PlastOPol: A Collaborative Data-driven Solution for Marine Litter Detection and Monitoring

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***Abstract*—Marine plastic pollution as a generally accepted global challenge has comprehensive impacts on our living environment. However, in practice, it is extremely difficult to monitor the severity of the problem based on the shortage of data and relevant tools. Thus, this has attracted academia and industry not only as an urgent environmental challenge but also as an interesting research problem. Many projects have been developed to collect relevant information with the help of beach clean-up volunteers and semi-professional. Although data collected by beach-cleaners cover large geographical areas and provide invaluable help in the effort of mapping marine litter hot-spots, the lack of uniformity in the classification systems, combined with the irregularity of clean-up activities makes it difficult to obtain the full picture. This issue further impacts on the information processing, analysis, and decision-support potential of the available tools. In this paper, we provide a collaborative data-driven solution to monitor marine litter along the coast. It includes a mobile application to collect images, a back-end server to map and train the classification model, and a general database to store and manage related data. A user study was conducted in Ålesund city in Norway to test user-friendliness but also to analyse the users' motivation to take part in citizen science projects. This work aims to contribute to the United Nations' sustainable development goals 14 for life under water and 11 for sustainable cities and communities.**

***Index Terms*—Data-driven solution, litter detection, litter classification, marine litter, mobile application, data collection**

I. Introduction

In spite of the many research projects addressing the isse of marine litter, there are considerable gaps in our understanding of their sources and floating behaviour as highlighted by Haarr et al. [11]. Solid evidence of marine litter composition and sources is essential to effective policy measures. Marine litter can be categorized into sea-based or land-based items according to their origins. The former comes from sea-based anthropogenic activities including offshore oil production, ocean shipping, and tourism. More specifically, in Norway, many are coming from the fishing industry [2]. The debris originating from land-based activities can be carried to the sea by wind or rivers [5]. This multi-source scenario makes it a more difficult task to analyze and track marine litter if we want to identify suitable methods to tackle the challenge brought by plastic. The results could potentially bring more solid knowledge for us to understand this complex environmental issues.

However, such work inevitably requires collaborative data-gathering from a huge amount of sources including high numbers of people and a high level of organization. Multiple stakeholders should work coordinately to implement the Sustainable Development Goals [1]. Many studies have been conducted globally with the goal of registering the occurrence and analyzing the sources of marine litter [3], [15]. The goal is to reduce the volunteers' personnel demands [6] and personnel fatigue in clean-up and monitoring activities. More recently, several solutions for recognizing litter were developed using mobile devices [17], [18]. These contributions used cameras to collect images, while the classification was performed on a server and the results were sent back to the users. Such systems reduce the performance requirements for users' devices, and the whole process usually takes longer and is more unstable due to the more frequent communication for upload and download requests. Besides, the centralized architecture is easy to deploy but heavily relies on the central node service quality. In addition, general information is still missing for higher level decision makers because the litter classification is not standardized.

In this paper, we address these limitations by introducing a collaborative data-driven solution. It aims to become a tool to connect information with volunteers and decision-makers. This solution divides the marine litter detection and recognition processes into three different software components - data generation, collection, and management. Every component executes individually and communicate with the other components via the designed unified application program interface(API). It is to be noted that a machine-learning-based object detector is applied in our solution. The algorithm was trained by our previous work by Cordova et al. [4]. It was implemented with TensorFlow Lite framework's corresponding libraries. This is also well integrated with the the proposed solution.

II. RELATED WORK

There are two main methods for litter detection: aerial photography, and on site direct observation. The first approach applies computer vision methods. For example, [3] investigated the use of fixed monitoring points to collect information about marine debris found in rivers near the sea. Their observation stations could provide reliable information, but the main drawback of their solution relies on the fact that it is static. Monitoring litter from distributed workstations would be potentially costly and time-consuming. Unmanned Aerial Systems (UAS) have also been used. Those are portable solutions that use remote image acquisition systems, which are usually integrated with machine learning approaches to produce accurate litter detection results. Examples include detection on images taken by drones [10] or on open-access pictures taken by satellites [21]. However to ensure accuracy, more complex image acquisition, cleaning, and processing operations are required. These requirements limit the detection range and increase associated costs. So even if they are applicable to some government or research organizations, it is hard for the general public involved in citizen science projects to deploy them. On the other hand, observer-based approaches are more traditional and depend on human labor. Based on this, many organizations have built their own applications. For instance, the Spanish government developed a web app, MARLIT, to gather information on marine litter on their beaches. Volunteers can use it to record floating litter on the sea during their beach cleaning-up activities with the help of drones [7]. However, MARLIT does not include litter classification. [9] proposed a Web-based solution intended to collect litter classification data. In their proposed solution, JRC Floating Litter Monitoring Application, users can associate geo-position and sizes to the litter items.

Regardless of the source (in-shore litter [16], beach refuse [12], [13] or offshore waste [22]), most of the existing systems support the classification of litter based on the type of material, i.e., plastic, textile, glass, among others. Nevertheless, through our communication with volunteer organizations, we have noted the importance of identifying the industry source of the litter for more effective and targeted policy-making to tackle marine plastic pollution. Based on this conclusion, we searched the Standard and Poor's Global Industry Classification Standard (GICS) [14] and defined a category in terms of different industry types (e.g., fishing, construction, and tourism).

Another issue relates to the volunteers' engagement in the process of litter occurrence registration. An online education platform, Marine Debris Tracker, held a competition to foster more user engagement [20] while Marine Litter Watch built a community for litter collection communities to share their knowledge and implemented a tool to collect litter data on beaches [8]. The data collection process, promoted by those initiatives can be of high speed and efficiency. On the other hand, data-sharing procedures, which could be helpful for litter processing companies, organizations, and government departments, have not been well developed yet.

To present an affordable and viable solution to these problems, we designed a system to help detect and classify marine litter and build a new data-sharing platform related to litter occurrence. And the contributions of this paper to this initiative are:

- A collaborative platform was designed to reduce the requirements of personnel for data collection;
- An algorithm was implemented to detect marine litter on images and save time during data registration;
- A unified standard format for data management was extracted;

III. SYSTEM DESIGN

Figure 1 shows the system architecture. The system is composed of the mobile layer, server layer, and data management layer which are responsible for data generation, collection, and management respectively. Starting with the mobile layer, marine litter data is generated through a mobile application. Then it is encoded and transferred to the local server through API and decoded in the server layer. The data management layer would reformat the data and store and manage it in a relational database.

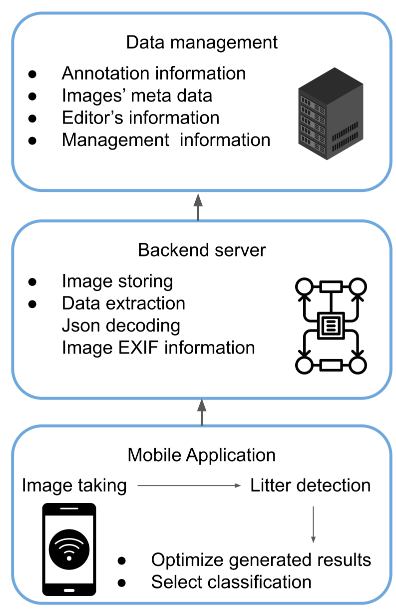


Fig. 1: Architecture for the proposed system for litter monitoring based on a mobile application.

According to this system architecture, the mobile application should allow users to take pictures, modify the annotations and upload data to the server. Besides, due to the reason that most litter-collecting activities happen in rural areas, the internet connection might not be as stable as expected.

The application should not require the usage of any internet connection except for uploading the data. The server layer deals with data transformation and extraction while the data management layer is basically a database server. For the former one, it can process images and annotation information. Images would be stored in PNG format while annotation information would be in JSON files due to the easy use and small memory required. To secure the data, restricting and validating the connection will also be implemented in this layer. The data management layer will organize the data. By storing the information required by the algorithm and the paths of images, authorized users could search and use the data collected.

IV. SYSTEM IMPLEMENTATION

Figure 2 shows the structure of the user interfaces on the mobile app. On the front page, users can choose whether to capture a new image, edit existing images or upload stored information. In the case of taking a new photo, the app will call the mobile camera and the image will be pre-processed by the machine-learning object detector. The EfficienDet model, proposed by Mingxing, Ruoming Pang, and Quoc [19], was implemented to detect the objects efficiently as explained in Cordova et al. [4]. By introducing a novel bi-directional feature network and modifying scaling rules to their previous model, EfficientDet could reach higher accuracy in real-time object detection. This makes it possible to process images in run time on mobile devices. Then, the editing interface will appear with the generated annotations. On this page, users are prompted to select the category of the litter (one from a list: fishery, transportation, electronics, food, household, construction, medical, tourism, and others) for each annotation or delete false positive box. After editing the generated results, they can mark their own instances of litter in cases where it is missed by the algorithm (false negatives) if possible. During the entire process, the change log is stored in the JSON file providing us with the necessary data for model modification. And when the save button on the right bottom corner is pressed, the images with annotations and the JSON files are stored in the folder built when the application is installed. Finally, on the upload page, users can upload the images along with the associated JSON to the server.

A PHP-based backend server was established for the project, utilizing XAMPP as a software stack to facilitate connection with a MySQL database and Apache HTTP server to manage data transformation. The workflow of the backend server is depicted in Figure 3. Upon receipt of a request from the HTTP protocol, the server first verifies the availability of the image and JSON files. If either of these files is absent, an error message is returned to the user. In the event that both files are present, the image is stored in a permanent directory, and the server proceeds to extract relevant data from the accompanying EXIF and JSON files, subsequently transforming the data for storage in the database. Upon completion of these operations, a message confirming the success of the process is sent back to the application.

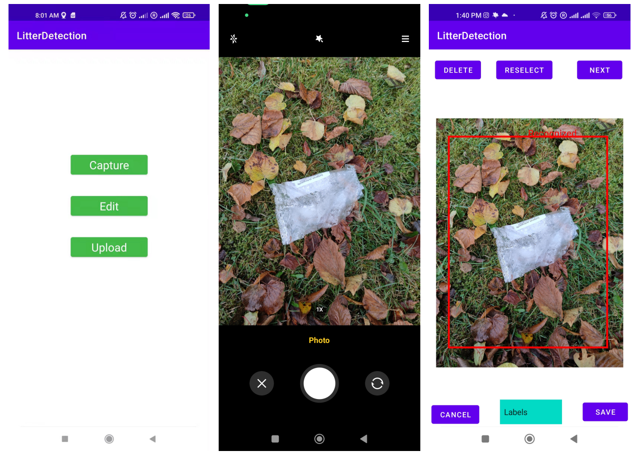


Fig. 2: Screenshots of the interface of the mobile application.

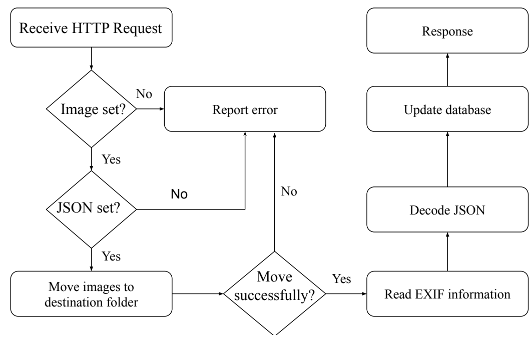


Fig. 3: Flow chart of backend PHP program.

With respect to the database, the Entity Relationship (ER) model that defines the adopted data model is shown in Figure 4. The tables can be divided into three parts based on the information stored. One part is the user identity (blue box). In these tables, users of the mobile application would be registered as ”uploaders” which means they can only write into the database, nor can they read or edit after uploading. The annotation part (orange box) stores basic information about annotations, including annotation types and editors. The remaining part of the database is related to annotation information. Besides storing the basic information of the picture, such as the image metadata and the annotation position, the location and time are also recorded.

With the help of the back-end server and database engine, the organizations who would like to join our project could be assigned as different users of the database.

V. RESULT ANALYSIS

The system was tested by the authors and 42 pictures were uploaded to the server.

Table I shows examples from the application. The first row presents the results detected by the machine learning model and the second row contains the images after the edition and classification selection. In these pictures, if the object was detected by the algorithm, it would have red annotation. The

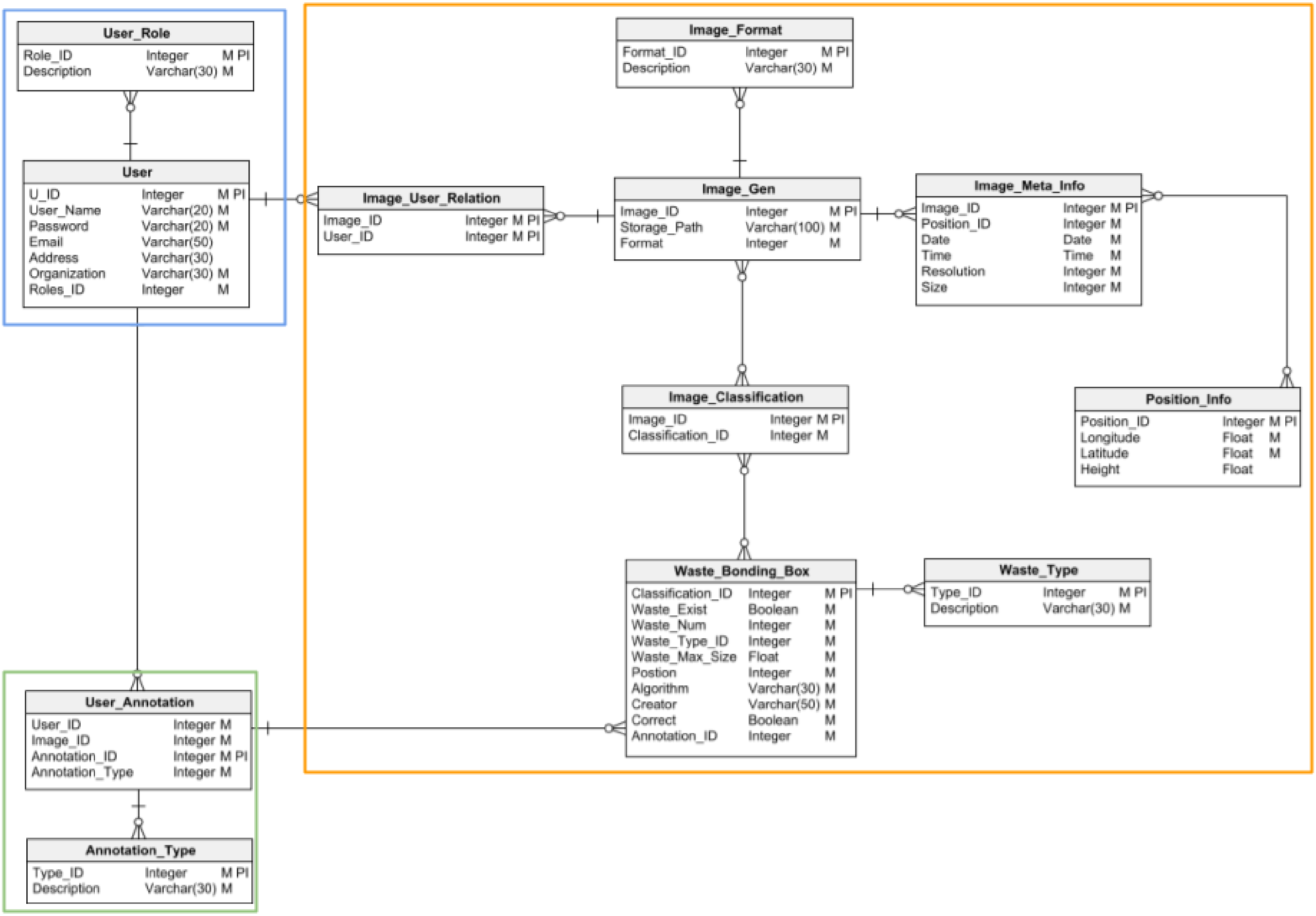


Fig. 4: ER Model for the Backend Relational Database

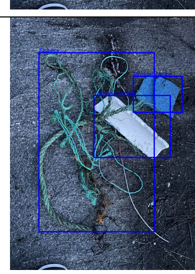
	case1	case2	case3	case4	case5
Results generated by algorithm					
Results after editing and category selection					

TABLE I: Examples of Marine Litter Detection and Classification Results blue boxes were added manually after all the generated results are checked. It can be seen that some items would not be recognized by the algorithm and thus human supervision is required. Case 1 illustrates the expected results while the other cases demonstrate certain problems both from the algorithm and users. Case 2 showed the possible fault when several objects were in the picture while case 3 was an example of the problem related to a dark background. Not only the number of objects appearing in the picture but also the brightness will influence the accuracy. Besides the ratio of the object to the whole image can affect the final results. Case 4 shows when the object was too small in the picture while it is too big in Case 5. In both cases, the algorithm failed to detect the objects. These cases illustrate the importance of user training for this data collection activity. But since every changing log is preserved, it can still be a resource for algorithm training.

By analyzing all the pictures from the server, there are 60 items needed to be recognized while only 41 items are detected successfully. And even among these annotations, six annotations needed to be modified (two were falsely positive and two were larger than expected). So, the final accuracy could be calculated as 58.3% for this algorithm. This accuracy is not high for now which is caused by the small amount of training data. Until now, we are still in the early process of this project and collecting data for further analysis. By getting information about the annotations and modification information, we can iteratively improve our algorithm. The second drawback is the category. As a temporary solution, we used an exciting image source for object detection where the classification used in this project is not considered. To avoid misunderstanding and help build the data source, all the categories need to be selected by the users.

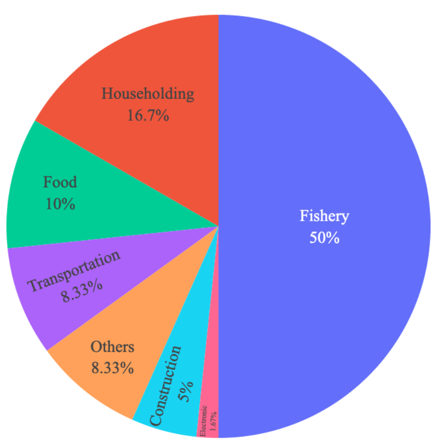


Fig. 5: Distribution of different categories

Figure 5 presents the distribution of different categories. Although there are 9 kinds of marine litter, there is no litter that comes from medical waste and tourism. Fishery litter stands out occupying half of the labels and household also leads the way with 10 objects recognized. By contrast, the objects classified as transportation, food, and others are close to each other (8%, 10 %, 8%). Little was recognized as electronics and construction.

VI. Limitation and Future Work

This paper presents an application designed for the purpose of detecting litter and gathering data to aid in the development of machine-learning algorithms. The application's functionality has been tested, and it has been found to effectively achieve its objective of collecting data for training machine learning models. However, there are some limitations with the current version that need to be addressed. Firstly, the current detection algorithm is not entirely accurate. Secondly, the user interface lacks intuitiveness, and therefore requires guidelines during usage. Thirdly, the system's generalization can be improved to facilitate a wider scope of use.

In light of these limitations, future work will focus on the following areas. Firstly, the data will be visualized to aid volunteer organizations in gaining a better understanding of the spatial and temporal aspects of the data and making plans for their volunteer activities. Secondly, the model will be retrained or new algorithms will be attempted to produce a more customized and precise model, based on the type of material and industry classification of litter. Thirdly, user studies will be conducted with citizen scientists to aid in the design of the application's UI and increase public involvement.

VII. Acknowledgements

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References

[1] Mario Biggeri. A "decade for action" on sdg localisation, 2021.

[2] Lene Buhl-Mortensen and Pal Buhl-Mortensen. Marine litter in the nordic seas: Distribution composition and abundance. *Marine Pollution Bulletin*, 125(1):260–270, 2017.

[3] Roberto Crosti, Antonella Arcangeli, Ilaria Campana, Miriam Paraboschi, and Daniel González-Fernández. 'down to the river': amount, composition, and economic sector of litter entering the marine compartment, through the tiber river in the western mediterranean sea. *Rendiconti Lincei. Scienze Fisiche e Naturali*, 29:859–866, 2018.

[4] Manuel Córdova, Allan Pinto, Christina Carrozzo Hellevik, Saleh Abdel-Afou Alaliyat, Ibrahim A. Hameed, Helio Pedrini, and Ricardo da S. Torres. Litter detection with deep learning: A comparative study. *Sensors*, 22(2), 2022.

[5] US EPA. Learn about aquatic trash.

[6] Michael Fulton, Jungseok Hong, Md Jahidul Islam, and Junaed Sattar. Robotic detection of marine litter using deep visual detection models. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 5752–5758, 2019.

[7] Odei Garcia-Garin, Toni Monleón-Getino, Pere López-Brosa, Asunción Borrell, Alex Aguilar, Ricardo Borja-Robalino, Luis Cardona, and Morgana Vighi. Automatic detection and quantification of floating marine macro-litter in aerial images: Introducing a novel deep learning approach connected to a web application in r. *Environmental Pollution*, 273:116490, 2021.

[8] Mariana Golumbeanu, Magda Nenciu, Madalina Galatchi, Victor Niţă, E Anton, Andra Oros, Christos Ioakeimidis, and Constança Belchior. Marine litter watch app as a tool for ecological education and awareness raising along the romanian black sea coast. *Journal of environmental protection and ecology*, 18:348–362, 05 2017.

[9] D González-Fernández, G Hanke, M Pogojeva, N Machitadze, Y Kotelnikova, I Tretiak, O Savenko, K Bilashvili, N Gelashvili, A Fedorov, et al. Floating marine macro litter in the black sea: Toward baselines for large scale assessment. *Environmental Pollution*, 309:119816, 2022.

[10] Gil Gonçalves, Umberto Andriolo, Luís Pinto, and Filipa Bessa. Mapping marine litter using uas on a beach-dune system: a multidisciplinary approach. *Science of The Total Environment*, 706:135742, 2020.

[11] Marthe Larsen Haarr, Jannike Falk-Andersson, and Joan Fabres. Global marine litter research 2015–2020: geographical and methodological trends. *Science of The Total Environment*, page 153162, 2022.

[12] Mitsuko Hidaka, Daisuke Matsuoka, Daisuke Sugiyama, Koshiro Murakami, and Shin'ichiro Kako. Pixel-level image classification for detecting beach litter using a deep learning approach. *Marine Pollution Bulletin*, 175:113371, 2022.

[13] Cecilia Martin, Stephen Parkes, Qiannan Zhang, Xiangliang Zhang, Matthew F. McCabe, and Carlos M. Duarte. Use of unmanned aerial vehicles for efficient beach litter monitoring. *Marine Pollution Bulletin*, 131:662–673, 2018.

[14] MSCI. Gics - global industry classification standard.

[15] Cristina Munari, Corinne Corbau, Umberto Simeoni, and Michele Mistri. Marine litter on mediterranean shores: Analysis of composition, spatial distribution and sources in north-western adriatic beaches. *Waste Management*, 49:483–490, 2016.

[16] Ping Ping, Effendy Kumala, Jerry Gao, and Guoyan Xu. Smart street litter detection and classification based on faster r-cnn and edge computing. *International Journal of Software Engineering and Knowledge Engineering*, 30(04):537–553, 2020.

[17] Farzana Shaikh, Nagma Kazi, Farheen Khan, and Zaid Thakur. Waste profiling and analysis using machine learning. In *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, pages 488–492, 2020.

[18] Maarten Sukel, Stevan Rudinac, and Marcel Worring. Urban object detection kit: A system for collection and analysis of street-level imagery. In *Proceedings of the 2020 International Conference on Multimedia Retrieval*, ICMR '20, page 509–516, New York, NY, USA, 2020. Association for Computing Machinery.

[19] Mingxing Tan, Ruoming Pang, and Quoc V Le. Efficientdet: Scalable and efficient object detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10781–10790, 2020.

[20] Cathy Teng, Kyriaki Kylili, and Constantinos Hadjistassou. Deploying deep learning to estimate the abundance of marine debris from video footage. *Marine Pollution Bulletin*, 183:114049, 2022.

[21] Konstantinos Topouzelis, Apostolos Papakonstantinou, and Shungudzemwoyo P Garaba. Detection of floating plastics from satellite and unmanned aerial systems (plastic litter project 2018). *International Journal of Applied Earth Observation and Geoinformation*, 79:175–183, 2019.

[22] Mattis Wolf, Katelijn van den Berg, Shungudzemwoyo P Garaba, Nina Gnann, Klaus Sattler, Frederic Stahl, and Oliver Zielinski. Machine learning for aquatic plastic litter detection, classification and quantification (aplastic-q). *Environmental Research Letters*, 15(11):114042, 2020.