Improved deep learning based litter detection in aquatic environments in Indonesia using drones

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***Abstract*— Millions of metric tons of plastic waste enter the ocean every year, posing a stress to the marine environment. Out of the rivers that are assessed to be responsible for 80% of the riverine plastic emissions, more than hundred are located in Indonesia. Indonesia is estimated to be the fifth most relevant riverine plastic waste source, indicating the importance of the country as a research area. Within this research, an open source deep learning based plastic waste assessment system was further improved, and applied to the Indonesian rivers Citarum, Cisadane and Tukad Saba. The systems key improvements were (i) training of the neural networks with much larger and more diverse plastic waste data sets, (ii) an adjusted classification system to make the waste assessment results more easily comparable to other waste monitoring methodologies, and (iii) waste assessment results were georeferenced for facilitating comparisons with other plastic litter monitoring methodologies and complementing net trawl surveys, field campaigns and clean-up activities. The improved deep learning based litter detection system had an overall accuracy of 83% for detecting litter in aquatic environments. The key findings of the research show that the system can be used for assessing waste type compositions, potentially identifying waste sources or plastic litter accumulation zones and empowering stakeholders with actionable information on a local and regional scale.**

Keywords*— Artificial Intelligence, Plastic Waste Monitoring, Convolutional Neural Network, Drone Survey, Indonesia

I. Introduction

The annual production of plastics worldwide is still on the rise, and large amounts of plastic waste is being accumulated in the environment year by year. Jambeck et al. estimated that 4.8 to 12.7 million metric tonnes (MT) entered the oceans in the year 2010 [1], and Borelle et al. estimated that 19 to 23 million MT of plastics entered aquatic environments in 2016, still predicting growth in these plastics emissions, even if ambitious commitments set by governments will be implemented [2].

The aquatic environment is affected by plastic pollution in various ways, and due to plastics durable characteristics the impacts lead to long-term pollution [3, 4]. The impacts to the environment are diverse and include ingestion by animals, entanglement, chemical leaching and accumulation of toxic effects through microplastics uptake, breakdown into microplastics that may compromise also and human health, and the direct impacts on human livelihoods, for example through increased flood risk by blockage of urban drainage systems or negatively affecting tourism [4].

The most relevant sources for plastic waste emissions into the ocean are located in Asia, with model estimations by Jambeck et al. [1] suggesting China emitting the highest amount of plastic litter, followed by Indonesia. Recent modeling efforts for identifying riverine plastic emissions, Indonesia is estimated to be the fifth highest plastic waste emissions contributor globally [5], indicating the importance of the country as a research area.

More evidence-based data on plastic waste in the aquatic environment is needed for calibration of waste emission models, or provide actionable information to local authorities, waste management companies or even citizen science projects. Different monitoring types for plastic pollution in the environment exist: plastic tracking, active sampling, passive sampling, visual observations and citizen science [4]. The monitoring using visual observations also includes the machine learning based analysis of satellite imagery for detection or quantification of plastic litter [6, 7] or plastic litter detection drone imagery [8–10]. This study focuses on the waste quantification and waste type classification, where very high resolution is needed, which can be provided even with consumer electronic drones. Methodologies for plastic waste detection using the drone platform exist, where machine learning algorithms such as random forest, support vector machine, k-nearest neighbor and convolutional neural network (CNN) or other deep learning based methods are applied [8–12].

In this study, the methodology of the improved artificial intelligence (AI) based waste assessment is outlined, the survey area of the Indonesian river sites is described, and the results are given and discussed. The methodology of the waste assessment is based on the initial work by Wolf et al. [12], which used an AI-based waste assessment system for plastic litter detection in Cambodia. The waste assessment system described in this work is trained on plastic litter data sets that are up to six times larger and show plastic waste in much more diverse settings and originating from multiple ASEAN and European countries. The waste type classification system was revised for increased comparison capabilities with other

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plastic litter monitoring methodologies. Furthermore, the AI models' architectures and training details were adjusted. The waste assessment outputs were georeferenced and provided as shapefiles, so policymakers and authorities are enabled to perform further geospatial analysis on GIS software. The waste assessment was applied to the highly relevant rivers for plastic litter emission Cisadane and Citarum [5], both located in west Java, Indonesia, also the Tukad Saba located in Bali, Indonesia was surveyed. The evaluations of the AI models are outlined, key findings from the survey for waste composition analysis are given and waste assessment examples are provided. The results are discussed, and finally an outlook with further work is given.

II. METHODOLOGY

In this section the improvements of the AI-based plastic litter detection system are outlined, the updated plastic litter classification system is explained and the georeferencing of the waste assessment outputs is described.

A. Improved AI-based plastic litter detection

The method for the improved waste assessment is based on the plastic waste detection and quantification system (APLASTIC-Q) [12], which analyses imagery in a two-step approach to detect waste (PLD CNN) and consequently classify waste types (PLQ CNN) with two different CNNs.

The two CNNs of the open source APLASTIC-Q system [13] share similar architectures as described in the paper [12], except these changes. (i) Instead of the two dense layers that follow the four 2D convolutional layers, an additional 512 neuron dense layer was added before the output layer. The architectures use the same activation functions [14] and dropout layers [15]. (ii) Furthermore, due to additional classes in both novel datasets, the number of output neurons was increased for both CNNs. The PLD CNN was trained on eight classes, i.e. two extra classes organic debris and stones, and the PLQ CNN has 24 classes instead of 18, described in detail in Section II.B. Hence the PLD CNN has eight output neurons, and the PLQ CNN has 24. (iii) The input shape for both CNNs were increased to 128x128x3 from 100x100x3 (PLD CNN) and to 64x64x3 from 50x50x3 (PLD CNN). The 100-pixel edge length of the original tile size corresponds spatially to 20cm, which was often too small to capture larger garbage objects, such as Styrofoam food packaging. Therefore, the next power of 2 number 128 was used, which spatially corresponds to 25.6cm, which is an area increase of 63% compared to the original tile sizes. The edge length of the PLQ CNN tiles is required to be half of the length of the PLD CNN tiles, which resulted in 64x64x3.

The samples of both data sets were increased to 26,147 (PLD CNN) and 36,241 (PLQ CNN) and show plastic waste in the aquatic environment from ASEAN (see Section III.C) and European countries. Both datasets have been split into train (70%), validation (15%) and test (15%) data sets for training. The plastic waste samples mostly consisted of imagery with macroplastics in rivers, shores, beaches, accumulated in front of river dams or other artificial barriers and macroplastics trapped in vegetation. Compared with the dataset sizes of the original version of the APLASTIC-Q system with 6,892 for PLD CNN, and 6,026 for PLQ CNN, the data set was increased by a factor of 3.8 and 6.0, respectively.

The CNNs have been trained for 125 epochs (PLD CNN) and for 150 epochs (PLQ CNN). These epoch values were chosen after the training of both CNNs with larger epoch values, and the identification of the epoch ranges where the loss curves were increasing implying overfitting of the models. Besides the training details described in [12], L2 regularization [16] was added to the dense layers to reduce overfitting during optimization.

B. Improved plastic litter classification system

To capture a more nuanced image of the plastic waste situation with AI-based litter monitoring, and for better aligning these waste assessments with other methodologies, an improved waste classification system with regard to [12] was needed.

To address this, the classes of the PLQ CNN were adjusted to the following requirements. (1) Being able to capture the macroplastics that make up a large proportion in field surveys (such Top 10 items collected from [17]). (2) Enable a comparison of AI-based waste assessment to field survey results that were conducted in the same survey areas. (3) Waste classes have to be detectable by humans in the very high resolution RGB imagers (~0.2 cm Ground Sampling Distance GSD) to enable the annotation of real world data. Because of this, small or narrow items (such as cigarette butts and straws) out of the global Top 10 items [17] could not be added to the PLQ CNN class system.

To fulfill these requirements, the following class system for the PLQ CNN was established (Table 1). It consists of 15 plastic classes, 4 non-plastic waste classes, and 5 non-waste classes. The non-waste classes were necessary to enable the PLQ CNN a waste assessment correction in case of false positive plastic detection or overestimation of littered area of the PLD CNN. Out of the plastic waste classes, Low Density Polyethylen (LDPE) bags, Polyethylene Terephthalate (PET) bottles multilayer wrappers (both size classes), polystyrene items (both size classes) and other small plastics (also include plastic fragments were the most common in the surveyed areas, with respect to establish Top 10 waste items. Other waste items such as fishing gear or Pharmaceuticals and Personal Care Products (PPCP) items were rarely observed in the conducted drone monitoring surveys. However, it is likely that they play a more important role in other aquatic environments, such as suggested by Morales-Caselles [18].

TABLE I. 19 WASTE TYPE CLASSES OF PLQ-CNN, WITH 24 CLASSES IN TOTAL (NON-WASTE CLASSES DEPICTED IN GREY).

PLQ-CNN classes	***Material***
Bags LDPE robust	Plastic
Bags LDPE light	Plastic
Bags PET robust	Plastic
Wrappers < 10cm	Plastic
Wrappers > 10cm	Plastic
Bottles PET	Plastic
Polysterene < 20cm (mostly food packaging)	Plastic
Polystyrene > 20cm	Plastic
PPCP: bottle, medical waste, other	Plastic
Fishing gear	Plastic
Cups, cup lids, caps	Plastic
Other small plastics	Plastic
Other large plastic waste items	Plastic
Rubber	Rubber
Metal	Metal

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PLQ-CNN classes	Material
Glass	Glass
Other (waste)	Undefined
Sand	
Vegetation	
Wood	
Water	
Other (non-waste)	

C. Georeferencing of waste assessment

When running the previous plastic waste assessment with APLASTIC-Q, geospatial information of the input image was lost and hence, the PLD/PLQ CNN output only represented the detected classifications without any spatial reference. However, locating the classification data in a spatial reference system is crucial to better identify plastic litter in the real world and to assess the performance of the detection algorithm.

First, the PLD/PLQ CNN output is saved in a raster format having the same ratio as the input image. The input image is downsampled to the resolution of the PLD/PLQ CNN output image using the GDAL library [19]. The next step is to retrieve the geospatial information of the downsampled input image including the coordinate reference system (projected or geographic coordinates) and the geotransform, which is an affine transformation from the image coordinate space. Finally, the geospatial information of the input image can be applied to the PLD/PLQ CNN output data, resulting in a referenced output.

To make further analysis of the spatial data, it is desirable to convert the georeferenced output data of the waste assessment to a shapefile, as shapefiles store location and attribute information in a data frame as geographic features. For this purpose, each waste type of the APLASTIC-Q output data is masked and polygons for each waste type are created. With GeoPandas [20], all features are concatenated into one data frame and saved as a shapefile.

III. Survey Area

In this section the drone survey procedure is outlined, the survey area in Indonesia is described. Also, other application countries of APLASTIC-Q are shown.

A. Drone survey procedure

A DJI Phantom 4 Pro 2 drone was used for surveying. The drone is equipped with a CMOS RGB (Red, Green, Blue) camera sensor with 20MP. To monitor plastic waste in rivers using drones, drones were deployed in 2 different flying altitudes: 60 – 100m (Level A) and 6-8m (Level B). In Level A imagery, an area 250m upstream and 250m downstream of a located point of interest were covered, resulting in a minimum distance of 500m. Within this transect, an area with a width of 100m, transition from river to the land in the riverbank area was covered. Therefore, an area of at least 500m x 100m was covered following the course of the rivers. The achieved GSD for an altitude of 75m was 2cm. Both Level A and Level B imagery are captured providing 80% side- and overlap. Level A acquisition was done to obtain the general visualization in each surveyed locations and allow the identification of waste accumulation areas to be surveyed in the next step.

The Level B GSD of the imagery was around 0.2cm. For Level B, the drone had to be operated manually due to low flight altitude. Sites surveyed from Level B usually had a coverage of around 100m², which captured plastic waste accumulations at the riverbanks with moderate or high volume. Level B acquisition was done to obtain very high-resolution imagery of waste accumulations that enable the distinction between waste types; the Level B data was used for waste assessment with the APLASTIC-Q system. Data processing for both Level A and Level B was done Pix4D software to create orthoimages.

B. Survey area in Indonesia

Three rivers were monitored by the PT. LAPI ITB from the Bandung Institute of Technology in Indonesia with the aforementioned drone survey procedure: Cisadane River and Citarum River, both located in the west of Java, and Saba, located on Bali. Both Cisadane and Citarum play an important role in their communities and ecosystems around it but are both reported to be heavily polluted [21, 22]. The sources of pollution include both domestic and industrial waste. For the Citarum river, the contribution of pollution load from domestic waste was assessed to be 83.5%, followed by industrial waste 6.6% [23].

Drone monitoring was conducted in the Cisadane River from 9 – 11 April 2022, where a total number of six sites were monitored with Level B acquisition type. These Level B sites were located at the shore of the river mouth with vegetation dominated background (Fig. 1 A). Drone monitoring for the Citarum River sites was conducted from 22 – 24 April 2022, with a total of three Level B sites monitored. The Citarum Level B sites were also taken near the river mouth, but in an urban setting (Fig. 1 B). The drone monitoring of the Tukad Saba River was conducted from 13 – 15 May 2022, with a total of four Level B sites, also taken within a rather urban setting (Fig. 1 C).

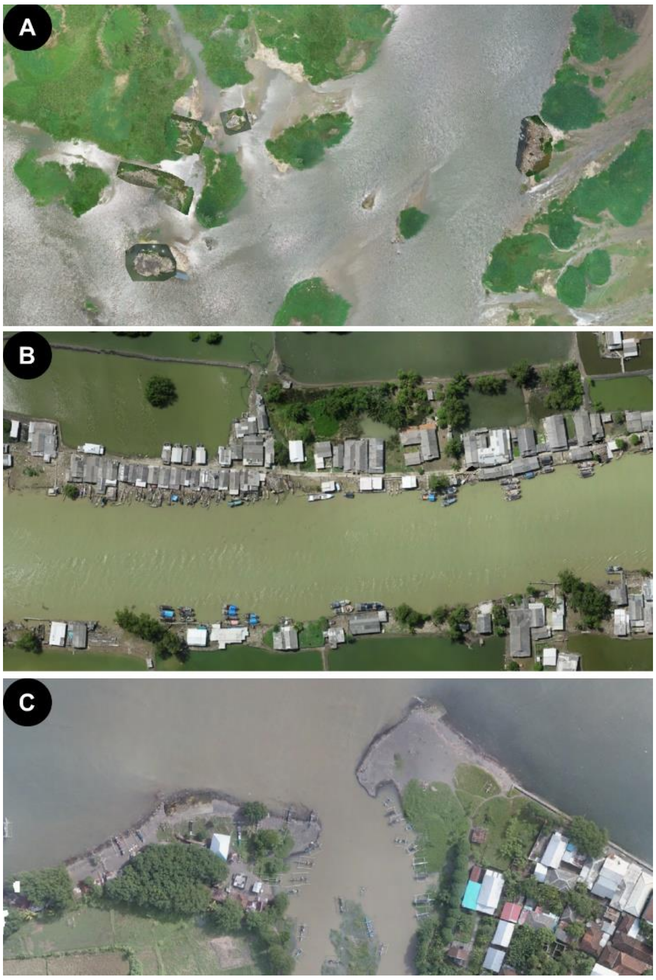

Fig. 1: Overview imagery of the three surveyed river mouths. (A) shows estuary of Cisadane River. Excerpt of underlying Level A imagery with five Level B plastic waste hotspots. Plastic waste hotspots show large waste accumulations at or near the shore, litter trapped in vegetation and waste that was previously burned. (B) shows mouth of Citarum River mouth with imagery taken in an urban setting. (C) shows mouth of Tukad Saba River.

C. *AI waste assessment conducted in Southeast Asia*

Plastic waste assessment based on the APLASTIC-Q system [12] was conducted in the Asian countries Cambodia (2019), with follow-up projects in Vietnam (2020-2021), the Philippines (2020-2021), and recently in Indonesia (2022) (Fig. 2). Within Europe, the AI-based plastic waste assessment was also used: in Germany (2021), in context of the 2021 European floods and in Bosnia and Herzegowina (2021), for monitoring plastic litter accumulated at the Visegrad dam at the Drina river. The diverse application background of the APLASTIC-Q system in terms of countries also captured plastic litter in various situation types: large waste accumulations, litter trapped in vegetation, plastics at beaches, and floating plastics.

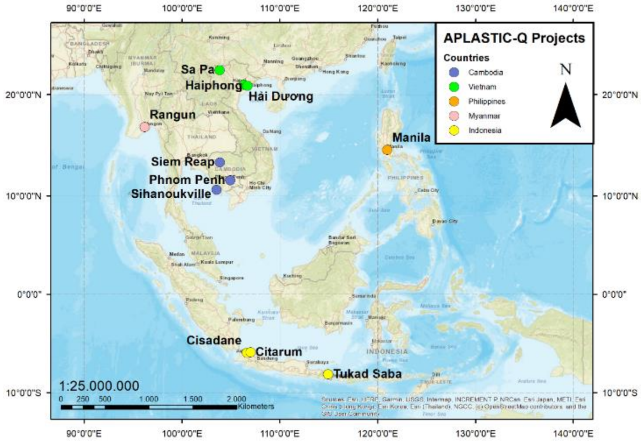

Fig. 2: Map with waste assessment projects conducted in Southeast Asia. River names are shown for Indonesia, city names are shown for the other countries. Other relevant rivers involved in the survey projects are Pasig River (the Philippines), Mekong (Cambodia) and Red River system (Viet Nam).

IV. Results

In this section the training results of the two CNNs are shown, together with a detailed classification report. The key findings of the survey are outlined and examples from the georeferenced waste assessment are given.

A. *Training of plastic waste detection and waste type classification CNNs*

After training of the PLD and PLQ CNNs, the overall accuracies on the test data were 83% and 58%, respectively. The train and validation loss and accuracy are depicted in Fig.3. The overall accuracies of the PLD and PLQ CNNs of the original publication were 83% and 71%, respectively, translating to stagnant overall accuracies for PLD CNN and a decrease of 13% for PLQ CNN. However, both improved PLD and PLQ CNNs show better waste assessments to new real-world data compared with the old CNNs. The weighted average of the PLD CNN calculated with 3922 test samples was for precision 82%, for recall 83%, and the f1-score was 82%. The weighted average of the PLQ CNN calculated with 5438 test samples was for precision 59%, for recall 58%, and the f1-score was 55%.

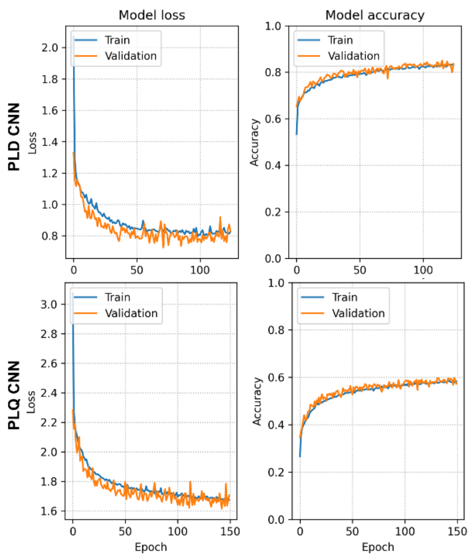

Fig. 3: Loss and accuracy curve of CNN training.

The confusion matrices of both PLD and PLQ CNN are depicted in Fig. 4. The PLD CNN performed with the highest f1-score on the non-waste classes 'Water' (0.96), 'Vegetation' (0.91) and 'Organic debris' (0.87). Followed by 'Litter – high' and 'Stones' (both 0.86), 'Other' (0.71), 'Sand' (0.70) and lastly 'Litter – low' (0.48).

The confusion matrix of the PLQ CNN shows that for a total of ten waste type classes, the test samples have not been classified correctly (or only once) by the classifier. These ten waste type classes consist of the seven plastic classes 'Bags LDPE robust, 'Bags PET robust', 'PPCP bottle', 'PPCP medical waste', 'PPCP other', 'Fishing gear', 'Caps and cup lids', and the three non-plastic waste classes 'Rubber', 'Metal' and 'Glass'. The other waste type classes were classified with an f1-score of at least 0.34 (non-plastic 'Other (waste)'). The test samples of the 'Bottles PET' were classified with the highest f1-score (0.63), followed by 'Polystyrene < 20cm' (0.55), 'Polystyrene > 20cm' and 'Other small plastics' (both 0.50), 'Other large plastic waste items' (0.45), 'Wrappers < 10cm' (0.43), 'Wrappers > 10cm' (0.37) and 'Bags LDPE light' (0.36). Waste type classes that essentially represent the same waste type, like 'Polysterene < 20cm' and 'Polysterene > 20cm' or 'Wrappers < 10cm' and 'Wrappers > 10cm', show high frequency in being mixed up by the classifier.

For most classes, the precision and recall values are similar with a maximum deviation of 0.1. However, for some classes the range between recall and precision is higher: the waste type class 'Bags LDPE light' is classified with a precision of 0.25 and a recall of 0.68 and the class 'Other large plastic waste items' is classified with a precision value of 0.83 and a recall value of 0.31. In addition, the two non-waste classes 'Sand' and 'Wood' show a significantly lower precision value than the recall value: 0.46 vs. 0.81 and 0.60 vs. 0.85 for the categories 'Sand' and 'Wood' respectively.

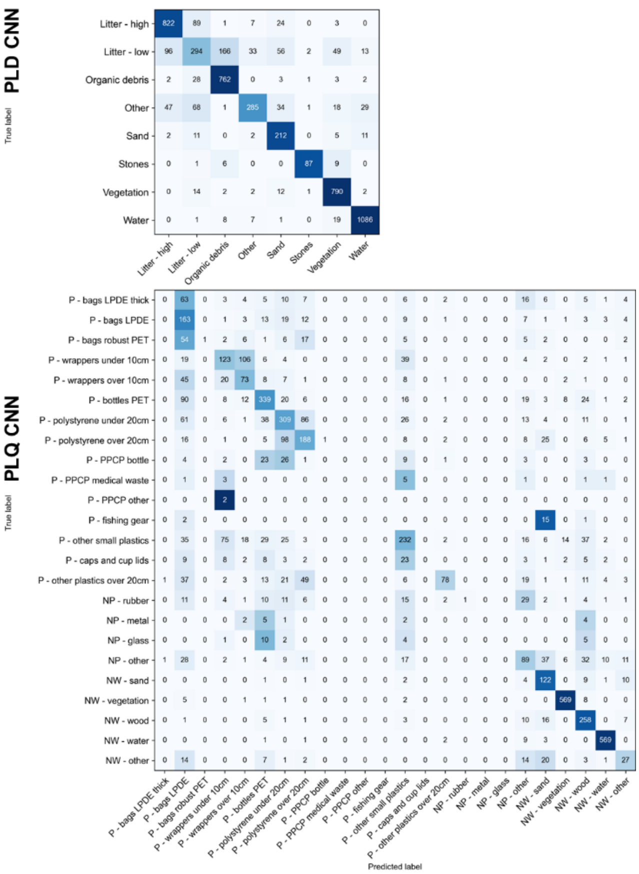

Fig. 4: Confusion matrices of PLD CNN and PLQ CNN.

B. *Georeferenced AI-based waste assessment in Indonesia*

The Level B imagery was analyzed with the improved waste assessment system described in this paper. The results in terms of waste shares for the most relevant waste categories of the three different surveyed rivers are depicted in Table II. Some of the waste categories – plastic bags, plastic wrappers, polystyrene items, plastic bottles and other small plastics – represent multiple waste type classes; for example, 'Polystyrene items' comprises of the waste type classes 'Polysterene < 20cm' and 'Polysterene < 20cm'.

The shares of the waste categories detected in the Cisadane river mouth generally were either the lowest shares for the category from all three river sites (plastic bags, plastic wrappers, plastic bottles) or the highest of all river sites (polystyrene items and other small plastics), shown in Table II. Plastic bags, plastic wrappers and plastic bottles are consistent with typical household waste, which likely links to the urban environment at the Citarum and Tukad Saba River mouths. Polystyrene items are capable of floating longer distances compared with other plastic waste items, and the waste category of other small plastics also comprises of weathered waste fragments amongst waste items; this could indicate that the survey sites of Cisadane are more likely to represent plastic litter sinks rather than plastic litter sources compared with the other river sites.

TABLE II. WASTE CATEGORIES THAT MADE UP THE LARGEST SHARES IN THE SURVEY SITES.

Waste categories	*Cisadane*	*Citarum*	*Tukad Saba*
Plastic bags	6%	13%	**15%**
Plastic wrappers	8%	11%	**20%**
Polystyrene items	**20%**	11%	14%
Plastic bottles	9%	**14%**	13%
Other small plastics	**48%**	28%	33%
Sum	91%	77%	95%

The georeferencing of the plastic waste assessment output was successfully implemented. Example results of the georeferenced waste assessment are depicted in Fig. 5. The output can be loaded as a shapefile that stores the geographic features in geographic information system software such as QGIS.

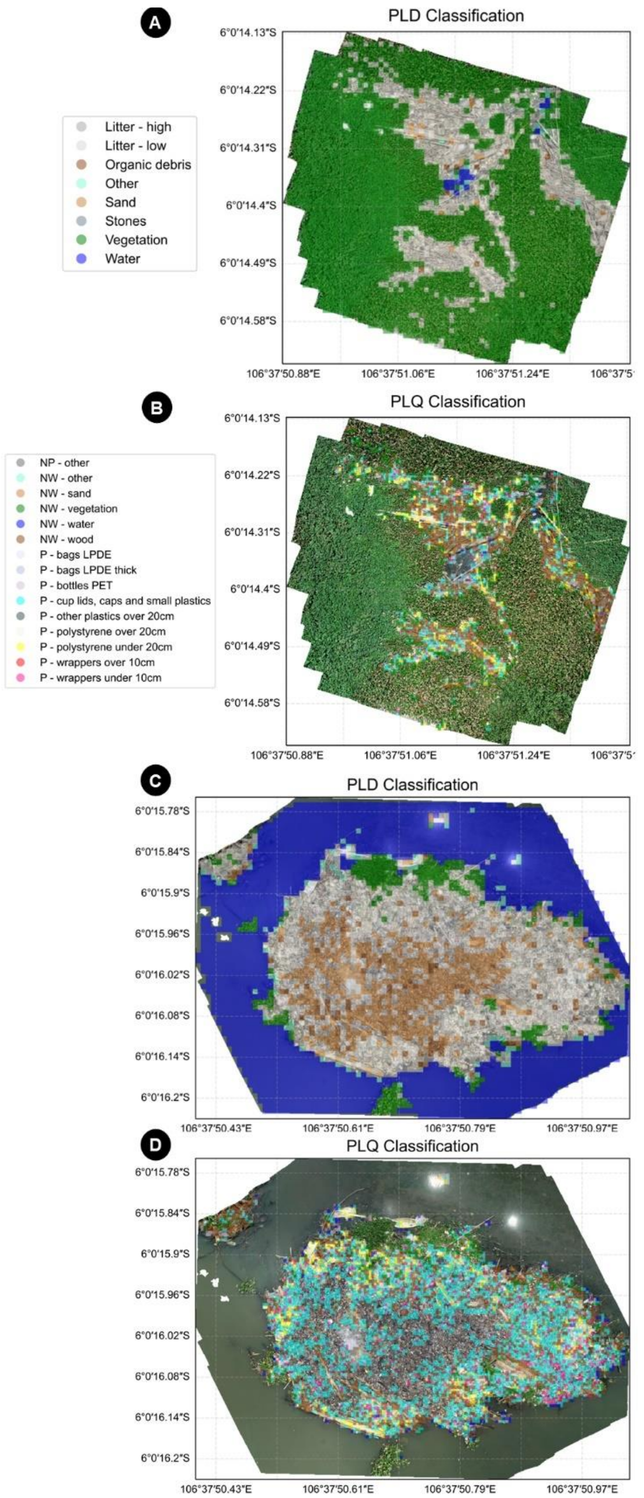

Fig. 5: Monitored accumulated plastic waste located at Cisadane river mouth near Jakarta, Indonesia. A shows georeferenced AI-based plastic litter detection for litter trapped in vegetation, B shows georeferenced waste type classification for littered areas. Similar waste assessment is shown below for a previously lit-up garbage pile: Plastic litter detection (C) and waste type classification (D).

V. Discussion

The plastic waste detection system is fueled with a manifold real world plastic waste data set from Southeast Asia and Europe. The algorithm can analyze large georeferenced TIFF files in a few minutes, and 20MP images in less than ten seconds, using a standard laptop. By georeferencing the output data of APLASTIC-Q, geographic information is added improving the evaluation of the performance of APLASTIC-Q. Additionally, the georeferenced data facilitates comparisons between the results of other plastic litter detection algorithms. Providing the output data as shapefiles, policymakers, authorities etc. are enabled to perform further geospatial analysis on GIS software.

The methodology described is limited to detecting plastic waste on the surface. The depth of waste was estimated empirically, which could lead to under or over estimations of waste volume estimates in some situations. Waste items found in the environment can be heavily weathered through physical forces, through UV-light exposure or can be covered with dirt as well. This challenging real-world data is making a significant number of waste items in the imagery unrecognizable, which should be considered for evaluation the overall accuracy of the waste type classifier PLQ CNN.

The overall accuracies of PLD and PLQ CNN indicate similar or worse performance of the classifiers compared with the original publication. However, the data sets show plastic waste in much more diverse settings and with increased non-waste classes and waste type classes. This leads to a more challenging optimization task presented in this study, making the original accuracies and the accuracies that were achieved in this study not directly comparable.

Some classes of the PLQ CNN were classified with a significantly lower precision score than their recall score. This indicates that the PLQ CNN is biased towards certain classes: 'Bags LDPE light', 'Sand' and 'Wood'. Several waste type classes were barely detected at all. When interpreting the AI-based waste assessments, these characteristics should be considered by the user.

Waste assessment was done for three rivers – Citarum, Cisadane and Tukad Saba – and the key findings about the waste type composition for these different rivers were presented. These results may indicate that the surveyed areas are points of plastic waste sources or accumulation zones, potentially enabling policy makers for better tailored actions against the plastic waste problem on a local and regional level.

VI. Conclusion and Future Work

The aim of this research was to quantify the amount and the various types of aquatic plastic debris and identify areas of high waste discharge and accumulation of plastic waste on a regional scale. Rivers with a high expected waste discharge were examined: Cisadane River, Citarum River, and Tukad Saba River. The machine learning algorithm APLASTIC-Q was applied for the identification of plastic pollution, its quantification and classification into several plastic types.

In this paper, an improved waste assessment methodology is described with the focus on utilizing cheap, accessible, and user-friendly consumer electronic drones combined with a limited computing power for the AI-based image analysis. The two-step approach of the drone survey with surveying the overview first and then capturing the waste hotspots in very high resolution afterwards, is straight forward to reproduce.

In the future, the enhanced APLASTIC-Q will be used as a tool for regular plastic waste assessment in Southeast Asian Countries as part of clean up missions. In addition, it is planned to further improve the quality of the algorithm by enlarging the dataset using images from different climate zones. Furthermore, APLASTIC-Q can also be used as backbone for a bridge monitoring tool using stationary cameras for continuous mobilized surface floating plastic waste monitoring to assess riverine plastic waste emissions over time [24]. and for a mobile system using unmanned surface vehicles (USV) [25]. The AI-based waste assessment could also help in the future to calibrate modeling efforts for estimating plastic loads leading into the ocean, or providing actionable information to policymakers [4].

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REFERENCES

[1] J. R. Jambeck *et al.,* "Marine pollution. Plastic waste inputs from land into the ocean," *Science (New York, N.Y.)*, vol. 347, no. 6223, pp. 768–771, 2015, doi: 10.1126/science.1260352.

[2] S. B. Borrelle *et al.,* "Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution," *Science*, early access. doi: 10.1126/science.aba3656.

[3] A. L. Andrady, Ed. *Plastics and the environment*. Hoboken, NJ: Wiley, 2004. [Online]. Available: http://onlinelibrary.wiley.com/book/10.1002/0471721557

[4] T. Emmerik and A. Schwarz, "Plastic debris in rivers," *Wiley Interdisciplinary Reviews: Water*, vol. 7, no. 1, e1398, 2020. doi: 10.1002/wat2.1398. [Online]. Available: https://wires.onlinelibrary.wiley.com/doi/full/10.1002/wat2.1398

[5] L. J. J. Meijer, T. van Emmerik, R. van der Ent, C. Schmidt, and L. Lebreton, "More than 1000 rivers account for 80% of global riverine plastic emissions into the ocean," *Science advances*, early access. doi: 10.1126/sciadv.aaz5803.

[6] A. D. Sakti *et al.,* "Identification of illegally dumped plastic waste in a highly polluted river in Indonesia using Sentinel-2 satellite imagery," *Sci Rep*, early access. doi: 10.1038/s41598-023-32087-5.

[7] T. Acuña-Ruz *et al.,* "Anthropogenic marine debris over beaches: Spectral characterization for remote sensing applications," *Remote Sensing of Environment*, vol. 217, pp. 309–322, 2018.

[8] F. Ramdani, R. S. Sianturi, M. T. Furqon, and M. T. Ananta, "Mapping riparian zone macro litter abundance using combination of optical and thermal sensor," *Sci Rep*, early access. doi: 10.1038/s41598-022-09974-4.

[9] L. Fallati, A. Polidori, C. Salvatore, L. Saponari, A. Savini, and P. Galli, "Anthropogenic Marine Debris assessment with Unmanned Aerial Vehicle imagery and deep learning: A case study along the beaches of the Republic of Maldives," *Science of The Total Environment*, vol. 693, p. 133581, 2019.

[10] C. Martin, S. Parkes, Q. Zhang, X. Zhang, M. F. McCabe, and C. M. Duarte, "Use of unmanned aerial vehicles for efficient beach litter monitoring," *Marine pollution bulletin*, vol. 131, pp. 662–673, 2018.

[11] G. Gonçalves, U. Andriolo, L. Gonçalves, P. Sobral, and F. Bessa, "Quantifying Marine Macro Litter Abundance on a Sandy Beach Using Unmanned Aerial Systems and Object-Oriented Machine Learning Methods," *Remote Sensing*, vol. 12, no. 16, p. 2599, 2020. doi: 10.3390/rs12162599. [Online]. Available: https://www.mdpi.com/2072-4292/12/16/2599

[12] M. Wolf *et al.,* "Machine learning for aquatic plastic litter detection, classification and quantification (APLASTIC-Q)," *Environ. Res. Lett.*, vol. 15, no. 11, p. 114042, 2020, doi: 10.1088/1748-9326/abbd01.

[13] GitHub. "GitHub - DFKI-NI/APLASTIC-Q: AI-based plastic waste assessment of drone images." https://github.com/DFKI-NI/APLASTIC-Q (accessed Apr. 17, 2023).

[14] V. Nair and G. E. Hinton, "Rectified linear units improve restricted boltzmann machines," in *Proceedings of the 27th international conference on machine learning (ICML-10)*, pp. 807–814.

[15] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[16] C. Cortes, M. Mohri, and A. Rostamizadeh, "L2 regularization for learning kernels," *arXiv preprint arXiv:1205.2653*, 2012.

[17] *30th Anniversary International Coastal Cleanup*, 2016. [Online]. Available: https://tamug-ir.tdl.org/bitstream/handle/1969.3/29296/2016-data-release-1.pdf?sequence=1

[18] C. Morales-Caselles *et al.,* "An inshore–offshore sorting system revealed from global classification of ocean litter," *Nat Sustain*, vol. 4, no. 6, pp. 484–493, 2021. doi: 10.1038/s41893-021-00720-8. [Online]. Available: https://www.nature.com/articles/s41893-021-00720-8

[19] "GDAL — GDAL documentation." https://gdal.org/ (accessed Apr. 24, 2023).

[20] "GeoPandas 0.12.2 — GeoPandas 0.12.2+0.gefcb367.dirty documentation." https://geopandas.org/en/stable/ (accessed Apr. 24, 2023).

[21] M. Marselina, F. Wibowo, and A. Mushfiroh, "Water quality index assessment methods for surface water: A case study of the Citarum River in Indonesia," *Heliyon*, early access. doi: 10.1016/j.heliyon.2022.e09848.

[22] I. Namara, D. M. Hartono, Y. Latief, and S. S. Moersidik, "The Effect of Land Use Change on the Water Quality of Cisadane River Ofthe Tangerang City," *Journal of Engineering and Applied Sciences*, vol. 15, no. 9, pp. 2128–2134, 2020.

[23] M. R. Djuwita, D. M. Hartono, S. S. Mursidik, and T. E. B. Soesilo, "Pollution Load Allocation on Water Pollution Control in the Citarum River," *J. Eng. Technol. Sci.*, vol. 53, no. 1, p. 210112, 2021, doi: 10.5614/j.eng.technol.sci.2021.53.1.12.

[24] C. Lieshout, K. Oeveren, T. Emmerik, and E. Postma, "Automated River Plastic Monitoring Using Deep Learning and Cameras," *Earth and Space Science*, vol. 7, no. 8, e2019EA000960, 2020. doi: 10.1029/2019EA000960. [Online]. Available: https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019EA000960

[25] S. Armitage, K. Awty-Carroll, D. Clewley, and V. Martinez-Vicente, "Detection and Classification of Floating Plastic Litter Using a Vessel-Mounted Video Camera and Deep Learning," *Remote Sensing*, vol. 14, no. 14, p. 3425, 2022. doi: 10.3390/rs14143425. [Online]. Available: https://www.mdpi.com/2072-4292/14/14/3425