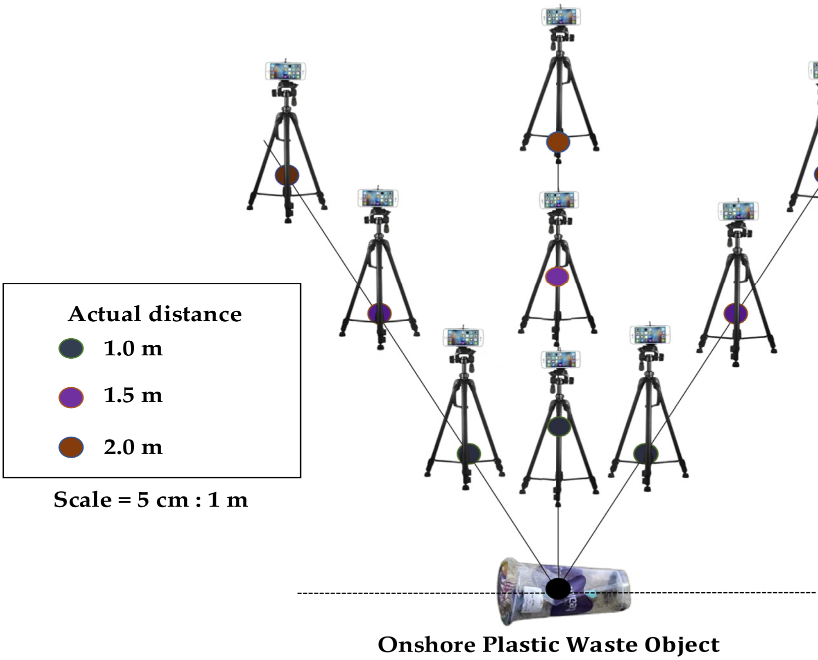

Fig. 3. The position of the tripod at various angles and distances.

Table 2
Parameter values used to represent the names of plastic waste dataset.

Parameter	Values	Description
M or I (device used)	M	Mapir Survey3W
	I	iPhone 12
Distance	1	1.0 m
	2	1.5 m
	3	2.0 m
Angle	1	0° at the center
	2	30° to the left
	3	30° to the right

Fig. 4. Annotation samples of RGB images (left column) and RGNIR images (right column)

Fig. 5. The sample of an overall flow of pre-processing steps for multiple plastic objects in an image.

Table 3
The details of the overall proposed datasets.

Dataset	Number of images	Number of plastic scenes	Number of plastic objects
RGB	405	45	1344
RGNIR	405	45	1344

works like YOLOv5, which require fixed input dimensions. This resizing step preserves aspect ratios to avoid distortion of the objects.

Finally, an open-source annotation tool, LabelImg, was used to draw ground-truth bounding boxes around plastic objects in the images illustrated in Fig. 4. To provide a comprehensive view of the pre-processing pipeline, Fig. 5 illustrates an image containing multiple plastic waste objects that underwent all pre-processing steps, including naming, cropping, resizing, and annotation. The consistent application of these pre-processing techniques ensures the reliability and reproducibility of the dataset for future research. Moreover, the uniformity across both RGB and RGNIR datasets, as shown in Table 3, allows for robust comparisons regarding the impact of incorporating near-infrared spectral information in object detection models.

Table 4
Comparison with the existing plastic waste dataset.

Dataset	Plastics waste images	Colour space	Background images	Annotated
WaDaBa [8]	4000	RGB	Black background	No
TrashNet [9]	482	RGB	White background	No
GINI [10]	Not stated	RGB	Landscape and street	Yes
RealWaste [11]	831	RGB	Concrete	No
BDWaste [12]	125	RGB	Concrete	No
COCO [13]	Not stated	RGB	Household	Yes
TACO [14]	Roughly 2000	RGB	Onshore	Yes
Proposed dataset	810	RGB and RGNIR	Onshore	Yes

4.1. Comparison with existing plastic waste datasets

Table 4 provides an overview of existing plastic waste datasets, highlighting their characteristics such as image count, color space, background settings, and annotation status. It is evident that while these datasets have been valuable for waste detection and classification, they predominantly rely on RGB color space and lack the inclusion of the NIR spectrum, which is crucial for comprehensive plastic waste identification.

The proposed dataset stands out due to its incorporation of both RGB and RGNIR images, enhancing the feature representation for plastic waste analysis. The inclusion of NIR spectra is crucial due to its ability to capture additional and more detailed information compared to RGB alone. This reason is because the NIR spectrum extends beyond the RGB wavelength, resulting in a greater number of pixel values and providing a richer source of data for analysis. This additional information can greatly improve the accuracy and reliability of machine-learning models in detecting and classifying plastic waste.

Furthermore, the environment in which the dataset is captured plays a vital role in its relevance and applicability; unlike some existing datasets that may not reflect real-life scenarios, such as those with artificial backgrounds or limited environmental diversity, the proposed dataset is captured in a natural and real-life environment, specifically onshore where plastic waste is naturally present. This environment realism contributes to the dataset's suitability for real-world applications and enhances the robustness of machine learning models trained on it.

The TACO dataset is advantageous for researchers due to its large image size, onshore capture, and annotation status, which are comparable to the proposed dataset [14]. However, it is essential to highlight that the TACO dataset exclusively utilizes RGB images. In contrast, the proposed dataset stands out by incorporating NIR images, thereby enhancing its comprehensiveness for plastic waste analysis. The availability of both RGB and RGNIR images, combined with already annotated data in YOLO coordinates format, streamlines the training process for modern machine learning models like YOLOv7, ensuring efficient utilization of the dataset for plastic waste detection and classification tasks.

Limitations

While this paper has introduced two valuable plastic waste datasets—comprising RGB and RGNIR images—there are several limitations to consider. Firstly, the datasets were collected from only three public locations in Kota Kinabalu, Sabah, which may not fully represent the diverse range of plastic waste encountered in various geographic and environmental contexts. This limited sampling could affect the generalizability of the findings.

Additionally, although extensive pre-processing was applied, the presence of noise or artifacts in the images cannot be entirely ruled out, potentially impacting the performance of machine learning models. Furthermore, while the datasets aim to facilitate comparisons between the two color spaces, they do not include other potential features or modalities, such as texture or shape analysis, which could further enhance detection accuracy.

Future work will involve augmenting the datasets to include a broader range of perspectives and conditions, but this expansion has not yet been realized. Consequently, while these datasets are a significant step forward in plastic waste detection research, ongoing efforts are needed to improve their comprehensiveness and applicability in real-world scenarios. Lastly, another approach for image detection is applying scattered data interpolation by triangulating the images [15–17].

Ethics Statement

The authors of this paper are aware of the ethical statements of this journal, and they agree with it.

Credit Author Statement

Conceptualization, Owen Tamin; Data curation, Owen Tamin; Formal analysis, Owen Tamin, Ervin Gubin Moung, Jamal Ahmad Dargham and Samsul Karim; Funding acquisition, Samsul Karim, Ashraf Osman Ibrahim, Nada Adam and Hadia Abdelgader Osman; Investigation, Owen Tamin; Methodology, Owen Tamin, Ervin Gubin Moung, Jamal Ahmad Dargham and Samsul Karim; Project administration, Samsul Karim and Ervin Gubin Moung; Software, Owen Tamin, Ervin Gubin Moung and Samsul Karim; Supervision, Samsul Karim and Ervin Gubin Moung; Validation, Owen Tamin and Samsul Karim; Visualization, Owen Tamin and Samsul Karim; Writing – original draft, Owen Tamin; Writing – review & editing, Owen Tamin, Ervin Gubin Moung, Jamal Ahmad Dargham, Samsul Karim, Ashraf Osman Ibrahim, Nada Adam and Hadia Abdelgader Osman.

Data Availability

RGB-and-RGNIR-Plastic-Waste-Database (Original data) (ZENODO).

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Declaration of Competing Interest

The authors declare no conflict of interest.

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