The classification of marine plastic waste based on high-resolution UAV imagery combined with deep learning algorithms – Sri Lanka case study

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The plastic problem

Mismanaged plastic waste resulting in pollution of the marine environment, coastlines and estuarine areas and riverbanks has reached a critical level, representing one of the most difficult environmental problems of our time. It is recognised as irreversible and globally ubiquitous, affecting marine ecosystems across the world.

Plastics contribute to climate change across the whole life cycle – from the extraction of fossil fuels as feedstock for plastics through to the climate change impacts of the end-of-life option for plastic waste [1].

A 2024 University of California/Berkeley Laboratory report on the impact of plastic production on the climate estimates that in 2019 the global production of primary plastics generated 5.3% of global greenhouse gas (GHG) emissions (excluding, agriculture, land use, land-use change and forestry). Under a conservative growth scenario, GHG emissions from primary plastic production would more than double by 2050 [2].

A comprehensive report led by the Center for International Environmental Law (2019), highlights how plastics produce greenhouse gas emissions across the life cycle [3] In brief, emissions occur from:

- **Extraction and transport:** leakage, fuel combustion, energy consumed during drilling for oil or gas, and land disturbance when forests or fields are cleared for drilling and pipelines.
- **Refining and manufacture:** the cracking of alkanes into olefins, the polymerisation and plasticisation of olefins into plastic resins, and other chemical refining processes.
- **Waste management:** incineration in the open (extremely high), recycling (moderate – and advantageous because it displaces new virgin plastic) and landfilling (least – but could increase with more biodegradable plastic releasing methane).
- **Plastic in the environment:** early reports suggest that plastic on the ocean surface and on coastlines, riverbanks and landscapes may release methane and other greenhouse gases [4], and that microplastics in the oceans may interfere with the ocean's capacity to absorb and sequester carbon dioxide. Further research is needed to confirm these findings.

It is its ubiquity, particularly disposal at end-of-life, that is globally problematic. Synthetic plastics are largely nonbiodegradable, tending to persist in natural environments. Only 9% of plastic waste is recycled [5]. It is difficult to recycle, slow to decay, expensive and polluting to burn, and breaks down into microplastics, tiny particles that enter the food chain and cause harm to animals and potentially humans.

The United Nations Environment Programme (UNEP) estimates that every year 19-23 million tonnes of plastic waste leaks into aquatic ecosystems, polluting lakes, rivers and seas.

Plastic pollution, it notes, alters habitats and natural processes, reducing ecosystems' ability to adapt to climate change, directly affecting millions of people's livelihoods, food production capabilities and social well-being.

Inger Andersen, UNEP Executive Director says… *we will not recycle our way out of the plastic pollution crisis: we need a systemic transformation to achieve the transition to a circular economy* [4] - that is, changing from the 'take-make-dispose' model to a more sustainable system focussed on 'reduce, reuse, repair and recycle' [6].

On 2 March 2022 the 5th United Nations Environment Assembly (UNEA 5.2) at its meeting in Nairobi resolved to 'end plastic pollution: towards an international legally binding instrument' (Resolution 5/14) noting with concern that the high and rapidly increasing levels of plastic pollution represent a serious environmental problem at a global scale, negatively impacting the environmental, social and economic dimensions of sustainable development [7].

It also resolved, under Resolution 10, to enhance the circular economy as a driver to achieving sustainable consumption and production.

The 2030 Agenda for Sustainable Development addresses the plastic pollution challenge under Sustainable Development Goal 14 through Target 14.1, which calls for prevention and significant reduction of all forms of marine pollution, particularly plastic litter and other land-based pollutants [8].

Plastic pollution also threatens the progress of other Sustainable Development Goals, with prominent impacts on:

- **SDG 12: Responsible Consumption and Production:** This goal aims to ensure sustainable consumption and production patterns. The current linear "take-make-waste" model for plastics is a primary driver of the pollution crisis and is fundamentally incompatible with achieving this goal. Tackling this requires a drastic reduction in single-use plastics and a transition to a circular economy.
- **SDG 13: Climate Action:** By fuelling demand for fossil fuels and generating substantial greenhouse gas (GHG) emissions, the plastics industry undermines global

efforts to combat climate change. Coordinated climate and plastics policies are essential to reduce these emissions.

- **SDG 3, 6, and 15 (Health, Water, and Ecosystems):** Harmful chemicals in plastics and the presence of microplastics in our air, water, and food chain pose risks to human health. Plastic pollution also clogs urban infrastructure, leading to flooding and the spread of water-borne diseases, and harms terrestrial biodiversity.

Emerging research has overturned earlier assumptions about the sources of marine plastic pollution. While large rivers were once considered the dominant contributors, recent studies indicate that many smaller, urban rivers near coastlines are responsible for a disproportionate share of plastic leakage — with approximately 1,000 rivers accounting for 80% of global ocean plastic input [9].

This evidence suggests that targeted interventions in urban coastal catchments — including improved litter collection, street-level waste management, and river-based cleanup — can significantly reduce the volume of plastic entering the marine environment [10].

However, decision-making is currently constrained by a major data gap. Much of the global understanding of plastic waste distribution relies on coarse modelling rather than direct measurement. The main challenge to achieve global assessment is low coverage and efficiency of traditional survey methodology. There is no widely available method to accurately assess the spatial and temporal extent of plastic waste at local, regional, or global scales. Nor do policymakers have access to tools that enable consistent, repeatable monitoring. This information deficit remains a major barrier to designing effective interventions and evaluating their impact.

Remote sensing, known for its ability to provide consistent, large-scale environmental information, has the potential to tackle debris monitoring, fill the gap between sparse in-situ surveys and provide relatively uniform coverage over large regions and long time periods. [11] have used Sentinel 2 Satellite images to detect patches of floating macro-plastics on sub-pixel scales by leveraging spectral shape and a Naïve Bayes algorithm with an accuracy of 86%. Similarly, [12] used Sentinel 2 data and Naïve Bayes to distinguish floating macro-plastic from seaweed in coastal waters with an accuracy of 87.25%. [13] developed an approach based on Sentinel 2 data and extreme gradient boosting for distinguishing suspect plastic debris from other plastic materials. [14] used the Sentinel 2 images and artificial targets to investigate the spectral properties, observing the weak to strong relationship between percentage pixel coverage and the spectral reflectance. This study highlights the importance of very high-resolution UAV datasets for validation and plastic monitoring in the aquatic environment.

While satellite imagery offered promising results, the monitoring of plastic litter from space is highly complex due to the constraints in spatial resolution of satellite images, the availability of training data, high signal-to-noise ratios due to the limited coverage of plastic per pixel, atmospheric and sea-surface effects, cloud presence, etc. In recent years, the number of studies utilizing UAV-derived orthophotos to detect, identify and quantify plastic debris with high accuracy on beaches, riverbanks, and water surfaces has increased. The high-resolution UAV data, coupled with deep learning classification and object detection models, offers a promising solution for automating debris identification, reducing time-consuming and labour-intensive manual surveys.

[15] proposed automatic mapping of plastics in rivers using UAV data and the YOLO v5 model, resulting in a mean average precision of 0.82. [16] used ultra-high resolution UAV images and Fast R-CNN to detect 14 different categories of debris on beaches. [17] used deep learning algorithms and UAV images to detect floating plastic items, resulting in a F1 score of 0.78. While [18] used UAV hyperspectral images and super pixel-based segmentation for plastic litter detection with high accuracy (F1 0.86).

Despite promising developments, challenges persist regarding spectral ambiguity, classification accuracy and standardization across platforms. This paper presents a multi-class deep learning algorithm for the automatic identification of different debris types on orthophotos produced from drone images.

Study area

Sri Lanka is a tropical island located in the northern Indian Ocean, positioned between latitudes 5° 55'' and 9° 51'' N and longitudes 79° 41'' and 81° 53'' E. The island covers a total land area of approximately 65.6 km² while its coastline extends over 1300 km and is characterized by diverse ecosystems including the lagoons, sandy beaches and coral reefs.

As an island nation, Sri Lanka is particularly vulnerable to coastal plastic litter accumulation due to the influence of seasonal monsoon weather patterns. Moreover, coastal plastic pollution is driven by a lack of local authorities' capacity for proper plastic waste management, high consumption of single-use plastic, fisheries debris and transboundary pollution.

It is estimated that in 2020 Sri Lanka generated 938.42 metric tonne daily (MT/D) of plastic waste, of which 300.3 MT/D is collected. Total uncollected waste is estimated at 638.12 MT/D of which about 8.45 MT/D is directly discharged to water sources [19]. According to research presented at [20] Sri Lanka ranks as the fifth highest contributor of plastic waste released into the ocean.

Sri Lanka's food and economic security are closely linked to the fisheries and tourism sectors. Coastal beaches represent one of the country's main tourist attraction and are an important source of income for local communities. However, the accumulation of plastic debris on beaches degrades their amenities and recreational value, often leading to a decline in visitor numbers. Consequently, coastal plastic pollution causes both economic losses for local communities and broader ecological damage to coastal ecosystems.

Beaches near to river mouths, particularly near large cities, are usually the most affected by debris accumulation. Therefore, we selected the coastal zone near the mount of the Kelani River as the primary study area (Figure 1). The Kelani River discharges to the Indian Ocean on the western coast of Sri Lanka, forming the northern boundary of the Colombo city area (near Mattakkuliya).

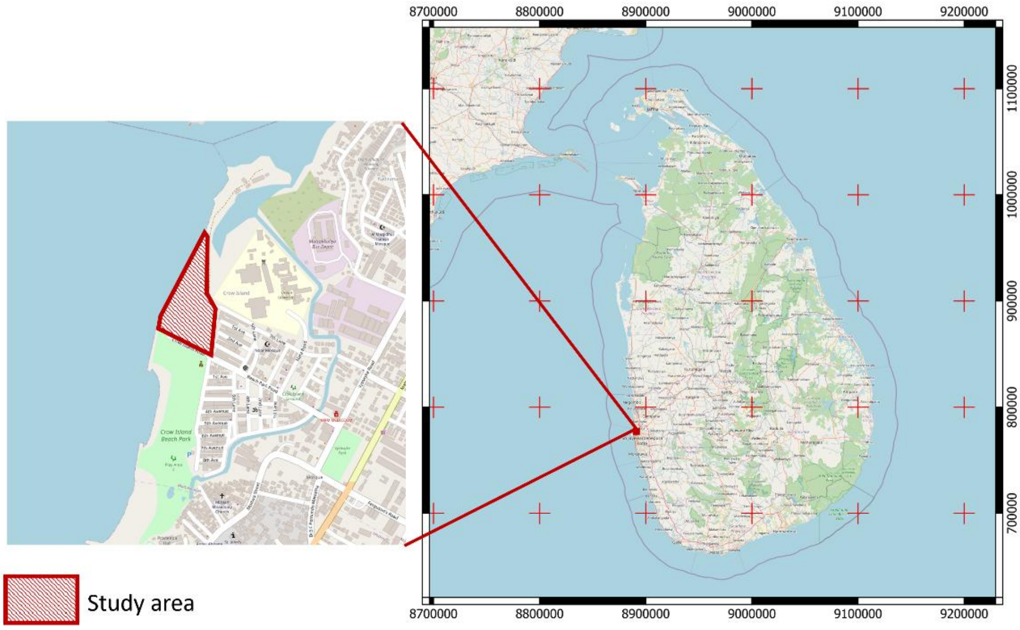
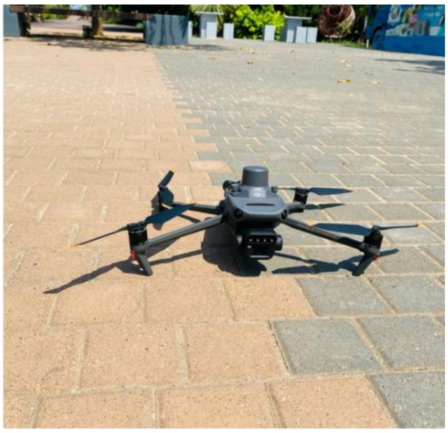


Figure 1. Study area

Data

The acquisition of the UAV image dataset was undertaken using a DJI Mavic 3 Enterprise UAV. This drone is equipped with both an RGB and a multispectral camera. The flying height was set to 20 metres, resulting in a ground sampling distance of 0.6 cm/pixels for the RGB camera. GNSS navigation in RTK mode was used to during data collection to enable precise georeferencing. In addition, several Ground Control Points (GCP) were installed before image acquisition and surveyed using GNSS RTK.

(a)



(b)

Figure 2. (a) Study area, (b) DJI Mavic 3 Enterprise

Methodology

The proposed methodology used in this paper consists of preprocessing, classification, and accuracy assessment. The workflow is presented in Figure 3.

Preprocessing

The captured UAV images are used to produce an orthophoto of the study area. For this task, the Structure-from-Motion algorithm implemented in the Agi soft Meta shape is used. Georeferencing of the collected data is performed by using an onboard real-time kinematic (RTK) global navigation satellite system receiver. The set of well-distributed ground control points (GCP) were used to assess the accuracy of the georeferencing.

In addition to the orthophoto, the digital surface model (DSM) is created. The DSM, visualised with hill shade rendering, assists the operators to evaluate the shape and size of the object with higher confidence.

The creation of a reliable training dataset is a critical step in developing an accurate semantic segmentation model. ~~Taking into account the characteristics of remote sensing images challenges such as boundary ambiguity, material ambiguity and annotation difficulties can significantly affect accuracy of semantic segmentation models.~~ Due to the intrinsic properties of remote sensing images, issues including boundary ambiguity, material ambiguity, and annotation challenges can significantly impact the performance of semantic segmentation models.

To create the training data and decrease errors by manual delineation of different items, object-based image analysis is used to segment orthophotography into non-overlapping polygons.

Each segment is then manually classified into one of the predefined classes based on a visual inspection of orthophoto and the DSM.

Although the segmentation of an image into objects can improve the delineation of individual items, the creation of high-quality training data remains a complex and challenging task. One major challenge is this study area is the high spatial overlap between classes, where object of different categories may be completely or partially occluded. Another major challenge is ambiguity in material identification, which is based on visually recognising the object type based on shape and inferring the material from which it is made. For example, the slippers can be made from rubber, plastic or foam. This problem is particularly pronounced when objects do not have distinctive shapes, making accurate labelling difficult despite ultra-high resolution.

While the main scope remains plastic items detection, other classes of interest were also defined, including plastic, wood, rubber, and textile. The class distribution is shown in Table 1.

Table 1. Class distribution

Class	Wood	Rubber	Plastic	Textile	Paper
Distribution	59.1 %	6.4 %	28.2 %	5.9 %	0.4 %

Once annotated, the dataset is split into training and test subsets to enable model learning and independent evaluation of the model's generalisation ability. 80% of the dataset is used for training and 20% for testing.

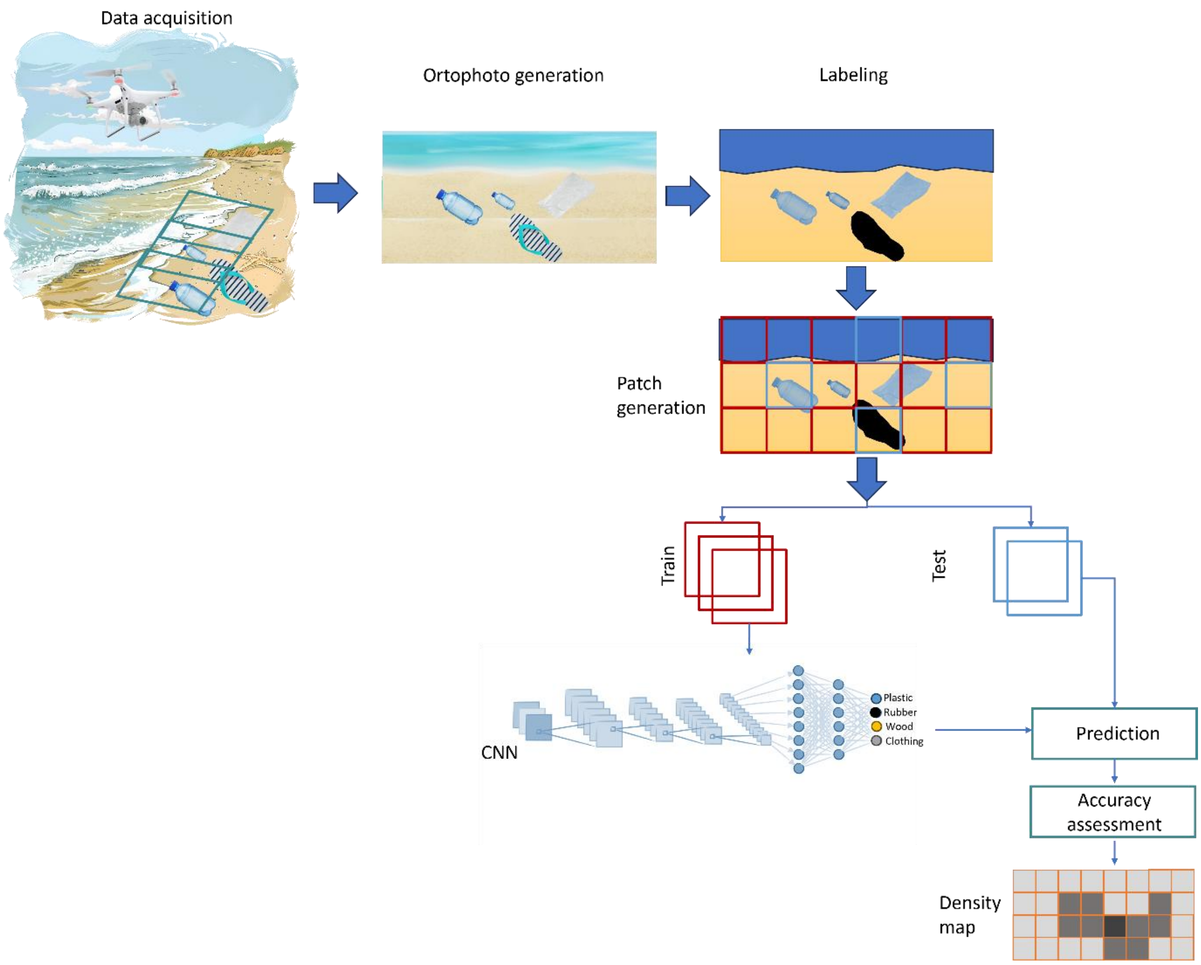


Figure 3. Workflow

Classification

In order to automatically detect marine debris in the orthophotography images, we developed a deep learning algorithm. Specifically, we implemented a Convolutional Neural Network architecture that uses Residual blocks [21]. Residual blocks consist of a convolutional layer, which extracts features from input images at different levels of hierarchy, a pooling layer that increases the abstraction level of extracted features, and batch normalization. Target debris items are segmented and classified within the five debris classes.

Accuracy assessment

Overall model performance is assessed by comparing model precision (P), recall (R), and F1-score (F1).

After accuracy assessment, the part of study area that is not used for training or testing purposes was predicted using the trained model. The predicted results are used to count the number of detected debris items and for density map creation.

Model implementation

The training and testing phase involved multiclass debris identification using semantic segmentation, based on ground truth data and prediction by the model. The model was trained using NVIDIA Tesla P100-PCI-E 16GB Graphics Processing Unit (GPU) on Google Collab, using TensorFlow. The model was trained using the Rectified Linear Unit (ReLU) activation function and a decaying learning rate. The batch size was 16 patches of 256 x 256 pixels.

Results and discussion

Table 2. Accuracy assessment results

Class	Precision	Recall	F1
Wood	0.75	0.98	0.85
Rubber	0.59	0.54	0.56
Plastic	0.91	0.76	0.83
Textile	0.81	0.38	0.52
Mean precision	0.77		
Mean recall	0.66		
F1	0.69		

The accuracy assessment results in Table 2 indicate that the developed model exhibits good overall performance with an F1-score of 0.69. Those results are comparable with previous studies such as [15] (F1= 0.76), [27] (F1= 0.49) or [28] (F1= 0.81) despite the higher complexity of the study area due to background noise and the high density of litter.

However, the model performance is characterized by high variance across different classes.

Wood remains the easiest class to detect for proposed model, boasting a Recall of 0.97, which implies that it captures almost each pixel belonging to this class. However, this high sensitivity comes at a cost to its precision of 0.75, suggesting that the model is likely to overpredict. Those findings are confirmed by visual interpretation of the results (Figure 4 (a) and (b)).

The plastic class shows strong classification performance, with a precision of 0.91 and a recall of 0.76 (Table 2). Those results indicate that the model can reliably detect plastic with relatively few misclassifications.

In contrast, the performance for the rubber class is noticeably lower, indicating that the model has difficulties both in correctly identifying instances and avoiding false classification. This is mostly due to the similar spectral characteristics with other classes (Figure 4 (a)). The model detects the rubber class with moderate overall performance. Although the model is capable of detecting the target class, there is a notable portion of both false positive and false negative classification.

Despite a high precision of 0.81, the textile class shows a low recall of 0.38 indicating that the model rarely assigns the class incorrectly but is ignoring more than 60% of the actual class area.

The model completely failed to identify the paper class, resulting in zeros across the board for precision, recall, and F1 (results have been excluded from the tables). This significantly pulled down overall model performance (mean precision, mean recall, and mean F1). With a distribution of 0.4%, this represents a classic symptom of class imbalance in the training set for this specific class.

Visual inspection of the results reveals confusion between the wood class and the black rubber object, shown in Figure 4(a), which can be attributed to their similar spectral characteristics in the RGB portion of the spectrum. Distinguishing different materials based on RGB images can be challenging due to high inter band correlation and colour and intensity mixing, especially for classes with subtle texture and reflectance differences [22].

Additionally, this study observed a misclassification of rubber objects as plastic. This may be related to the quality of training data, since most rubber objects in the study area consist of shoes and slippers. As these items can be manufactured from both plastic and rubber materials, ambiguities in the training data may occur leading to reduced classification accuracy during the evaluation process.

The visual inspection indication shows that the misclassification of all classes on patch edges (Figure 4 (c)) reduces the overall accuracy. This is mostly due to the limited context information in those regions. Similar findings are presented in [21] and [22].

Moreover, the model performance is affected by characteristics of plastic items varying in shape, size, colour etc. Visual inspection indicates that large items are correctly identified and easy to distinguish from surrounding objects. However, detecting the small items in a crowded image with different types of background is extremely challenging, leading to detection errors [25], [26].

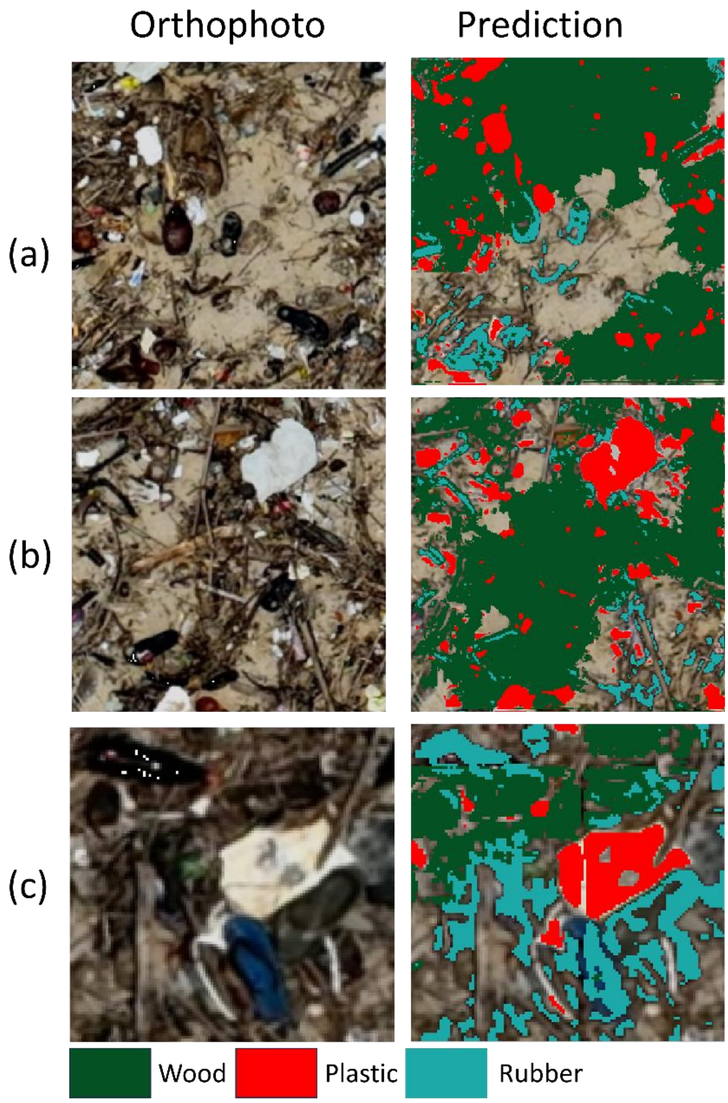


Figure 4. Visual comparison of prediction results

Based on the predicted results the density map is created using a high-resolution grid (1 m x 1 m cell) to show the accumulation patterns, distribution and density of plastic items in the study area (Figure 5). The trained algorithm has detected more than 7500 plastic items with average plastic litter density exceeding 4.62 items per square metre. Similar results were reported by Jang et al. [20], who found an average of 4.1 debris items larger than 25 mm per square metre of beach, based on a survey of 22 beaches along the coast of Sri Lanka.

In 2023 OSPAR adopted the threshold value for beach litter of 20 items per 100 metres of coastline which also represents the value agreed by the European Union [23]. Taking that into account the beach width (approximately 15 metres) and the average litter density, the study area exhibits an extreme level of anthropogenic contamination with ≈ 345 times higher litter density compared with the threshold value. This once again highlights the complexity of the study area.

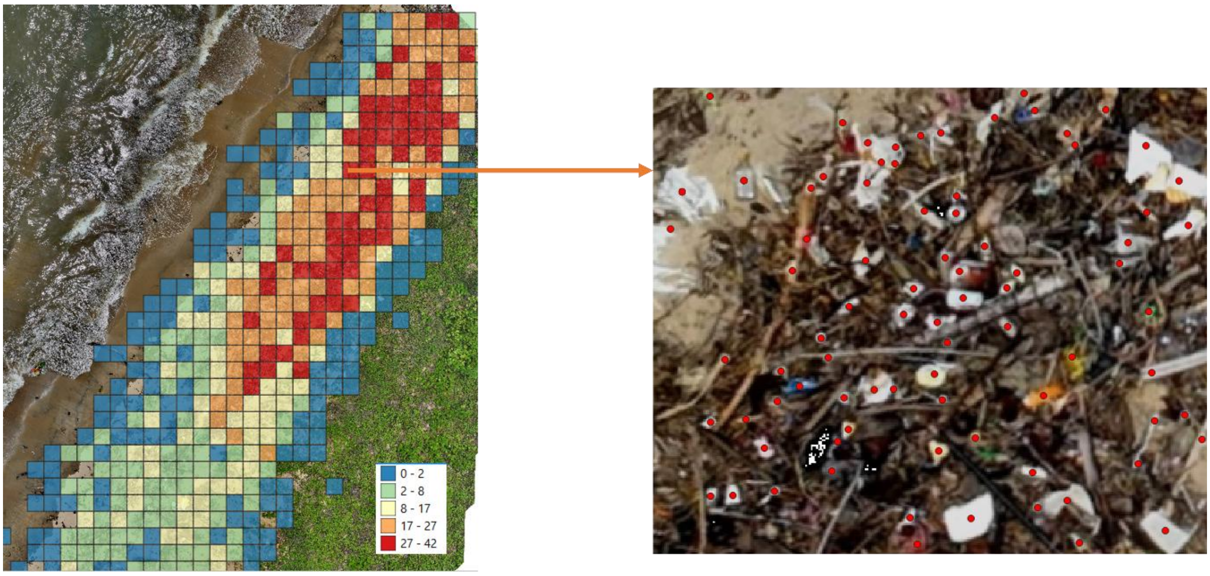


Figure 5. Density map of plastic pollution in study area

Conclusions

In this paper, the model for semantic segmentation of beach litter based on UAV and a deep learning algorithm is proposed. The results of the accuracy assessment and visual inspection shows that the algorithm provides good overall performance with high variance in performance between different classes. The model demonstrates a strong performance for plastic class with F1-score of 0.83. On another hand, the lowest accuracy was obtained for textile class (F1-score 0.52).

Our solution expands the capability of traditional beach and riverine litter surveys by enabling high-precision, UAV-based detection, quantification and classification of plastic waste across defined areas. By combining aerial survey technology with automated data processing, our system provides accurate baseline assessments and ongoing monitoring of plastic waste at 'hot spot' sites of interest. This level of accuracy is essential for identifying unsustainable practices, diagnosing infrastructure weaknesses, and informing evidence-based land-use controls and waste-management policy.

Globally, particularly in regions such as South East Asia and Africa, the scale of plastic pollution remains significantly underestimated due to the limited reach and cost of traditional survey methods. Our approach removes these limitations. The more extensively the system is deployed, the more comprehensive the dataset becomes—directly improving waste-reduction, recycling, and avoidance outcomes. The primary constraint is access to funding that allows communities, governments, and NGOs to carry out this critical work.

A practical example comes from Vietnam, where conventional plastic-survey results at identified hotspots prompted coordinated clean-up initiatives. These actions—driven collaboratively by local communities, local government, central agencies, and NGOs—were only possible once the true scale of the problem was quantified [24]. Our solution follows this same successful model, but with significantly enhanced accuracy, speed, and geographic reach.

As surveyors, our role is to supply reliable data that underpins decision-making. We anticipate our system becoming a cornerstone tool for local, regional, and national policy development. High-quality data enables communities and authorities to design effective interventions—whether targeted clean-up operations in beaches or mangrove ecosystems, localised recycling initiatives, or the establishment of circular waste-disposal systems.

Crucially, our platform supports continuous monitoring, enabling policymakers to evaluate the effectiveness of interventions and refine them as required. This adaptability is vital for achieving long-term objectives, such as eliminating the dumping of plastic waste into rivers and streams.

By providing a low-cost, easy-to-deploy, and highly accurate UAV-based monitoring solution, we equip communities and decision-makers with the evidence they need to develop, implement, and continually improve plastic-pollution mitigation strategies. Funding this solution will directly enhance environmental stewardship, support community-driven action, and strengthen policy responses in regions where the need is greatest.

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