

## AI IN SUPPORT TO WATER QUALITY MONITORING

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### Commission IV, WG IV/4

**KEY WORDS:** Artificial Intelligence; Convolutional Neural Networks; Citizen Science; Water monitoring;

### ABSTRACT:

This study explores the possibility of using Artificial Intelligence (AI) as a means to support water monitoring. More precisely, it addresses the issue of the quality and reliability of Citizen Science data. The paper addresses the tools and data of the SIMILE (Informative System for the Integrated Monitoring of Insubric Lakes and their Ecosystems) project in order to develop an open pre-filtering system for Volunteer Geographic Information (VGI) of lake water monitoring at the global scale. The goal is to automatically determine the presence of harmful phenomena (algae and foams) in the images uploaded by citizen scientists to reduce the time required for a manual check of the contributions. The task is challenging because of the heterogeneity of the data that consist in geotagged pictures taken without specific instructions. For this purpose, different tools and deep learning techniques have been tested (Clarifai platform, a Convolutional Neural Network (CNN), and an object detection algorithm called faster Region-based CNN (R-CNN). The original dataset composed by the observations of SIMILE – Lake Monitoring application, has been integrated with the results of both keyword and image searches on web engines (Google, Bing, etc) and crawling Flickr data. The performances of the different algorithms are presented for their capability of detecting the presence and correctly labelling the phenomenon together with some possible strategies to improving them in the future.

## 1. INTRODUCTION

### 1.1 SIMILE project and its context

Waterbodies play a key role in the mitigation of the impact of climate change. They also represent an essential resource available to billions of people for multiple uses. The importance of waterbodies is further highlighted by their inclusion in the sustainable development agenda (SDGs 6, 14, UN.org, 2019). Lake ecosystems are highly exposed to the consequences of global warming and the impact of human activities (Adrian et al., 2009; Vincent, 2009). The quality of lake water needs to be preserved, and recent scientific and technological development could provide a significant support to the cause. SIMILE (Informative System for the Integrated Monitoring of Insubric Lakes and their Ecosystems) is a project that involves academia (Politecnico di Milano – Lecco Campus; Fondazione Politecnico; SUPSI - University of Applied Sciences and Arts of Southern Switzerland), research bodies (Water Research Institute - National Research Council) and institutions (Lombardy Region; Ticino Canton in Switzerland), which are cooperating partners in the preservation of water quality in the Lugano-, Maggiore- and Como lakes. The main strategy of this cooperation aims at integrating the existing monitoring protocols with data coming from recently developed geospatial tools and techniques, such as the processing of satellite images (Luciani et al., 2020), of high frequency *in situ* sensors and also Citizen Science (Brovelli et al., 2019).

SIMILE – Lake Monitoring (Biraghi et al., 2020; Pessina et al., 2020) is a recently released cross-platform, open-source, mobile application, which has been developed to support the activities of the project related to Citizen Science (CS). The mobile application enables private citizens to share their observations of the lake environment through geo-referenced images of algae,

foams and litter, and the measurements of water parameters (transparency, temperature, pH, etc.). In addition, it promotes water-related events, it features a glossary and also a set of useful links that help improving the user's knowledge and awareness of the lake ecosystem. Registration to the app is optional and most of its functionalities can be used without registering. This means that everyone – including amateur and even malevolent users – can contribute freely to the project. This clearly implies the possible occurrence of irrelevant or inappropriate content. Even though the mobile application is designed to facilitate the upload of contributions by users, it is not the optimal tool for their subsequent management. In fact, it only contains an agile map view where all the observations and measurements are displayed with the same marker and one needs to open each observation in order to explore their content. A web application (<https://simile.com.polimi.it/SimileWebAdministrator/faces/index.xhtml>) has been developed to allow the partners of the project, and ultimately also environmental agencies, to edit and better analyse the data uploaded through the app. Moreover, the web application offers the possibility to filter observations according to time, position and all the other attributes that the mobile application features. This is a powerful tool – complementary to the mobile application – that enriches the set of data available that environmental agencies can study. However, it may also be regarded as a burden and an additional task for the employees who will actually elaborate the data. At the end of the project, the integration of new technologies (including the two apps) with the existing routines will be evaluated by the institutional partners. For this reason, the added value on the scientific level must be balanced with the additional workload weighing on the employees of the environmental agencies. As a consequence, the present study explores the development of a system for the pre-filtering of data which exploits Artificial Intelligence (AI) with the purpose of reducing

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the need of a manual check of the observations performed by the employees, thus simplifying the general workflow.

## 1.2 Integration of AI and CS

Until recently, Artificial Intelligence (AI) and Citizen Science (CS) were considered distinctly and were used independently (McClure et al., 2020). Their integration, however, can be helpful in addressing some of the challenges existing in both areas. Indeed, CS can be the source that provides large amounts of labelled data in order to feed and train Machine Learning (ML) algorithms, whereas ML can support CS in automating the validation of data or in sustaining user participation by giving automatic feedback to the volunteers. Even though the inclusion of AI in CS projects is expanding to various areas such as astronomy (Beaumont et al. 2014) and neuroscience (Keshavan et al. 2019), the main focus of their cooperative exploitation has been on biodiversity studies (Green et al., 2020; Lotfian et al., 2019; Terry et al., 2020; Torney et al., 2019).

This article aims at integrating ML in the SIMILE project in order to introduce an automatic identification and the validation of observations regarding water quality. More precisely, the presence of foams and algae is considered, as it is the most relevant and reported issue in the Insubric lakes. The availability of studies on the use of AI in order to identify phenomena linked to water quality is limited, and the majority of them – to the best of our knowledge – is based on detecting litter on the water surface (Garcia-Garin et al., 2021; Wolf et al., 2020). AI is also used to detect harmful algal blooms (HAB) by analysing satellite images (Hill et al., 2020). The final goal of the present study is to implement a tool for the detection of algae and foams in the images uploaded by the users of the SIMILE – Lake Monitoring mobile application. The findings of this research have been compared to those of a similar study (Samantaray et al., 2018) which deals with the detection of HAB both from aerial and from ground surveys.

The following chapter details all the steps required to develop this tool, starting from a definition of the dataset needed. The preparation of the data that will feed the alternative ML algorithms presented will be subsequently assessed, then, in the final section of the chapter, their performance will be analysed.

## 2. METHOD

### 2.1 Dataset acquisition

The initial dataset consisted of the images uploaded by the users of the SIMILE – Lake Monitoring mobile application, integrated with archive images received from the partners of the project. This dataset featured 35 images of algae, 32 of foams and 14 of clean water. Even though the images were very precise and context specific, the dataset was limited if compared to the one needed to train a ML model. In order to enlarge it, a web search has been carried out by exploiting search engines Google and Bing and by using as keywords the two phenomena (algae; foams), their synonyms (algal bloom and scum; froth and spume) and the corresponding Italian words (algh e fioriture algal; schiume). This manual research produced similar results both on Google and Bing, and it helped collect nearly one-hundred valid images for each phenomenon. As a means to acquire contents in other languages or unlabelled ones, a complementary search by image has been performed using 10 input images for each of the two phenomena on 5 search engines (Google, Bing, TinEye, StackPhoto, ShutterShock). Table 1 shows the number of valid images found using each input image on the search engines detailed above.

	ID	Google	Bing	TinEye	Stack Photo	Shutter shock
Algae	1	6	3	0	2	0
	2	0	0	0	0	0
	3	15	8	0	0	0
	4	0	0	0	0	0
	5	20	11	0	0	2
	6	24	30	0	0	2
	7	86	0	0	1	2
	8	7	0	0	0	0
	9	3	0	0	0	0
	10	8	1	0	0	1
	Tot	169	53	0	3	7
Foams	1	1	4	0	0	0
	2	1	1	0	0	0
	3	0	9	0	0	0
	4	0	0	0	0	0
	5	0	3	0	0	2
	6	4	0	0	0	0
	7	0	0	0	0	0
	8	4	2	0	1	0
	9	1	4	0	1	0
	10	2	3	0	0	1
	Tot	13	26	0	2	1

**Table 1.** Valid images for the different search engines used for the search by image

Thanks to this additional, manual search, 232 valid images of algae (73% from Google) and 49 valid images of foams (45% from Bing) have been collected. In very limited cases, images of algae have also been found by using images of foams as an input (5 images), and viceversa (2 images). A further research into the Flickr dataset has been performed, first by downloading all the images containing the hashtag “algae” or “foams”, then by manually checking all the results. Through this method, 82 valid images of algae have been gathered out of a total of 1012 downloaded images, and 101 images of foams out of 4094 downloaded images.

Some recurring elements have been noticed among the images that portrayed neither foams nor algae: from now on these will be labelled “false positives”. These elements generally trick the search engine as in some cases the images may look like the phenomena our study investigates. For instance, false positives for algae were landscapes with grass, water lilies, clean water surrounded by trees and vegetation, paintings and red metal powder. False positives for foams, instead, were cloudy satellite images, clouds in general, ice floating on water, snowflakes, glasses with drops of water, stones, waves and sun reflected on water. As the results will show later, the occurrence of certain false positives in the search by image could give some anticipations about the behaviour of the algorithm. More precisely, images containing the above-mentioned elements will have a high probability of being detected as false positives, especially as far as foams are concerned.

On the one hand, this process has considerably increased the number of images at our disposal. On the other, it has introduced elements of disturbance. As a matter of fact, algae and foams are unstable objects without fixed dimensions, whose shape, extension, colour and appearance (i.e. compact, dispersed, linear, scattered) may vary. They can be found in the sea, in lakes and smaller basins, and in rivers. Pictures can be taken from different observation points and with various inclinations of the camera. The diversity found in this larger dataset of images could not have been found by looking at the SIMILE project context alone, which takes into consideration only the Insubric Lakes.

Considering the global interest for these phenomena, including into the dataset a significant variety of their manifestations is clearly an added value for the pre-filtering system, because it helps increasing its usability beyond the framework of the SIMILE project.

## 2.2 Data preparation

After downloading the images, several pre-processing operations needed to be performed in order to elaborate the final dataset. The dataset was used to train two different algorithms: a Convolutional neural network (CNN) and an object-detection algorithm called faster Region-based CNN (R-CNN). It is important to notice how the two algorithms – which will be detailed in the following section – partially required different pre-processing operations, as it will be explained below.

**Remove duplicate images:** Considering that the images were obtained from multiple sources, some of them appeared twice or even more times, but were labelled under different names. In order to remove the duplicates a script was implemented so as to obtain the pixel values of an image. Using a hash function called MD5 (<https://en.wikipedia.org/wiki/MD5>), a hexadecimal code (an alphanumeric string such as 21933563820f99833ad07aac2e818a6b) was generated based on the image pixel value. The code generated was compared among the images: those with an identical value were considered duplicates, then the exceeding copies were removed from the dataset.

**Label the images:** When using the CNN algorithm, the images could be put in a folder labelled with the name of the phenomenon in order to generate the labels from the structure of the directory. This has been done by using the `flow_from_directory` function in Keras (<https://keras.io/api/preprocessing/image/>). In order to label the images using the object-detection algorithm, the phenomenon needed to be identified within each image by drawing one or more bounding boxes around it, and assigning a label corresponding to each phenomenon (algae or foam). In order to perform this action, a tool for image annotation written in Python, called `LabelImg` (<https://github.com/tzutalin/labelImg>), was used. The output consisted of the image and a homonymous XML file (Extensible Markup Language) containing the coordinates of the bounding boxes and the label name. The labelled images were then uploaded on a platform called Roboflow (<https://roboflow.com/>), which helped performing the following processing steps, needed only for the object-detection algorithm.

**Augment the images:** Once the images along with their XML files were added to Roboflow, it was possible to verify whether all of them were labelled, and to control and modify the location of bounding boxes in case they were outside the border of the image. In order to increase the amount of input data two augmentation steps were applied to all images. A horizontal flip and an image rotation of  $\pm 15$  produced two augmented versions for each image. Figure 1 shows a sample of the dataset following data augmentation.

**Export to the required output format:** Once the dataset was ready, it could be exported to the format needed for the model. Roboflow provides the opportunity to choose the output format based on the algorithm one wishes to train. Then one can either download the dataset on a local machine or get the URL of the data. The format required in this study was TFRecord, a TensorFlow format that stores the sequence of binary records ([https://www.tensorflow.org/tutorials/load\\_data/tfrecord](https://www.tensorflow.org/tutorials/load_data/tfrecord)).

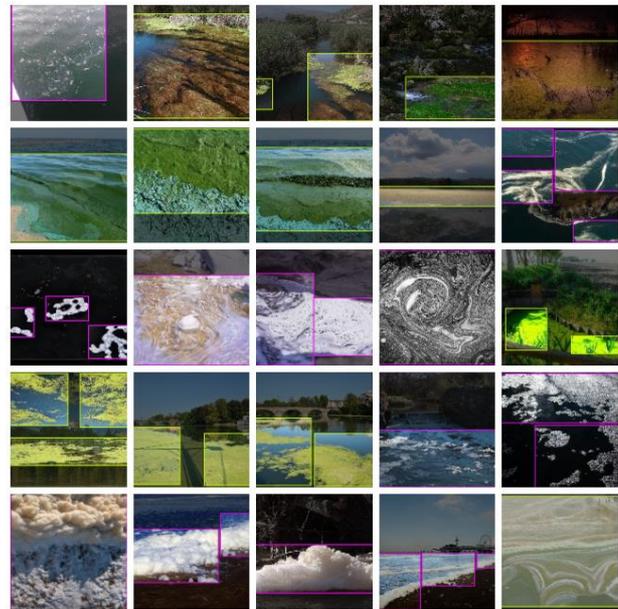


Figure 1. Sample of dataset images after data augmentation

## 2.3 Tools and approaches

In order to perform an automatic identification of water quality phenomena (here algae and foams), three approaches were considered, as explained below.

**Clarifai:** Clarifai (<https://www.clarifai.com/>) is an AI platform for computer vision, natural language processing and automatic speech recognition. It offers pre-trained models as well as the opportunity of training a model using a custom dataset. The services can be used through Clarifai API, which has a high-speed response return and can be integrated in AI-based mobile or web applications. Our first attempt was done by building a custom model using the initial dataset of 60 images of both foam and algae classes. Because of limitations concerning the number of free API calls (1000 free calls), the black box regarding the structure and parameters of the model and the peculiarity of the case studied, it was decided to construct and train a new CNN custom model. It is important to note that the pre-trained models available on Clarifai (<https://www.clarifai.com/developers/pre-trained-models>) are very efficient in the detection of objects in images. The pre-trained models include a general model detecting a variety of objects, as well as more specific models such as face recognition and the detection of humans and cars, to name a few. Even though this initial attempt with Clarifai was characterised by the availability of a limited dataset (30 images for algae and 27 for foams) and other limitations, it showed promising results that encouraged us to continue with a more detailed approach.

**Convolutional neural network (CNN):** CNN is a deep learning algorithm which initially has been used to study the brain's visual cortex and is now widely used to identify patterns for image processing and sound recognition (Albawi et al., 2018). Thanks to the availability of large amounts of data, as well as to the recent advances made in computing power, CNN models have achieved a high level of performance in the identification of patterns in complicated visual tasks, which sometimes is superior to the abilities of a human being (Gu et al., 2017). When using a CNN model, a kernel (filter) functioning as a moving window is



1. perform image annotation by drawing bounding boxes around the object of interest in the image and label them with *algae* or *foams* tag;
2. apply data augmentation (e.g. image rotation, horizontal or vertical flip, etc.) to address the lack of input images;
3. finalise the dataset and extract the required data format for the model (in our case: TFRecords format);
4. select and configure the pre-trained model;
5. train the model using the updated dataset and monitor loss, mAP and recall while training;
6. evaluate model performance and adjust its parameters;
7. observe the results of predicted bounding boxes on the test dataset.

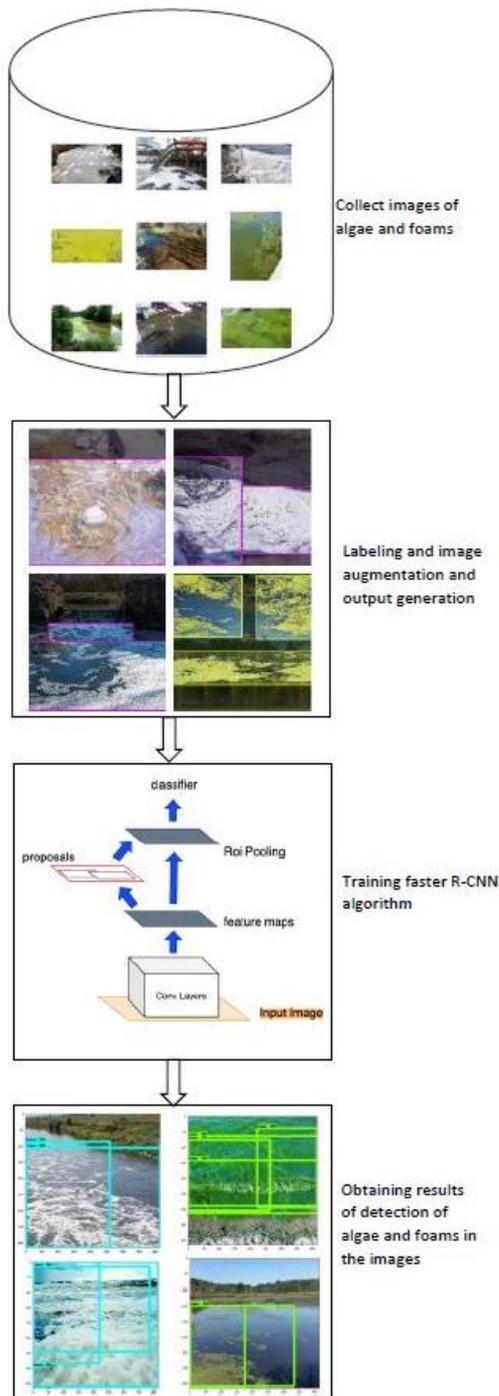


Figure 4. Training steps of R-CNN model

### 3. RESULTS AND DISCUSSION

#### 3.1 Model performance

**CNN:** The results obtained by using CNN show that the model has learned relatively well on the training dataset. However, in the validation dataset we can observe some noises in the accuracy with values fluctuating between over 90% and 50% (Figure 5). Although after epoch 120 we observe more stability in the validation accuracy/loss, due to the observed gap between training and validation accuracy/loss it can be concluded that the model is suffering from high variance and thus overfitting. This behaviour could be due to the relatively small amount of data used to train the CNN or to the heterogeneity in the dataset. However, in order to have a better understanding of the cause of this fluctuation, changes in different parameters need to be tested in the future. A solution for the limited size of the dataset could be found by using transfer learning, that is, by using the weights of the pre-trained models on large datasets. The present study has not tested this solution, so it remains as a hint for future investigations.

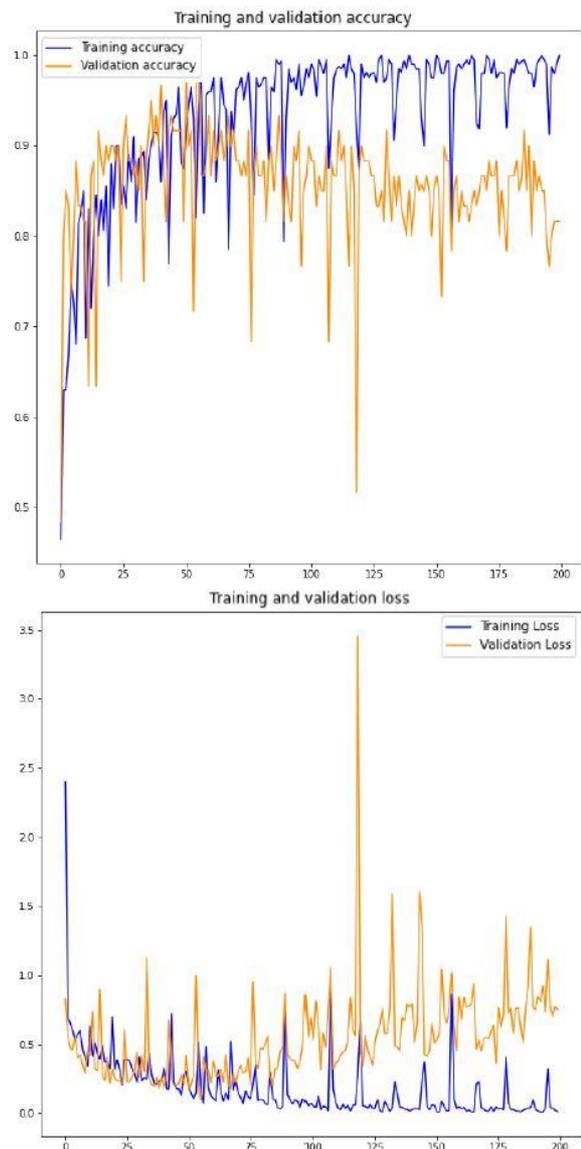
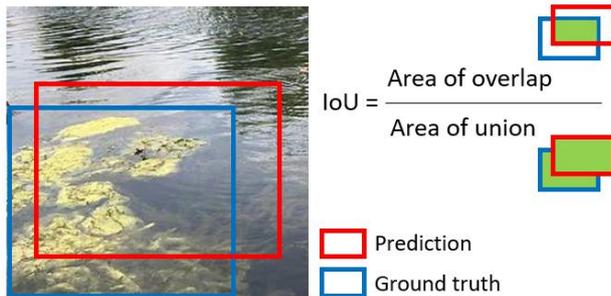


Figure 5. CNN performance. x axis: number of epochs, y axis  
Top: Accuracy; Bottom: Loss.

**Object detection:** the three runs were compared with regard to model performance in order to consider the ability of the model to classify the object and to define its location correctly. A possible index for model evaluation is a measurement of the overlap between the predicted bounding box and the ground truth bounding box, which is called IoU (Intersection over Union, see Figure 6).



**Figure 6.** Intersect over Union (IoU), visual explanation

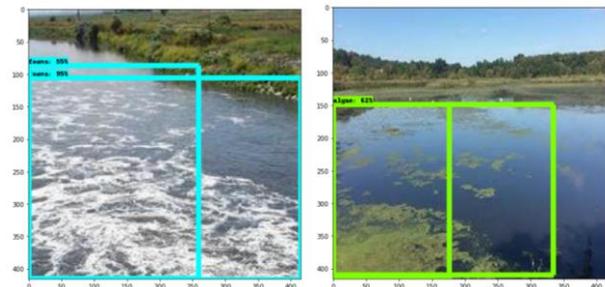
Therefore, IoU can be set as a threshold in order to consider whether a prediction is true or whether it is a false positive. For instance, setting IoU threshold to 0.5, if the IoU of the prediction is above this threshold, it is considered as true positive, if below it is considered as a not precise detection. The IoU threshold value was set to 0.5, then the average recall and mAP were compared.

Training steps	Average recall	mAP	Training time
1000	44.5 %	12.5 %	Approx. 30 min
10,000	41.6 %	17.6 %	Approx. 5 hrs
20,000	44.6 %	19.9 %	Approx. 8 hrs

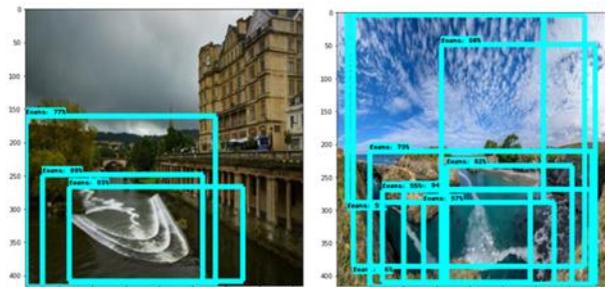
**Table 2.** Indicators of model performance

The results shown in Table 2 highlight that with 20'000 steps the model performs better with a higher mAP. Even though the results of the recall performed with 1'000 steps are closer to those performed with 20'000 steps – and also higher than the recall with 10'000 steps – the mAP increased as we trained the model with more steps. That is to say, the model learns early to predict the phenomena, but the location of detected phenomena improves by increasing the number of steps. The results can be compared with the few existing studies on object detection of HAB (Kumar & Bhandarkar, 2017; Samantaray et al., 2018). Even though the recall and mAP for faster R-CNN are lower than what they achieved, considering that the object of identification were two phenomena, and also that the dataset was heterogeneous and small, the results are still promising for the detection of more than one phenomenon, given that the model is trained on a larger dataset. The results of predicted classes and bounding boxes on some of the test set images (using the model trained with 20'000 steps) are presented in support to the discussion of model performance (Figures 7-11). The model performs better in the detection of algae than foams. Several cases of false positives have been detected in which clouds, stones or light reflected on water were identified as foams. However, the positive aspect is that no false negative was detected for foams, and all the false positive bounding boxes featured in images that included also

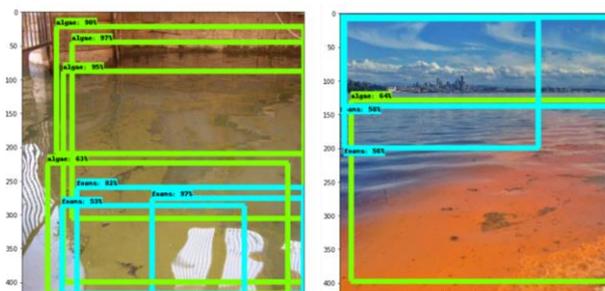
actual foams (Figure 8) or algae (Figure 9). It is interesting to note that no cases of false positives for algae were detected. However, there were cases where algae were not detected (n. 3 false negative), especially in those images where the phenomenon was particularly extended and covered the whole image. In those cases, a contrast with clean water or other elements was not available (Figure 10). The testing of the model with images of clean water showed that in no image the presence of algae was predicted (no false positives). On the contrary, as far as foams are concerned, most of the images containing the reflection of light on clean water were predicted as false positives, as expected (Figure 11). In conclusion, the model works well with algae, but it needs more investigation regarding foams. The model correctly predicts foams when foam is in the image, but it also predicts many false positives.



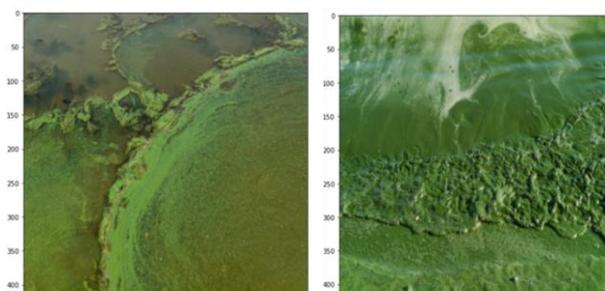
**Figure 7.** True positives for foams and algae (correctly detected and located)



**Figure 8.** True and false positives (clouds, right) for foams



**Figure 9.** True positives for algae and false positive for foams (reflection of light, left and clouds, right)



**Figure 10.** False negatives for algae (not detected)

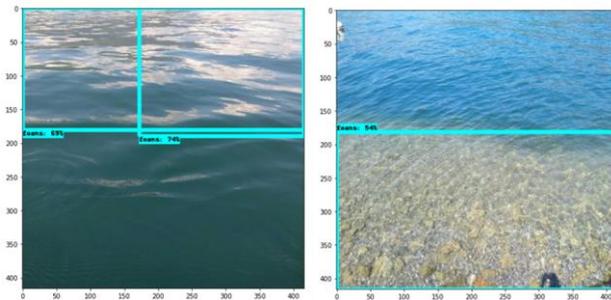


Figure 11. False positives for foams on clean water

### 3.2 Conclusions

Advances in ML and particularly in computer vision have resulted in many studies that integrate such techniques in their research. CS is among the areas whose integration with ML techniques has received attention in recent years. This article discussed how to integrate ML in a CS application focused on detecting harmful phenomena (i.e. algae and foams) that affect the quality of lake water. Various algorithms have been tested in order to address the aim of an automatic identification of algae and foams in images collected by citizen scientists. Among the various approaches tested, the faster R-CNN object detection algorithm proved to be more suitable, with a performance closer to what other, similar studies have achieved.

However, this research presents some aspects that would benefit from further investigation. For example, one could try the proposed approach using a larger dataset, as the one used here has proved to be too small when considering the complexity and peculiarity of the issue that this study investigated. A larger dataset could also allow for the introduction of more specific tags in order to better distinguish the phenomena analysed and their various manifestations (e.g., compact, linear or scattered algae or foams), hopefully reducing the number of false positives.

In addition to this, among the available algorithms for object detection, only faster R-CNN was trained. However, other algorithms such as SSD (Single Shot Detector), YOLO (You Only Look Once) or R-FCN (Region-based Fully Convolutional Networks) could be trained in order to have a clearer understanding of which performs best in the detection of harmful phenomena in lake water. Finally, another important aspect that can be explored is that of performing predictions considering the location of an image, and not only its content, in such a way that if a model predicts algae or foam in an area with a low probability of occurrence for such phenomena, this will negatively affect the reliability of the prediction.

At the current stage of development this tool may support environmental agencies, but it still presents some aspects that need to be improved, so it cannot fully substitute a manual check if total accuracy in the manifestation of these phenomena is required.

### ACKNOWLEDGEMENTS

The research described in this paper is part of SIMILE project (ID: 523544), which has been funded with the support from the European Commission within the Interreg Italy-Switzerland 2014-2021 programme.

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