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Position Paper

The PlastOPol system for marine litter monitoring by citizen scientists

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ABSTRACT

Marine plastic pollution has in recent decades become ubiquitous, posing threats to flora, fauna, and potentially human health. Proper monitoring and registration of litter occurrences are, therefore, of paramount importance to support better-informed decision-making. In this paper, we introduce the PlastOPol marine litter monitoring system. PlastOPol integrates external data sources on beached litter with data collected through citizen science initiatives based on the use of a mobile application (App). The App relies on state-of-the-art machine-learning approaches for litter detection and registration. The system also supports a human-in-the-loop strategy based on which improved versions of litter detection models are created over time thanks to annotations by citizen scientists. Finally, the system includes a geographic visualization tool to support the analysis of litter distribution data by decision-makers. This system has the potential to create a direct path between citizens, researchers, and decision-makers on the issue of marine litter. Finally, the paper presents compelling usage scenarios of the proposed monitoring system and discusses the evaluation of the App through a user study. The user study suggests that the PlastOPol system is an effective and valuable tool to monitor and communicate marine litter.

1. Introduction

Marine litter has become ubiquitous, posing threats to flora, fauna, and potentially human health (MacLeod et al., 2021; Rahman et al., 2021) According to the United Nations Environment Programme (UNEP), approximately 11 million tonnes of litter are poured into the oceans annually (UN Environment Program, 2023). Among the most common types of litter, plastic represents the large part because of its longer decomposition time and the huge amount being produced and discarded which creates a process of accumulation (Gregory, 2009; Kubowicz and Booth, 2017; Obbard et al., 2014). For instance, the proportion of plastic debris is up to 80% in marine litter (Barnes et al., 2009). Plastics can cause entanglement and thereby pose a threat to organisms and ecosystems at large (Woods et al., 2019). Plastic is also widely documented to enter the food chain through various pathways (Santos et al., 2021) and carry pathogens (Kirstein et al., 2016).

Generally, marine debris can be categorized into sea-based or land-based. Sea-based human activities such as offshore oil production, shipping, fishing, aquaculture, and tourism are behind the first. Land-based production and use followed by transport to sea from wind and rivers explain the second category (Anon, 2023). This multi-source scenario, added to the complexity of hydrodynamic systems (Maximenko et al., 2019) makes analysis and tracking of marine litter challenging (Provencher et al., 2022). Knowledge is building up; however, too little is known about the behaviour of plastic at sea and in sediment, as well as its sources and sinks.

Addressing the aforementioned challenges requires extensive data collection and analysis of the sources, distribution, and quantities of litter over large geographical areas. The OSPAR Commission has issued guidelines for the monitoring of marine litter (Vollaire, 2023), which involves citizen science. Indeed, citizen science has proven to be an effective way of collecting large datasets on litter (Rech et al., 2015; Syakti et al., 2017). Citizen science involves the participation of civil society in data collection for scientific studies (Ballard et al., 2017;

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Nelms et al., 2022). In addition to increasing sampling size and spatial distribution (Rech et al., 2015; Haarr et al., 2020; Hidalgo-Ruz and Thiel, 2013) in an affordable way, citizen science has the corollary effects of raising public awareness and the potential to empower citizens to contribute to decision-making processes by informing relevant policies. It also gives citizens a unique possibility to improve their own knowledge about the case investigated and the research methods (Ballard et al., 2017; Dickinson et al., 2012), fostering a sense of responsibility (Ballard et al., 2017) and connectedness to the environment (Schuttler et al., 2018). In addition, citizen scientists have shown their ability to be involved in multiple parts of the research process, going beyond the traditional crowdsourcing approach, as discussed by Cyvin (2022). The European Citizen Science Association identifies, as one of its 10 principles, the potential for citizen scientists to be involved meaningfully in multiple stages of the scientific process (European Citizen Science Association, 2023).

Many studies have been conducted around the world to understand the sources of litter (Munari et al., 2016; Crosti et al., 2018) using simple form-based tools to record litter occurrence including through citizen science initiatives (Nelms et al., 2022). These tools aim to collect scientific data with minimal effort on the part of the volunteers. Some solutions were evaluated on mobile devices (Sukel et al., 2020; Shaikh et al., 2020). However, to the best of our knowledge, this is the first time that an object detection solution for marine litter is offered without the need for a continuous network connection to a server. This enables citizen scientists to work remotely, storing their data temporarily on a mobile phone, and then sending it to a server when a connection is restored.

To present an affordable and viable solution for these problems, in this paper, we introduce PlastOPol, a software infrastructure to support litter monitoring and data sharing. PlastOPol integrates existing datasets on marine litter with data collected from citizen scientists by means of a mobile App. Our solution uses an efficient and effective state-of-the-art machine learning approach, EfficientDet-d0 (Tan et al., 2020), to detect litter on photos (Córdova et al., 2022). Our mobile user interface allows the user to edit and draw new detections in the case of false positives or missing items. This allows the App to be improved over time, as most effective detection models are expected to be created based on the labelled datasets provided by users. Additionally, the user can label the litter instances choosing from a predefined list of categories and also upload the images along with their annotations to an integrated data management solution. The categories, defined in terms of different industry types (e.g., fishing, construction, and tourism) based on Standard and Poor's Global Industry Classification Standard (GICS), allow the characterization of sources of litter. Finally, the PlastOPol infrastructure includes a geographic visualization tool to support the analysis of litter distribution.

In short, the contributions of this paper are:

- We introduce a new system for marine litter monitoring enabling data collection by citizen scientists.
- We introduce a mobile application for litter occurrence registration without the need for a continuous connection.
- We introduce an integrated database design for litter occurrence registration and data sharing.
- The proposed mobile App relies on state-of-the-art machine-learning object detectors whose model can be improved over time based on annotations by citizen scientists.
- We introduce a geographic visualization tool that supports the analysis of litter distribution.
- We present and discuss a user study to assess the potential of PlastOPol to support citizen science tasks.

The monitoring system is validated through a user study involving the use of the mobile application by potential citizen scientists, 28 high school pupils. The evaluation performed with the stakeholders shows that the PlastOPol infrastructure is a promising platform to study marine litter pollution.

This paper is organized as follows. Section 2 gives an overview of relevant related work. Section 3 details the PlastOPol system for marine litter monitoring, highlighting its main components. Section 4 presents and discusses a user study including a user experience evaluation and a mapping of interest in citizen science. Finally, Section 5 outlines our conclusions and points out relevant venues for future research using the system.

2. Related work

Monitoring systems for marine litter are being developed around the world. Some of these approaches involve machine vision applied to images collected by devices such as webcams in fixed points, Unmanned Aerial Vehicles (UAV), vessels, or satellites Jambeck and Johnsen (2015), de Vries et al. (2021). For example, Kako et al. (2012) and Crosti et al. (2018) used fixed points to monitor marine debris found in coastal areas and rivers near the sea respectively. The main drawback is that this approach is "static" and deploying this approach over larger geographical areas would be costly. When it comes to UAVs, examples include object detection on images taken by drones (Gonçalves et al., 2020) or open-access pictures taken by satellites (Topouzelis et al., 2019). These approaches are similar to the more recently popular monitoring with cameras onboard vessels (Armitage et al., 2022). However, cleaning, and processing operations are required to ensure reliability. This limits the detection range and increases associated costs. Those approaches, are often combined with other operations and used by government and research organizations rather than the general public. Another limitation is that these systems only apply to large objects, such as those trapped in gyres, and are therefore not suitable for small objects typically found along the coasts sometimes hidden by rocks, soil and vegetation.

On the other hand, citizen science initiatives have mainly relied on human observation and manual recording, or photos taken through mobile phone applications. National or regional projects such as MARLIT, NauticAttiva or Debris Tracker allow participants to gather and record images and the location of litter in their areas (Garcia-Garin et al., 2021; Jambeck and Johnsen, 2015; Scardino et al., 2022). However, none of these solutions use object detection and classification of the litter. Web portals also exist such as in González and Hanke's (González and Hanke, 2017) JRC Floating Litter Monitoring Application, which allows users to record categories and sizes of litter found. The Norwegian web portal Rydde (Rydde, 2023) allows volunteers to register their findings in detailed categories and to perform statistics at national or regional levels. The novelty of the PlastOPol App is that it integrates the useful elements of different existing tools and technology into one comprehensive system. Object detection is used to identify the litter on images combines with human expert judgment, for the categorization of the litter objects according to the industry they originate from. The new data is then added to the database aggregating all the data on litter collected since 2013 along the Norwegian coast (a system with global potential) and visualized in a spatio-temporal interactive map. This will be detailed in the next section.

3. PlastOPol monitoring system

This section introduces the PlastOPol monitoring system, detailing its main components.

3.1. Overview

This section provides a functional and architectural view of the PlastOPol system.

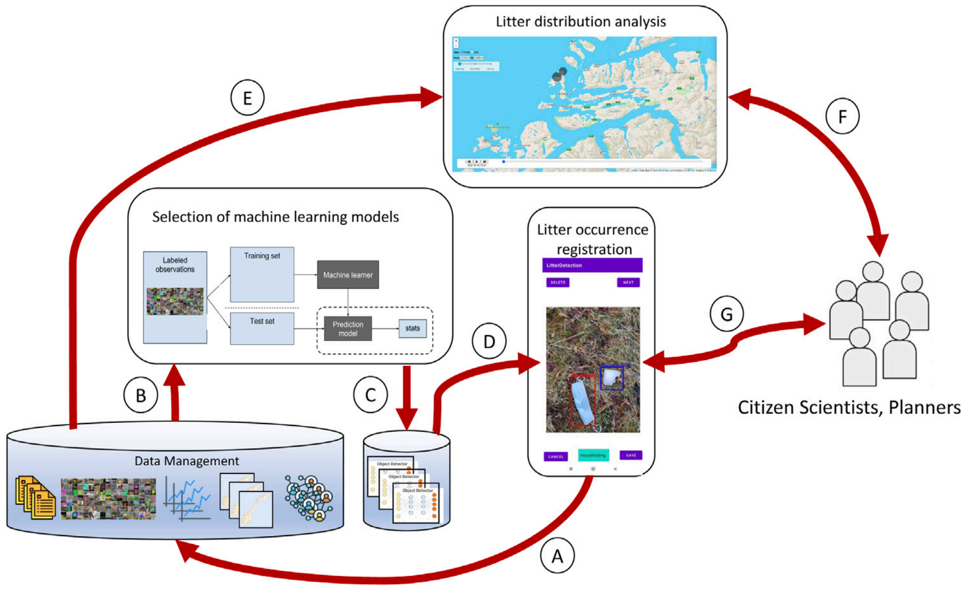

Fig. 1. Schematic functional view of the PlastOPol monitoring system.

3.1.1. Functional view

Fig. 1 presents a functional view of the PlastOPol monitoring system. Citizen scientists register the occurrence of litter by means of a mobile application (arrow G in the figure). The App not only supports the registration of the type of litter and its location but also collects feedback from citizen scientists regarding litter detection accuracy (arrow A). The mobile App includes a litter detector based on a state-of-the-art object detector (Córdova et al., 2022). Therefore, annotations provided by citizen scientists are used (B) to retrain the object detector and thus improve the overall effectiveness of the detector over time, as the retrained models (C) are used to generate new versions of the App (D). Data on litter occurrence (e.g., location, type) as well as data from external sources are also stored in a data management module. This information is sent (E) to a web map-based visualization tool that supports litter distribution analysis (F) by stakeholders (e.g., planners).

3.2. Litter data management

With respect to the database, the Entity-Relationship (ER) model that defines the adopted data model is shown in Fig. 2. The tables can be divided into three categories based on the information stored. One part is the user identity (blue box). In these tables, users are registered and assigned to different roles. They can be either "uploaders" (write-only), administrators, or users (read-only). The part of the data model dedicated to annotation is highlighted in orange. Basic information on annotations is defined here, including annotation types and editors. The remaining part of the database (highlighted in green) is related to annotation information (e.g., annotation type). In the proposed data model, besides storing the basic information of the picture, such as the image metadata and the annotation position, the location and time are also recorded.

3.3. Litter detection

One of the most important tasks in the computer vision area is object detection. This task involves two sub-tasks, one for localizing objects and the other for classifying them. The former generates bounding boxes, wrapping as much as possible the detected object, and predicting their coordinates as output, whereas the latter is responsible for defining their categories (Ye and Doermann, 2015).

In this work, EfficientDet-d0 (Tan et al., 2020) was used for detecting litter. EfficientDet-d0 is a compact neural network designed for running in devices with computational constraints, such as mobile devices, which uses EfficientNet (Tan and Le, 2019) as the backbone. EfficientNet is composed of a weighted bi-directional feature pyramid network for fast and robust multi-scale feature extraction.

To train EfficientDet-d0 (Tan et al., 2020), we used the source code and hyper-parameters made publicly available by the authors in their official GitHub (Google, 2023). Moreover, the PlastOPol dataset (Córdova et al., 2022) was used to train the model, which is a publicly available dataset that contains 2418 images with a total of 5300 instances of litter in natural settings.

Our litter detection component uses an input image size of 300×300 pixels and generates up to 100 detections per image. Those detections are filtered by a confidence score of 0.4 and an Intersection over Union (IoU) of 0.5. The reader may refer to Córdova et al. (2022) for a detailed description of the methods used to compare existing machine learning models and identify the one that performed best in the case of litter detection.

Finally, our mobile application relies on an efficient and effective machine-learning approach for detecting litter. Additionally, its interface allows the user to edit and draw new detections in the case of false positives or missing detections. These functionalities allow the accuracy to be improved over time, as most effective detection models are expected to be created based on newly labelled datasets provided by users.

3.4. Mobile application for litter occurrence registration

In this section, we introduce a mobile application to support marine litter monitoring through litter occurrence registration, which is explained in more detail in Liu et al. (2023). The App allows for litter detection, classification, and forwarding of the collected information to an integrated database.

Fig. 3 presents screenshots of the app. The first screen (left) contains available options for interaction. The figure in the middle shows an example of detection (highlighted in red). The final figure (right) shows the list of labels that can be assigned to a detected object.

3.5. Litter distribution visualization

The PlastOPol system also includes a web-based interactive geographic visualization platform to support the analysis of the distribution

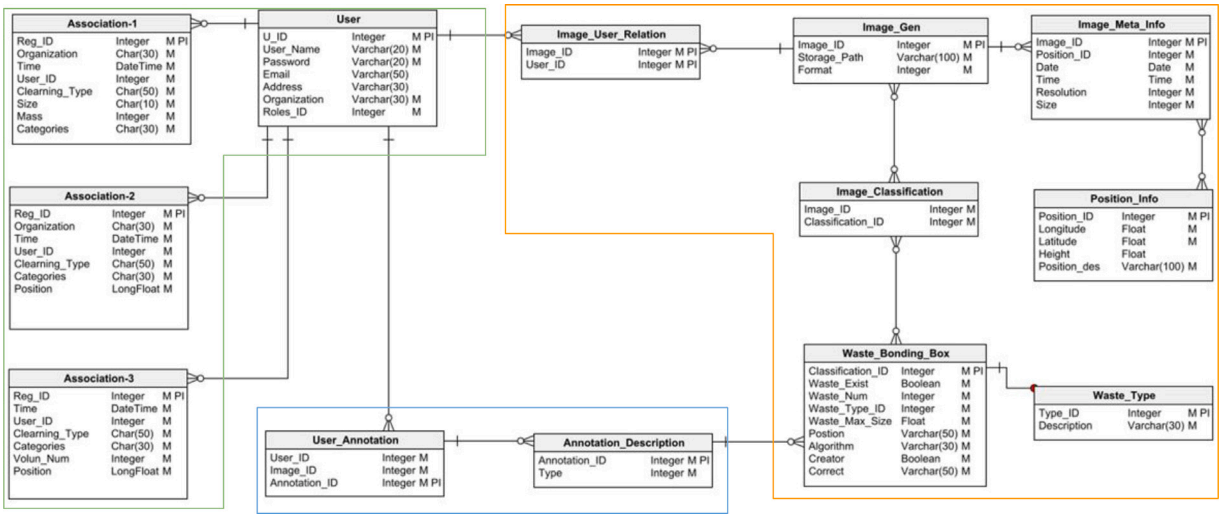

Fig. 2. Entity-relationship model for the backend relational database.

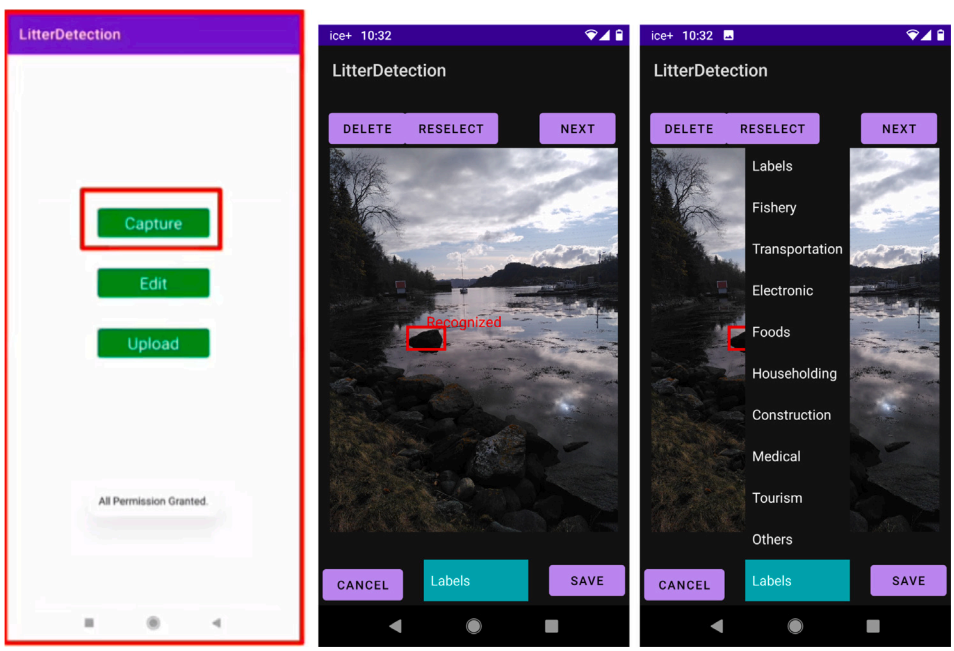

Fig. 3. Screenshots of the interface of the mobile application.

of collected data over time. Fig. 4 presents a screenshot of the geographic visualization tool. On the top-left of the interface (area labelled as A in the figure), users may customize the visualization, by filtering out data based on time and litter type. The occurrence of collected data is presented as red circles on a map. The size of the circles is proportional to the amount of litter found at that specific location. Finally, time controls (B) can be used to support analysis of the evolution of litter occurrences in different locations over time.

For more details regarding implementation aspects, the reader may refer to Liu et al. (2023).

4. User study

This section presents the user study conducted to validate the data acquisition process based on a citizen science initiative and evaluate the App by the users.

4.1. Study settings

A high school first-grade class of 28 pupils (age of 15–16) following an education program to become researchers ("forskerlinje") took part in the user study in Ålesund, Norway. They first filled in a consent form, in accordance with our national authorities for research data (sikt, 2023), as well as local institutional guidelines, allowing the project team to use the data collected through the survey. The full survey is available in the supplementary material. Then, they were given a short lecture about the issue of plastic pollution and associated research challenges, clean-up activities, concepts and models of citizen science, and the basics of machine learning. The students were given a simple introduction to how to use the PlastOPol App including each step from capturing an image to selecting labels and correcting the object detection to uploading the files. Litter items were spread around a lab

Fig. 4. Geographic visualization platform for litter collection recorded from 2013 to 2021.

and the pupils were asked to find them, take photos, confirm or correct the bounding boxes around the objects, label each item, and upload the files.

As the PlastOPol App currently only exists for Android phones, we distributed eight Android phones (Samsung Galaxy S8) for the students to use in groups of four with the App ready to use. The pupils were then asked to fill in a Likert-scale-based questionnaire on their experience of the App with some open questions for more specific feedback. The Likert scales were 5-point scores from 1 to 5 detailing each phase of the App. In addition, some open questions allowed users to provide feedback on potential issues or improvements in the workflow.

Finally, they were also asked to place their involvement with PlastOPol based on the Skrögel & Kolleck's model (Schrögel and Kolleck, 2019) of citizen science engagement,[1] place themselves in an ideal project using the same model along the axis with Normative focus (x), Epistemic focus (z), and Reach (y); and finally write a comment asking "Describe how you think an ideal citizen science project where you are participating should be. What should your role be? How and Why?"[2]

4.2. Results

The Likert scales were presented as ordinal, with the median presented for each category in Fig. 5 below. The highest score of 4 was given to the Capture function, whereby a photo is captured with a litter object and the model detects the object. The same median score of 4 was also given to selecting labels, uploading, and to the user profile question on familiarity with Apps. The lowest score of 2 was given to how likely the pupils were to use this App when cleaning an area. Finally, a median score of 3 was given to "adding and deleting objects", in cases of false negatives or positives, and to the speed of the uploading process.

As to the feedback in the open fields, the suggestions included improving the intuitiveness of the interface, gamifying it, increasing the speed, and decreasing the 'number of steps' (Respondent 1). A small selection of quotes to the question on suggestions or comments related to the use of the App is provided as follows:

- *"To make it a bit easier to navigate the App, like make it a bit more obvious where to click when uploading a picture".* (Respondent 2)

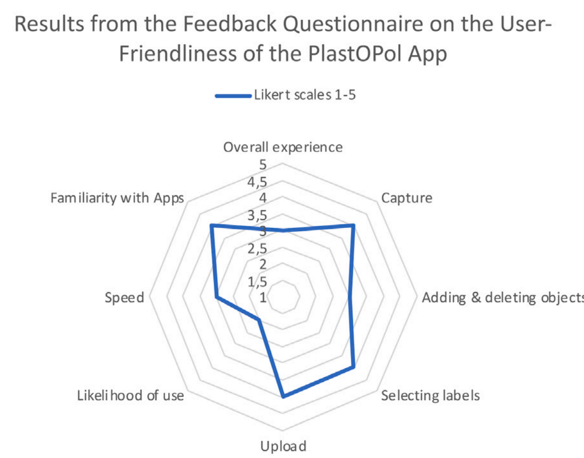

Fig. 5. This figure shows the scores on a Likert scale of 1–5 for each question of the feedback questionnaire, available in the Supplementary Material (N = 28).

- *"People are impatient, the App needs to be faster".* (Respondent 3)
- *"[Make it] so that you don't have to save, click next, and then upload, make it so that everything happens at the same time. So that the photo uploads when you are finished editing".* (Respondent 4)
- *"A bit more appealing and make it a bit more fun to use, like give rewards and make the App more vibrant (but not too much). And make it easier to use".* (Respondent 5)

4.3. Citizen science engagement

Nearly all the students completed the tasks of placing the current PlastOPol project within the model by Schrögel and Kolleck (2019) and describing their involvement in an ideal Citizen Science (CS) project. Four students misunderstood the model or did not follow the instructions. Therefore, four answers were excluded. The difference between the description of the current CS project (PlastOPol) and a description of their ideal involvement was then visualized as a bar graph (Fig. 6). Three possible outcomes were chosen, to visualize the results. Change towards more involvement: the student placed a cross further to the right in the model compared to the PlastOPol project (Fig. 7), (more involvement); Neutral: no change in involvement between PlastOPol

[1] By the authors, the PlastOPol project is found to be placed as visualized in Fig. 7.

[2] Translated by the authors.

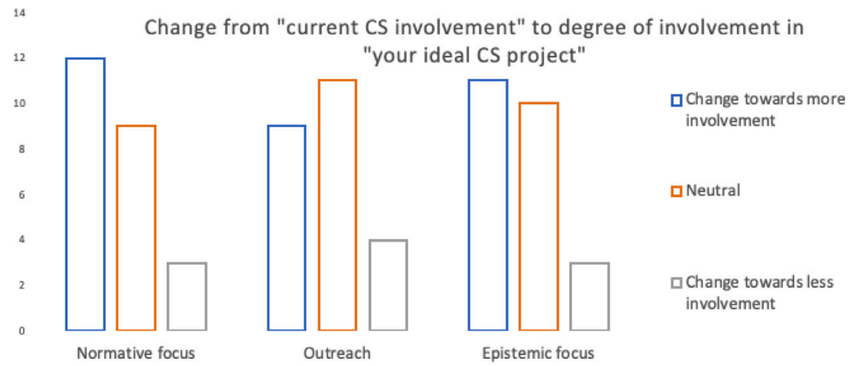

Fig. 6. Results from students placing current, and an imagined future Citizen Science (CS) project into the model of Schrögel and Kolleck (2019) ($N = 24$).

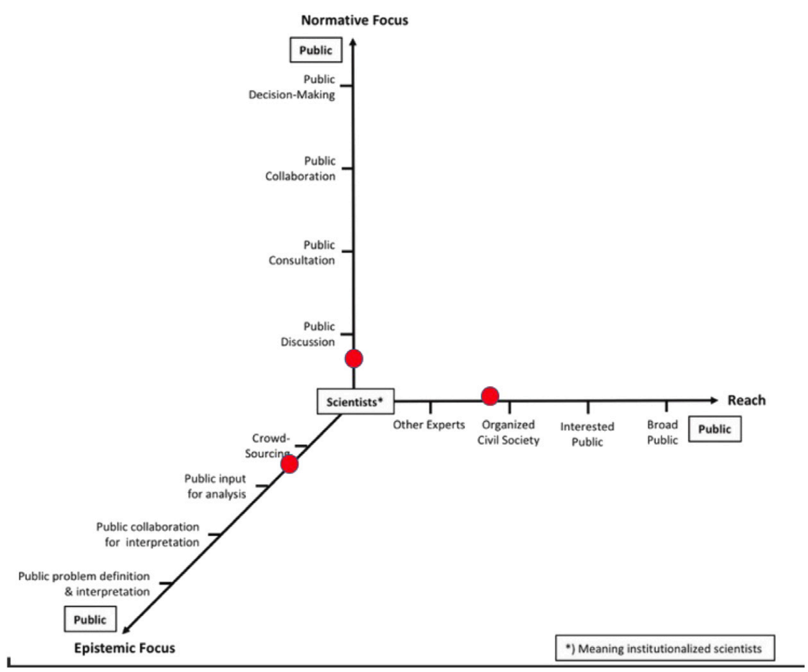

Fig. 7. Adapted from Skrögel & Kolleck's model (Schrögel and Kolleck, 2019) showing the different possible levels of engagement in citizen science projects. The red dots indicate the placement of the PlastOPol project by the authors of this paper.

and an ideal project and Change towards less involvement: the students placed a cross further inwards towards the origin of the axis.

The open text relating to their ideal involvement was coded inductively, resulting in 35 subcategories. Based on thematic similarities, it was thereafter, also inductively reduced (condensed) to five main categories, visualized in Table 1 following the method in Thomas (2006).

4.4. Analysis and discussion

A few discussion points are to be noted. The first is that school students of the age of 15–16 following an education path in research have very high literacy levels when it comes to using mobile applications, which is reflected in the question on familiarity with Apps. It is also interesting to note that the score for "likelihood of using the App" was very low. This can be attributed to the fact that the students were not used to participating in beach-cleaning activities. The App is designed to support both research and beach-cleaning activities. Users that do not fall into those categories are likely not to use the App.

Another point is that the settings were slightly artificial as they were in a laboratory and with borrowed phones. The PlastOPol model was trained using real photos from volunteers taken in outdoor settings. This could explain the relatively low accuracy rate of the App in this case, using "clean" waste, i.e., with visible labels rather than worn off through the effects of weathering. The lab settings were chosen for practical reasons and due to bad weather conditions. As we provided the pupils with phones, we were not able to test the download operation; however, the adaptation of the App to every type of mobile phone lies outside the scope of this study.

4.5. Potential for higher involvement in citizen science projects

The open-ended questions (Table 1) related to the motivation to participate in citizen science studies (A) revealed that the pupils wanted easy tools and projects that felt relevant to their daily lives. As an example, one of the pupils highlighted that a project on public transport would be engaging. Several students also pointed to the fact that it should not be too much work. This is contradictory to other students commenting about the grade of involvement (E), where multiple of the respondents wanted to be heard and also influence international or national authorities. On the other hand, both "gathering data" and perspectives of their lack of knowledge and therefore limited ability to real contributions were mentioned by several students. These perspectives partly contradict research on the possibilities for in-depth

Table 1
Overview of the results from the inductive analysis of open questions regarding the pupils' ideal future Citizen Science project regarding the degree of involvement (translated by the authors). Inductively created headlines in bold followed by an explanation.

Motivation for participation (A)	Feedback to the researchers (B)	Helping the researchers (C)	Learning (D)	Grade of involvement (E)
Something that affects my daily life ([e.g.] public transport). Should be easy to participate, and interesting. Not too much work.	Contribute with feedback, argue, discuss with the researchers (x3).	Help out with experiments, gather data, analyze and verify if it works in "real life."	Practical and theoretical learning when participating in discussions, listen to presentations. Brainstorming, asking questions, following the process and seeing the solutions.	Gather data (x5), influence nationally or internationally (x2). Be heard (x4). Quite ideal to us (current project edt.). My role should be to mirror society. It should be open to all, some could do more, some could do less.

citizen science involvement (Horowitz et al., 2016; Somaweera and Somaweera, 2021), but also reveal an open and reflective mind and perhaps lack of self-confidence on the part of the pupils regarding their own competences.

Interestingly, one of the categories (Table 1, E) became "learning". Multiple pupils mentioned their own potential to learn when describing their possible involvement in research. They mentioned how their learning process could be enhanced by joining discussions with researchers and following the research. It is of interest that none of the pupils mentioned directly how their contribution could broaden the perspectives of the researchers, even though the focus on their role as representatives of general society might overlap somehow (E). It might be of interest for future research to introduce several elements of the research process before conducting a similar survey. Currently it is not clear whether the pupils themselves have a clear distinction between e.g., giving feedback to the researchers (B) and helping the researchers (C). There might also be an overlap, but the distinction within this inductive analysis goes between delivering information (feedback, B) and active involvement (help, C). Overall, it was clear that nearly all of the pupils either wanted to participate in projects with a similar degree of involvement as in PlastOPol (Fig. 7) or with a higher degree of involvement from the model of Skrögel & Kolleck (Schrögel and Kolleck, 2019). The normative focus axis got the highest number of pupils wanting a higher degree of involvement in an imagined project. Most of these pupils also wanted to be a part of public decision-making in a future hypothetical project.

The "outreach" axis got fewer responses towards more involvement. This result is a bit contrary to some of the responses to the open question, where multiple pupils highlighted the value of reaching the whole society, in citizen science project implementation. We hereby see the use of the citizen science model in Schrögel and Kolleck (2019) as well suited to evaluate the degree of involvement towards citizen scientists, and research upon their wishes for how similar projects should be carried out, also using this model with pupils. The complexity of the model, including the terminology, could within these circumstances benefit from simplification. Finally, we would argue that an additional category for projects involving machine learning, where citizen science data contributes to actively training the model could be created on the axis with the epistemic focus, perhaps somewhere between "Public input for analysis" and "Public collaboration for interpretation".

The wishes of the students for a higher degree of involvement and the nature of the system proposed to create possibilities for using the PlastOPol App as a tool within the school curriculum. The assessment performed demonstrated the potential for high-quality automated object detection, enabling the creation of large datasets, as well as the possibility of involving the general public. It enables communicating data to decision-makers, and students, who, based on our case study seem to be able to participate and want a higher degree of involvement. Cooperation with schools over a longer period of time seems like an appropriate way of implementing this, but it must be prioritized in terms of grants and budgeting as well as human resources. Using citizen scientists for crowdsourcing as well as a higher degree of citizen science involvement in research is to a great degree in line with the EU priorities for research, for instance, as seen in the latest Horizon Europe calls.

5. Conclusions

This paper introduced PlastOPol, a new litter monitoring system based on citizen science. PlastOPol includes a mobile App that employs state-of-the-art machine learning methods for supporting litter detection and occurrence registrations, a database solution for storing acquired data, and an interactive geographic visualization platform that supports spatio-temporal analysis of litter collection efforts, and by extension litter distribution. The proposed human-in-the-loop approach ensures that better litter detection models, benefitting from ever-growing labelled datasets, will be used in the App and lead to more effective and efficient annotations in the future in a kind of continuous positive feedback loop. This can further be implemented in research and litter monitoring programmes to potentially automate the recording process and provide a more objective evaluation of the quantities of litter than currently in place. To the best of our knowledge, this is the first initiative in the literature that integrates such technologies to support citizen science initiatives for litter monitoring.

A user study was conducted with potential citizen scientists (high school pupils). Findings demonstrate the potential of PlastOPol in engaging citizen scientists in the litter occurrence annotation process, as well as a wish for a high degree of involvement among the High-School pupils, when asked how their ideal citizen science project should be designed.

Future work will focus on the assessment of the PlastOPol system in other usage scenarios in the context of beach-cleaning activities, such as planning and litter occurrence registration. We also plan to investigate the integration of datasets collected in the PlastOPol system with others produced in the context of litter monitoring initiatives (e.g., Falk-Andersson et al., 2022). Finally, we aim to integrate a feedback mechanism that allows citizen scientists to keep track of the results of the projects and continue to participate in various forms, including the communication of results to policymakers, the research community, and civil society.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Di Wu, Jincheng Liu, Ricardo da Silva Torres, Ibrahim A. Hameed, Christina Carrozzo Hellevik report financial support was provided by Regional Research Fund Møre and Romsdal.

Data availability

Data will be made available on request

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.envsoft.2023.105784.

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