CITIZEN SCIENCE:
THEORY AND PRACTICE

The Potential of Deep Learning Object Detection in Citizen-Driven Snail Host Monitoring to Map Putative Disease Transmission Sites

COLLECTION:
AI IN CITIZEN SCIENCE

RESEARCH PAPER

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ubiquity press

ABSTRACT

Schistosomiasis is a neglected tropical disease caused by parasitic flukes transmitted by freshwater snails. Despite increasing efforts of mass drug administration, schistosomiasis remains a public health concern and the World Health Organization recommends complementary snail control. To address the need for broad-scale and actual snail distribution data to guide snail control, we adopted a citizen science approach and recruited citizen scientists (CSs) to perform weekly snail sampling in an endemic setting in Uganda. Snails were identified, sorted and counted according to genus, and photographed; and the photos were uploaded for expert-led validation and feedback. However, expert validation is time-consuming and introduces a delay in verified data output. Thus, artificial intelligence could provide a solution by means of automated detection and counting of multiple snails collected from the field. Trained on approximately 2,500 citizen-collected images, the resulting model can simultaneously detect and count *Biomphalaria* and *Radix* snails with average precision of 98.1% and 98.8%, respectively. The object detection model also agreed with the expert's decision, on average, for 98.8% of the test images and can be run in real time (24.6 images per second). We conclude that the automatic and instant detection can rapidly and reliably validate data submitted by CSs in the field, ultimately minimizing expert validation efforts and thereby facilitating the mapping of putative schistosomiasis transmission sites. An extension to a mobile application could equip CSs in remote areas with instant learning opportunities and expert-like identification skills, overcoming the need for on-site training and extensive expert intervention.

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KEYWORDS:
Object detection; schistosomiasis; snail monitoring; citizen science; Sub-Saharan Africa

TO CITE THIS ARTICLE:
Chan, KH, Tumusiime, J, Jacobs, L and Huyse, T. 2024. The Potential of Deep Learning Object Detection in Citizen-Driven Snail Host Monitoring to Map Putative Disease Transmission Sites. *Citizen Science: Theory and Practice*, X(X): X, pp. 1–15. DOI: https://doi.org/10.5334/cstp.724

INTRODUCTION

Snail-borne parasitic diseases form a major public health and economic challenge for Sub-Saharan Africa (SSA) (World Health Organization 2022a). Among these diseases, schistosomiasis and fasciolosis, also known as respectively snail fever and liver fluke disease, are the most prevalent. They are caused by *Schistosoma* and *Fasciola* parasites that use specific freshwater snails (*Biomphalaria* and *Bulinus* snails for *Schistosoma* and *Radix* snails for *Fasciola* parasites) to complete their life cycles. Contraction of these diseases can occur through water contact in sites where infected snail hosts are present. Schistosomiasis is usually not a fatal disease, but chronic infection in humans can lead to severe complications like liver and bladder fibrosis, infertility, stunted growth and cognitive impairment in children (Gryseels et al. 2006). It affects more than 200 million people worldwide, but it can also lead to production losses in the livestock industry since some schistosome species also infect animals (World Health Organization 2022a). Fasciolosis, however, predominantly affects livestock worldwide, with associated global economic losses of more than US$3.2 billion per year (Mehmood et al. 2017), but depending on cultural practices, human infections also occur, mainly in Asia and South America (Caravedo and Cabada 2020).

To control human schistosomiasis infections and morbidity, mass drug administration of the drug praziquantel has been implemented in the past few decades, targeting school-aged children (Gray et al. 2010). This helped to significantly lower the prevalence of human infections (Kokaliaris et al. 2022), but the disease is still widespread, and a meta-analysis has shown that drug treatment without snail control has significantly less impact (Sokolow et al. 2016). The World Health Organization now advocates complementing drug treatment with snail control and community involvement to sustainably control the disease (World Health Organization 2022b). Active, broad-scale and regular snail monitoring has therefore become more urgent in providing the necessary information to guide targeted, local snail control. Targeted snail control involves the application of the snail control strategy (physical, chemical, or biological) only in areas that are contributing to schistosomiasis transmission, thus minimizing the environmental impact while controlling disease spread (Allan et al. 2020).

However, the traditional specialist-dominated sampling strategy may not suffice to handle the long-term snail sampling program, particularly when there are very few malacological snail experts in sub-Saharan Africa (Shiff 2017), and beyond. Moreover, many of the endemic areas are remote and sometimes hard to reach, complicating routine monitoring. This is where citizen science comes in, since data collection by citizens can generate high-resolution datasets, which scientists alone cannot achieve (Ashepet et al. 2021).

The ATRAP project, which stands for Action Towards Reducing Aquatic S nail-B orne Parasitic D iseases, was launched in 2019 to investigate the potential of recruiting citizen scientists (CSs) to monitor freshwater snail hosts in two endemic settings. The project partnered together with local leaders to select 25 citizens each in the Lake Albert region in western Uganda and in Kongo Central in the Democratic Republic of Congo (DRC). After two days of initial training in safety measures, morphological snail identification, and field sampling techniques, the CSs performed weekly monitoring at 77 fixed waterbodies (an average of 3 sites per CS) in each country. Snails were first identified morphologically to genus level using a simplified key adopted from Brown (1994). Then they were counted, photographed, and the photographs were uploaded to an online data collection platform using KoBoToolbox (Available from: https://www.kobotoolbox.org/). More information on the site selection and training process, and detailed information on the study design can be found in Brees et al. (2021) and Tumusiime et al. (2024). The snail species belonging to the genera *Biomphalaria*, *Bulinus*, and *Radix* were the prime targets to be sampled and analyzed for their population dynamics to infer putative schistosomiasis and fasciolosis hotspots.

The citizen-collected images, along with the submitted snail identification and counts, were semi-automatically validated by experts through a preset python script. If inaccurate results were noticed in the validation session, experts would record this and provide individual feedback to improve the CS's performance (Brees et al. 2021). Although the CSs generally performed well after the initial training, the preliminary results showed that the accuracy of snail identification tended to improve after refresher trainings and personal feedback sessions after these validation rounds (Tumusiime et al. 2024). However, this procedure of producing expert validation, providing refresher trainings, and in-person communication is time-consuming and labor-intensive. The validation of each submitted report takes two minutes, thus one year of weekly sampling of 77 sites would require at least 130 working hours. With non-stop data submissions, the validation rate might not keep up with the data inflow. Not only would this introduce a delay in verified data output, but it would further create a lag in timely incorporation of feedback to the next sampling round, impeding improvement in CSs' accuracy because they might have to wait for weeks for feedback. Moreover, it would also limit the potential for upscaling to other regions with more CSs.

Automating the whole image validation process by adopting artificial intelligence may assist the specialists' validation work and loosen the constraints on the scale of verified data output. With the advancement of computing power, the use of computer vision with deep learning algorithms such as Convolutional Neural Network (CNN) has been growing in popularity in different fields to automate repetitive and labor-intensive research procedures, such as pest counting, timber defects identification, and wildlife monitoring (Chen et al. 2014; Hong et al. 2021; Ramesh et al. 2021). One convincing example is the work from Norouzzadeh et al. (2018), presenting a deep learning image classification model based on CNN to classify the Snapshot Serengeti camera trap dataset of 3.2 million images with up to 96.6% accuracy. Recent research also shows the feasibility of automating the identification process; classifications of microscopic pictures of schistosome parasites and snail hosts by computer vision applications had a similar accuracy as classifications by experts (Tallam et al., 2021). Nonetheless, the CNN image classification model deployed in that project was limited to classifying a single specimen in each image. It cannot, therefore, be implemented in our citizen science workflow, since the number of snail specimens per picture can be as high as 100 snails. The object detection model, which is developed upon image classification (Girshick et al. 2014), would be a suitable alternative because it can automatically detect multiple objects and identify the specific class of each object in one input image. Indeed, object detection algorithms have been applied to ecological research (Eikelboom et al. 2019; Hatton-Jones et al. 2021) and in citizen science projects more frequently in recent years (Bowley et al. 2019). For example, Eikelboom et al. (2019) have trained a RetinaNet model based on an aerial image dataset (561 images with 10,284 animals) to detect, count, and estimate the animal populations.

Despite the promising examples of AI, object detection on pictures of snails obtained directly in the field has not been explored. The image captured in the field by citizens imposes another layer of detection difficulty, for example, images with lower resolution and lower quality due to the mud covering the snails. Even with the model performing well, it does not necessarily mean that the model surpasses trained CSs' performance. As reported by Tumusiime et al. (2024), the CSs performed very well on snail identification, with misidentifications being less than 0.02% for all genera, based on the 5,398 reports that were submitted. Only if the model consistently produces equal or better accuracy than the CSs can it function as a reliable validation tool to automatically screen CS submissions, minimize labor-intensive expert work, and reduce delays in feedback and verified output.

Herein, we aim to provide a proof of concept that object detection techniques can be applied to automate and thereby speed up validation of citizen-collected data. We demonstrate the implementation of the object detection algorithm, You Only Look Once (YOLOv4) (Bochkovskiy et al. 2020) in detecting, identifying, and counting the snail specimens on citizen-collected images with a small dataset of approximately 2,500 images with, in total, 25,000 snails. We aim to study how accurately the object detection model can detect different genera of targeted host snails. By comparing the model performance with that of trained CSs, ultimately, we evaluate the potential of using such a model to validate the submissions from CSs to facilitate the mapping of putative snail-borne disease transmission sites.

METHODOLOGY

DATA COLLECTION

The data used in this paper was limited to the snail collection from Uganda that took place between 1st March 2020 and 5th October 2021. We did not include the data from DRC because the monitoring started later and thus the data was generated after this project started. Snail sampling was performed by 25 CSs at 77 fixed water body sites in Uganda on a weekly basis. Snails were scooped for 30 minutes, then sorted and counted according to the targeted genera: *Biomphalaria*, *Radix*, and *Bulinus*. All other species (including *Gyraulus* species, which have a morphology similar to *Biomphalaria* species but are not involved in schistosomiasis transmission) were grouped under the category "Pool". Pictures of all the sorted snails were taken by the front camera of a Huawei Y7 smartphone. The images and snail counts were then submitted to the online KoBoToolbox platform in 1024 × 768 format and later verified by experts.

DATASET PREPARATION

During the above sampling period, a total of 4,224 images were submitted by the CSs. Among these, 1,740 images were submitted as *Biomphalaria* spp.,1,344 images as *Radix* spp., 427 images as *Bulinus* spp., and 713 images as "Pool." After verifying and excluding images with faulty identifications or counts, images of bad quality with obvious object occlusion, severe blurriness from dirty camera lens, lost focus, or dimmed lighting were removed from the dataset to ensure data quality. Images containing densely clustered snails, mostly from the "Pool" category, were also removed to avoid mislabeling and overlapping of the annotated bounding boxes. The *Bulinus* snails were also excluded due to the very low reported numbers. Altogether, 1,638 images were discarded, leaving a total of 2,586 images qualified to be used for the object detection dataset.

The first 591 images were manually annotated with bounding boxes and class labels in LabelImg software (Tzutalin 2015). A total of 6 classes of labels were annotated, including *Biomphalaria*, *Radix*, *Gyraulus*, and three other sympatric or co-occurring morphologically distinct snail groups from the "Pool" snail group ("Triangular," "Round," "Spiral" shape). As the preliminary results showed that including *Gyraulus* labels led to more accurate detection of *Biomphalaria* species, *Gyraulus* was included in the dataset to reduce the chance for sites being wrongly assigned as potential transmission locations for schistosomiasis. The "Pool" snails were also included to improve the model ability to differentiate different snails in our dataset.

The remaining 1,995 unannotated images were annotated with a simple two-step approach. A prototype model was first trained based on the 591 manually annotated images. Later the unannotated images were fed into the prototype model so the model could automatically annotate the snail species that occur in the unannotated images. To secure a correctly labelled dataset, all these automatically annotated labels and bounding boxes were later approved or corrected by experts manually. The newly annotated images were then combined with the manually annotated images to form a fully annotated dataset.

MODEL TRAINING AND CROSS-VALIDATION

Cross-validation with resampling was implemented to estimate the actual model performance. A total of 250 images of *Biomphalaria* and *Radix* were first randomly subtracted from the total dataset as a test set to check if the model can accurately detect unseen data. Then the remaining dataset was randomly shuffled and split into train/validation datasets with an 8:2 ratio for five times (Table 1); where each train set was used to train one candidate model, and each validation set was used for assessing the performance of the candidate model (Alexandropoulos et al. 2019) for each resampling. Whereas *Biomphalaria* and *Radix* images were split into the 8:2 ratio, the Pool species (specifically the triangular and spiral) were not strictly in the 8:2 ratio because the distribution of Pool species was not balanced across the Pool images.

		TRAIN	VALIDATION	TEST
Number of individual snails	*Biomphalaria* spp.	11,417	2,966	1,410
	Radix spp.	5,530	1,274	902
	"Pool" — (Round shape)	694	206	/
	"Pool" — (Triangular shape)	146	22	/
	"Pool" — (Spiral shape)	1,327	375	/
	Gyraulus spp.	941	228	/
Number of images		1,868	468	250

Table 1 Dataset distribution after the split for cross-validation and the number of labels for each class of citizen-generated images for the best candidate model. Note that the test set of 250 images was first randomly selected and separated from the fully annotated dataset. Then the remaining images were randomly assigned to the train and validation dataset in an 8:2 ratio.

Upon dataset preparation, five YOLOv4 models were trained within the Google Colab Pro virtual environment that provided online GPU (Graphics Processing Unit) deployment (Nvidia(R) Tesla(R) P100 GPU). Transfer learning was adopted here because of the relatively small sample size. The idea behind this is that the "knowledge" gained from one dataset could be transferred/re-used to learn different classes from other datasets to speed up the training process. In practice, pre-existing weights (which are the learnable parameters that define model output) trained on the other dataset, usually a more generalized and larger dataset, were used as a foundation to initiate the training of another smaller/desired dataset that the operator wished to learn (Tan et al. 2018). YOLOv4 weights pre-trained on the Microsoft COCO dataset, which consists of 330,000 images from 80 classes of objects (Lin et al. 2014), have been considered as standard go-to pre-trained weights due to the vast knowledge accumulated in the dataset and were used in the original YOLOv4 study (Bochkovskiy et al. 2020). Thus, they were used as pre-trained weights to initialize our training.

The configuration, layer structure, and hyperparameters of the models mostly followed the default setting from the YOLOv4 official Github page (Bochkovskiy et al. 2020) (Supplemental File 1: Table 1). The batch size was set to 64 and the maximum batches were calculated by the number of classes multiplied 2,000 times (i.e., 14,000 batches). The image input size was set to 608 × 608. Image augmentations were randomly applied at each training iteration, such as saturation, exposure, and hue transformation, as well as a mosaic augmentation to improve training quality (Bochkovskiy et al. 2020). Considering the small dataset and the accurate model performance trained by default settings, we considered that further hyperparameter tuning would not be very beneficial and it was not further pursued.

CITIZEN SCIENTISTS' PERFORMANCE

The expert validation of CSs submissions were performed based on an image-wise approach in which an entire image would be classified into only one snail genus classification (Brees et al. 2021). It required CSs to correctly identify the genus of the snails and only include snail specimens belonging to that genus into a visually clear image for submission. Otherwise, the submission would be validated as incorrect. For example, if there was one *Radix* included

in the submissions for *Biomphalaria*, the entire submission would be classified as incorrect. Here, the accuracy of a CS submission is evaluated:

$$Accuracy = \frac{Correct\,submission}{Total\,submission}$$

MODEL PERFORMANCE

Once trained, each candidate model was tested with the validation dataset and the detection accuracy was verified through the A verage P recision (AP) of each class of labels. The AP was calculated by three metrics: namely P recision, R ecall and intersection over U nion (IOU). Precision and r ecall were calculated for each class of objects through the confusion matrix:

1. T rue Positive (TP), where the individual snail in the image was correctly detected in the correct location and with correct identification;
2. F alse P ositive (FP), where the detection of an individual snail was incorrectly made in a specific location where this snail specimen did not occur;
3. F alse N egative (FN), where no detection was made despite the presence of the snail specimen in that specific location on the image; and
4. T rue N egative (TN), where no detection was made in an area without snails (it was ignored in these calculations).
5. Precision is the ratio of the correct individual snail detection over all the detections made by the model:

$$Precision = \frac{TP}{TP + FP}$$

Recall is the ratio of correct individual snail detections over the overall ground truth, which is the true number of the snails in the image:

$$Recall = \frac{TP}{TP + FN}$$

IOU describes the spatial accuracy of the prediction towards the ground truth in the image. It is calculated by the overlapping area of the predicted and ground truth bounding boxes over the total area of these two boxes. The higher the IOU, the more accurate the predicted location and size of the bounding box to the ground truth.

$$Intersection\,Over\,Union = \frac{BoundingBox_{ground\,truth} \cap BoundingBox_{prediction}}{BoundingBox_{ground\,truth} \cup BoundingBox_{prediction}}$$

Through the P recision-R ecall curve with a 50% IOU threshold following Everingham et al. (2010), the A rea U nder the precision-recall C urve (AUC) of each snail class is then calculated as the AP. AP represents the accuracy of predicting one specific object class under a certain IOU threshold regardless of the confidence. Notably, only the AP for the targeted snails (i.e., *Biomphalaria* and *Radix*) were reported because the remaining snail groups (i.e., *Gyraulus* and "Pool") were irrelevant to the validation process. The AP for the targeted snails along with the IOU of the candidate model was then reported. For a bigger picture of model accuracy in identifying all classes of snails, the F1 score, which represents the harmonic mean for precision, and recall rate were also calculated:

$$F_1 = 2 \cdot \frac{Precision \times Recall}{Precision + Recall}$$

Upon evaluating five candidate models for their AP in detecting the two targeted snails, the best performing candidate was selected as the final model.

EVALUATION

Since the expert validation was conducted on an image-wise basis, using AP (object-wise approach) to compare with the expert validation would not be appropriate nor fair. Considering this, an image-wise evaluation was adopted for the detections made by the best candidate model and the identifications conducted by the CSs. Only if all detection(s) from the model or the identification(s) from the CS matched with the expert-validated results, would they be counted as "1" and otherwise as "0" for agreement and disagreement, respectively. The agreement accuracy was then calculated by the sum of the number of agreements over all the images. The number of correctly detected snails was also evaluated with the snail counts submitted by the CSs.

$$Agreement = \begin{cases} 1, if\ detection = expert\ validation \\ 0, if\ detection \neq expert\ validation \end{cases}$$

$$Agreement\,accuracy = \frac{\sum_{j=1}^{n} Agreement_j}{Number\,of\,images(n)}$$

This approach was adopted for the test set (see Table 1, n = 250) to evaluate if the model would perform the same as expert validation in the unseen images. It was also tested with all the *Biomphalaria* and *Radix* reports ever submitted by the CSs (n = 3,084), regardless of the report correctness, image quality, and inclusion to the cross-validation process, for an overview of whether the model could replace the entire process of expert validation (Figure 1).

Lastly, the frame rate of detection (Frames Per Second: FPS) was evaluated within the Colab environment with Nvidia(R) T4 GPU for its runtime. If the model performed well in both the image-based validation as well as the count agreement, this would eliminate the need for *post-hoc* expert validation and counting by the CSs, respectively.

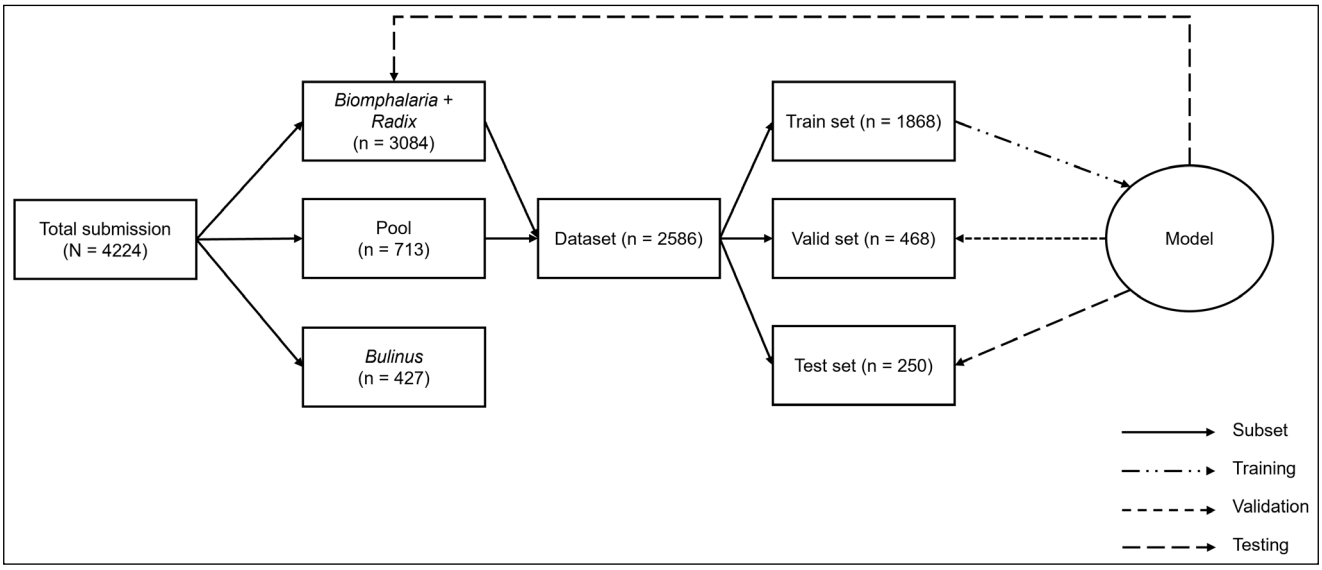

Figure 1 The workflow for training-validation-testing of the citizen-collected images of snail species, and the respective sample size. Note that only *Biomphalaria*, *Radix*, and "Pool" submissions were included in the dataset (n = 2,586) for model cross-validation. The test set was firstly separated from the dataset and then the remaining dataset was split into 8:2 ratio for the train and validation sets. Once the model was trained, it was tested against the test set (n = 250) and all the targeted snails ever submitted (n = 3,084).

MODEL DEPLOYMENT TO WEB APPLICATION PROGRAMMING INTERFACE

With the results showing promising accuracy, an open-access web application was developed to deploy the best candidate model (https://snaildetector.africamuseum.be/) with the Flask web framework. Because the object detection models normally require high computational power to function optimally (such as the need for GPU), the deployment to a web application programming interface (API) can lower the requirement of such use, considering that technological limitations may be encountered by citizen science projects based in sub-Saharan countries. The web API is hosted by the Royal Museum for Central Africa, Belgium, and run by a Linux server using 4 central processing units (CPUs) Intel(R) Xeon(R) Gold 5115 CPU and 6GB RAM.

RESULTS

CITIZEN SCIENTISTS' PERFORMANCE

During the given data collection period, a total of 4,224 images were collected, and among these, 1,740 images were identified by CSs as images containing *Biomphalaria* and 1,344 as images containing *Radix* snail specimens. The CSs were generally accurate throughout the whole period of the data collection, with accuracy attaining 98.97% and 95.68% for *Biomphalaria* and *Radix*, respectively (Supplemental File 1: Table 2). Noticeably, the accuracy on *Radix* at the initial stage of the monitoring was only around 80%, but through feedback, it improved over time and reached a stable state of around 95%.

MODEL PERFORMANCE AND EVALUATION

In terms of the object detection model, the candidate models performed similarly on the detection for *Biomphalaria* and *Radix* (Supplemental File 1: Table 3). Taking the best candidate model as the final model, its F_1-score reached 0.93 with a confidence threshold of 0.25. Particularly, the AP for *Biomphalaria* and *Radix* attained 98.13% and 98.79%, respectively (Figures 2 and 3). When this model was tested against the test set, the agreement accuracy reached 97.54% and 100% for *Biomphalaria* and *Radix*, respectively. If the model was further tested against all the *Biomphalaria* and *Radix* reports ever submitted by the CSs since the first sampling, without any preprocessing procedures (Figure 1), the model still performed similarly to the CSs but with slightly lower agreement accuracy. More specifically, the model aligned less with the expert validation for *Biomphalaria* identification (Supplemental File1: Table 4). This drop in alignment accuracy resulted mostly from unqualified images with high blurriness, images taken with the lens "zoomed out," and images with clustered snails.

In a more detailed note, the agreement for both *Biomphalaria* and *Radix* remained stable for images with less than 100 snail specimens per image counted by the CSs (around 95% and 98%, respectively) (Supplemental File 1: Table 2). Only when there were more than 100 snail specimens on the image did the agreement begin to drop to around 90%. Similarly, while there was a positive relationship between the CSs snail count and the one conducted by the model, the mismatch began to emerge from around 100 snails per image onwards (Supplemental File 2: Figure 1).

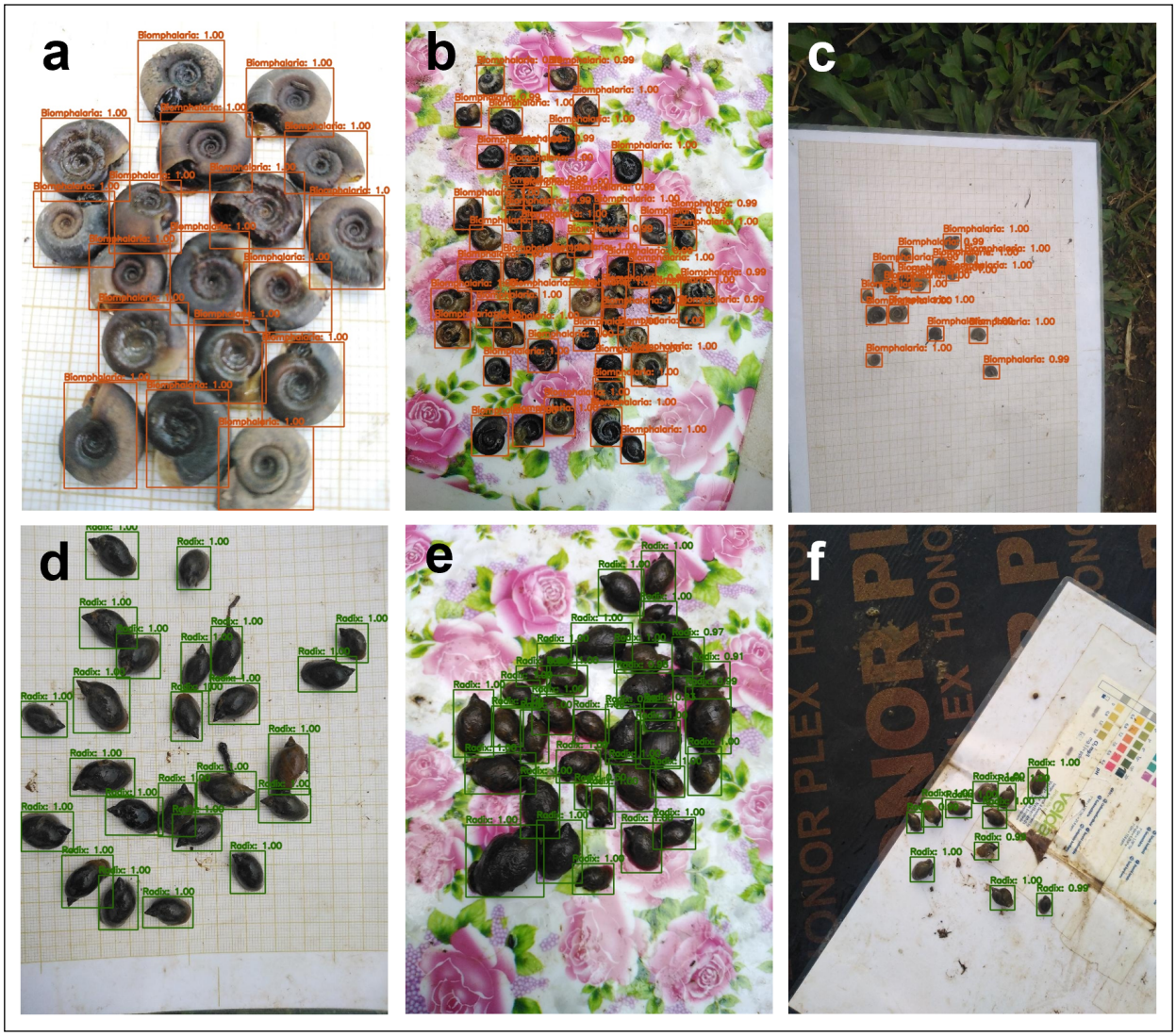

Figure 2 Examples of the detections on *Biomphalaria* **(a, b, c)** and *Radix* **(d, e, f)** snail specimens collected and correctly identified by the citizen scientists. Note that the orange boxes were *Biomphalaria* detections and the green boxes were *Radix* detections.

This suggests that the object detection would perform well for images with snail numbers lower than 100. And lastly, the model ran through the validation set of 468 images in 19 seconds, resulting in an FPS of 24.6 image/s.

WEB APPLICATION PROGRAMMING INTERFACE

With internet access, this application allows users with a smartphone to upload batches of images taken in the field to the API. It will then provide detailed results on the detection(s) (e.g., bounding box coordinates, detection confidence, and class count) for further data analysis (Figure 4). It also supports the voluntary upload of images with detailed descriptions (e.g., geographical locations) to compile a snail image database for future model training purposes. As the API was connected with CPUs only, the inference time was about two seconds/image (0.5 FPS), which was slower than the speed for the validation set with GPU usage.

DISCUSSION

Citizen science can considerably expand the spatial coverage and temporal resolution of the traditional academic monitoring of disease vectors (Palmer et al. 2017; Brees et al. 2021). But with more data, there are also more challenges regarding the manual handling of the influx of larger amounts of data, and the need for data validation before turning the data into insightful information. Here, we present a proof of concept of how deep learning object detection could contribute to solving these challenges by training an object detection model with a comparatively small dataset of around 2,500 snail images. The final model exhibits high accuracy in detecting both targeted snail genera (*Biomphalaria* and *Radix*) on object- (around 98% AP) and image-level evaluation (around 98% agreement accuracy). The model even presents almost

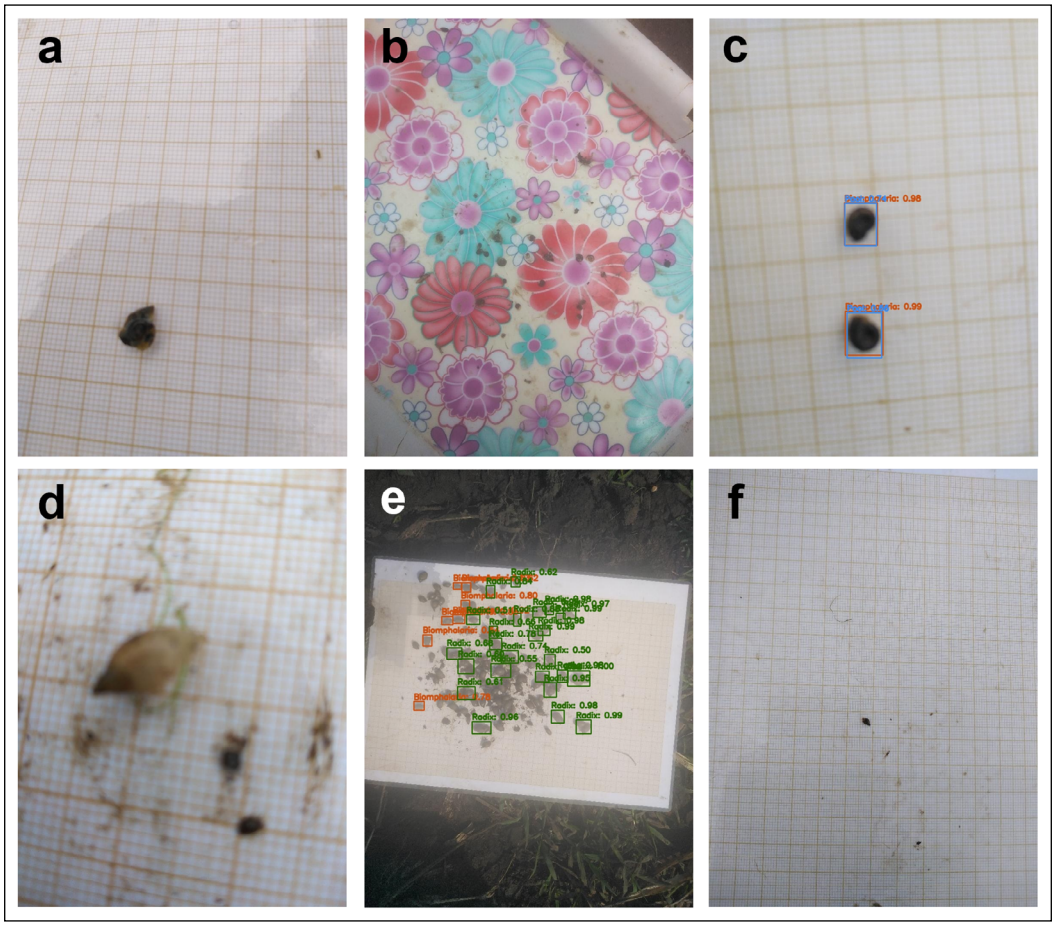

Figure 3 Examples of images submitted as *Biomphalaria* **(a, b, c)** and *Radix* **(d, e, f)** by citizen scientists where the model detection could not align with the expert validation. Note that the snails were either blurred (a, c, d) or too zoomed out (*b*, *e*, *f*). The orange boxes were *Biomphalaria* detections and green boxes were *Radix* detections.

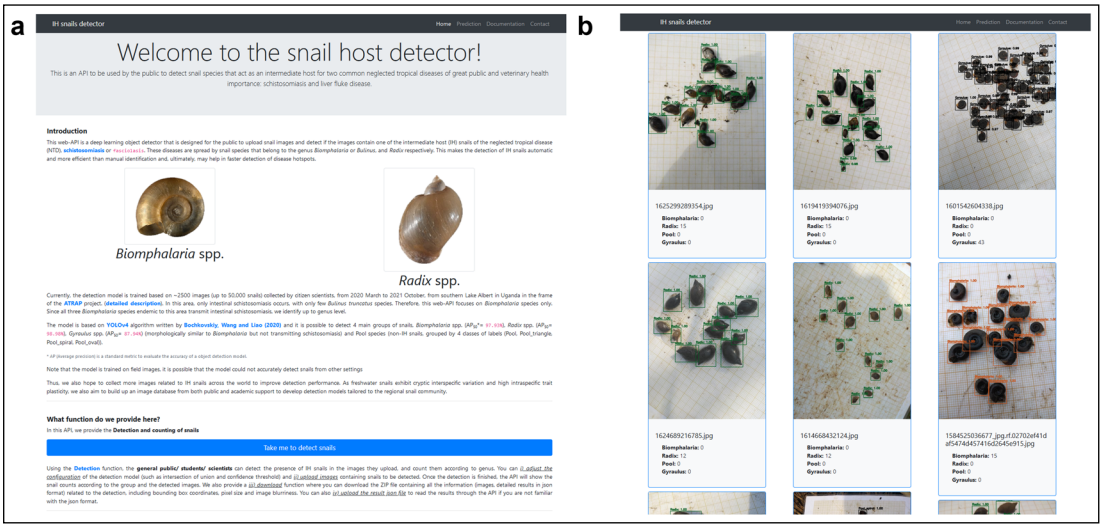

Figure 4 (a) The front page of the web application programming interface (API) and **(b)** the detection results. In the front page (*a*), it provides the introduction of the ATRAP and the overall status of the detection model. Users can also access the prediction page to select their preferable detection setting, upload their snail images collected from the field for detection, and download the detection results in compressed files once the images are detected. For the detection results (*b*), the API will provide snails images with bounding boxes, counting the number of *Biomphalaria*, *Radix*, *Gyraulus*, and "Pool" snails in the image. Here, we show some example images of *Biomphalaria* (*o range*), *Radix* (*g reen*) and "Pool" snails (*b lack*) collected from the field and put on A4 size graph paper (from the test set). Please refer to https://snaildetector.africamuseum.be/ for further details (Royal Museum for Central Africa 2024).

equal performance to the trained CSs (Supplemental File 1: Table 4). Also, with proper equipment, the model could be operated at 24 FPS, a speed far superior to human validation. Compared with the image classification model developed by Tallam et al. (2021), which can identify single snail specimens based on microscopy images, the current object detection model can accurately detect and count up to 100 snails simultaneously within the same low-resolution image collected from the field by citizens. These advancements further demonstrate that object detection could be a viable alternative approach to the labor-intensive and time-consuming data validation process that was implemented in the ATRAP project (Brees et al. 2021).

IMPLICATIONS FOR CITIZEN SCIENCE

Apart from the benefits of minimizing the data validation time and effort for the experts, the object detection model offers numerous opportunities to foster citizen science programs through integration with multimedia. Here, we embedded the model to a website , where citizen scientists and any interested citizens with an internet connection could freely upload their field snail images and receive prompt feedback from the model. Compared with the current non-AI-based approach (manual data validation, in-person feedback, and refresher trainings) that might cause delays of weeks to months, this AI implementation would empower citizens to bypass the lengthy traditional expert validation procedures and continuously build expert-like detection skills on the genus level without delay. With the easy implementation and maneuverability of the Flask framework, this API also allows future modification to serve other purposes, such as including other AI models for other disease vectors, including a dashboard to visualize vector distributions, or providing educational videos for outreach purposes.

Yet, our web API , by nature, requires an internet connection, which is still not always accessible or affordable in the Global South. For SSA alone, a quarter of the population has no internet access, and the median internet costs are the highest in the world (Tryphone et al. 2023). As recently developed YOLO models have much smaller storage size and are compatible with mobile phones (Lawal et al. 2023; Zeng et al. 2023), the object detection model can be adapted to a mobile application with an offline detection function where an internet connection is not required during the sampling. They can then receive instant feedback in the field from the offline model and upload images to the data platform only when they have access to the internet. Along with the explosive growth of mobile phone ownerships in SSA (Carney et al. 2023), this mobile adaptation can favor the upscaling of ATRAP to new areas, or very remote areas, where it is hard to organize regular refresher trainings. Once installed, the offline model can sustainably guide and train the CSs onsite by providing immediate response to validate and correct their submission, potentially replacing the onsite training conducted by the experts. Consequently, the human resources previously devoted to training can be redirected to more community-focused activities, such as volunteer retention and outreach. By incorporating easy-to-understand educational materials such as infographics and pictograms to visualize disease symptoms, risks, and preventive measures, the application can further equip CSs to raise awareness among their peers by responding to the growing digitization in SSA.

Although here we focus on the detection of snails, this technology can also be adapted to other vector-borne disease monitoring projects, which often require frequent data collection and validation over an extensive area, with few experts available to validate the data and train the CSs (Ashepet et al. 2021). For example, in the project of Pernat et al. (2021), more than 25,000 CSs contributed to mosquito monitoring and sampling in Germany for 8 years, generating 138,000 samples for experts to validate. While the authors did not specify the working hours for validation, one could only anticipate a substantial amount of work in identifying each mosquito and providing feedback. Instead, a similar project focusing on mosquito monitoring in SSA noticed such challenges and released an image identification model to identify the different species of mosquitoes (Pataki et al. 2021). They further integrated the model into the citizen science pipeline to boost the data collection process, assist risk model building, and promote awareness (Carney et al. 2022, 2023). Nevertheless, their model was constrained by the single object identification, and the requirement of a hand-held magnifier to capture individual mosquito images, which limited the surveying potential on mosquito population dynamics. By extending to object detection, it would open other opportunities such as mass trapping to speed up the entire data pipeline and refine the data quality.

LIMITATIONS AND FUTURE PERSPECTIVES

Despite the benefits and potential applications raised above, our study was also limited by some factors. First and foremost, our model was trained only to the snail genus level, rather than the species level. The species identity is, however, important in determining the potential risk for schistosomiasis. For example, 18 out of the 35 described *Biomphalaria* snails can transmit *Schistosoma mansoni,* while the other nine species are resistant to infection (Brown 1994; Lin et al. 2020). This means that our method could result in false positives; in other words, sites that harbor snail species that cannot transmit the

disease could be identified as potential schistosomiasis hotspots. While this risk should have minimal impact here because in the area we operated, and in Uganda generally, all the species of *Biomphalaria* (*B. pfeifferi, B. sudanica, B. stanleyi, B. choanomphala*, and *B. smithi*) are natural hosts of *S. mansoni* (Brown 1994), it should be taken into consideration if one aims to implement object detection on snail monitoring.

Species-level snail identification often relies on morphological characteristics of internal organs like the reproductive and digestive systems, which cannot be studied without snail dissection (Brown 1994). On the visual level, the intra- and inter-specific differences can be very subtle and deceptive even to experienced malacologists (Plam et al. 2008; Schniebs et al. 2022). Based on shell morphology alone, one could identify up to species level only if high-quality microscopic pictures are available, followed by advanced geometric morphometrics using landmark analyses (Mahilum and Demayo 2014; Palasio et al. 2017; Quenu et al. 2020). Although malacologists could also resort to DNA sequencing for better accuracy (Palasio et al. 2017), visual-based identification should still be the more cost-effective and suitable method for large-scale monitoring, considering that molecular work is very costly. Thus, AI-assisted research towards discovering new visual features for snail species identification should be attempted, as it was by Tsutsumi et al. (2023), who have successfully extracted the deep features of mandible images to distinguish different families of primates by using Variational AutoEncoder (VAE) in the absence of any landmark data. Because VAE can discover nonlinear features while maintaining interpretability, it is a suitable tool to explore the deep visual features of snail shell morphology and may open a gateway to improving our model to species-level detection.

With a limited dataset of 2,500 images collected in Uganda only, one could also expect that our model might not generalize well and would generate more false positives when it is exposed to new regions for monitoring, considering the geographic variation in snail morphology (Teodoro et al. 2010; Patel et al. 2015). Although updating models by collecting new images specific to these regions would be feasible, the substantial sampling and labeling effort would not be sustainable for the expansion of the monitoring. Instead, a viable and more cost-effective solution could be to use snail pictures or snail specimens from local museums to complement the morphological variance in the training dataset. Creative methods that make use of generative AI, such as that used by Toda et al. (2020), who generated synthetic datasets from seed specimens to detect seed types, have demonstrated the potential for how museum specimens could be utilized in the age of deep learning.

Meanwhile, any adoption of the object detection into citizen science should also take the data quality into consideration. In our raw dataset, the CSs submitted many images with high numbers of snails (>100), snails piled on top of each other, very low/high zooming, or heavily blurred images. Not only did this hamper the sample size for model training, but this also often led to underperformance of the detection and undermined the agreement accuracy. In Figure 3, the examples show that these bad images would distract the model and produce disagreement. It was also noticeable that the agreement accuracy of snail detection dropped with higher snail numbers, especially those exceeding 100 snails per image (Supplemental File 1: Table 5). Although preprocessing could be done, clear photography guidelines should be formulated to ensure good data quality and secure a consistent model performance. Otherwise, instance segmentation that allows labelling the exact coverage of the snails and detects the pixel-wise object outline could be a viable solution to circumvent this issue, particularly for clustering of snails. Recent studies of applying segmentation to other biological systems, such as microbes, leaves, and seeds, have already demonstrated successful differentiation of objects from densely packed, clustering situations (Kulikov and Lempitsky 2020; Toda et al. 2020).

Another caveat should be noted in regard to the efforts in labeling the data for training. Here, we adopted a two-step labelling approach to avoid the tedious and repetitive work of labeling more than 20,000 snails by training a prototype model to label 80% of the data. But it was still labor-intensive to evaluate the prototype and cross-check the annotations made by the prototype. Instead, extending our current approach of two-step labelling to active learning could largely reduce the efforts. Active learning is an iterative process that requires a human "oracle" and a "learner" model. Within this process, the learner will generate queries of labels from an unlabeled dataset and the oracle will have to verify such queries for the learner to learn over time (Settles 2009). It is particularly useful to reduce the high labelling costs in object detection. For example, Norouzzadeh et al. (2021) have demonstrated that only 14,100 images were needed to label a 3.2 million–image dataset by this approach (less than 0.5% of manual labelling effort). Otherwise, semi-supervised learning that exploits the use of pseudo labels (Lee, 2013) could be a good alternative as it requires little data to train. For example, the FixMatch algorithm that combines pseudo-labelling and consistency regularization requires only 2.5% of the original dataset to achieve similar accuracy (Sohn et al. 2020). These methods could boost the entire training procedure and accommodate larger datasets collected by citizen scientists.

CONCLUSION

The current proof of concept has shown that the automatic and instant object detection can rapidly and reliably validate data generated by CSs in the field. Our best model detects the targeted host snails, *Biomphalaria* and *Radix* species, with up to 98% in model accuracy (AP) and agreement with CSs under a fast pace of 24 FPS. Although the model is limited to genus-level detection and its generalization could be challenged by geographical differences due to the limited dataset, this AI technology still holds huge potential for improvement and allows adaptations to many facets of citizen science and parasitology. Particularly, by implementing such a detection model into a mobile application, the prompt feedback could equip citizen scientists with instant learning opportunities and expert-like identification skills. It is a great tool to overcome the need for on-site training and extensive expert intervention to transfer these skills, allowing upscaling and monitoring in remote areas. Such technological empowerment to the community would also strengthen social capacity and expedite data output. Even more, it could redirect the human resources for face-to-face meetings into more community-focused aspects like science communication, volunteer retention, and outreach. In conclusion, integrating deep learning object detection with data collection tools is a promising avenue for future snail monitoring programs, achieving both educational and scientific objectives at the same time.

DATA ACCESSIBILITY STATEMENT

Model weights, labelled image dataset, and accuracy evaluation can be found in 10.5281/zenodo.11411726. Please contact the corresponding author (KC) for further details if needed.

SUPPLEMENTAL MATERIALS

The supplemental file for this article can be found as follows:

- **Supplemental File 1.** Tables for training hyperparameters and details of each accuracy evaluation. DOI: https://doi.org/10.5334/cstp.724.s1
- **Supplemental File 2.** Figure for the counting difference between CSs and the final model. DOI: https://doi.org/10.5334/cstp.724.s2

ETHICS AND CONSENT

This study was approved by the Mbarara University of Science and Technology Ethical Review Committee with reference number MUREC 1/7, and by the Uganda National Council of Science and Technology under the reference number NS148ES. In addition, written consent was sought from the CSs who participated in this study. The extent of disclosure of the information they provided and their facilitation were fully discussed and formalised in a memorandum of understanding before the commencement of the data collection process. This memorandum was renewed annually following a refresher training to allow the CSs to share their experiences and expectations. All CSs were informed on the safety measurements during initial training, provided with protective gear, and asked to digitally confirm if the protective gear is worn before the start of the sampling.

ACKNOWLEDGEMENTS

We would like to thank all the citizen scientists most heartily for all their help: Alinda Hassan, Chotum Friday, Atanasi Marisel, Opio Isingoma, Ategeka Augustine, Bahemuka Bob, Masereka Haruna, Sebakara Fobius, Nyamahunge Imelda, Businge Zabron, Tumusiime Janet, Nsenga David, Night Marygoret, Kyaligonza Noeline, Mwesige Robert, Barisigara Gard, Tusingwire Henry, Natabi Specioza, Nakingi Rose, Bamuturaki Charles, Kamukama Josias, Nuwagaba Emmanuel, Tweheyo Julius, Bahungirehe Crezestom, Ategeka Rogers, Unimu Hadijah and Fuwarinyo Richard. We also sincerely thank Jef Brees and Noelia Valderrama Bhraunxs for the validation on the CS's submissions.

FUNDING INFORMATION

The ATRAP (Action Towards Reducing Aquatic Snail-Borne Parasitic Diseases) project was financed by the Development Cooperation program of the Royal Museum for Central Africa with the support of the Belgian Directorate-General Development Cooperation and Humanitarian Aid.

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR CONTRIBUTIONS

KC, LJ, and TH were responsible for conceptualization. KC was responsible for design, image annotation, experiments and analysis. JT provided feedback to the citizen scientists. KC prepared the first draft and all the authors contributed equally to the revising, proofreading and approved version before submission.

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TO CITE THIS ARTICLE:
Chan, KH, Tumusiime, J, Jacobs, L and Huyse, T. 2024. The Potential of Deep Learning Object Detection in Citizen-Driven Snail Host Monitoring to Map Putative Disease Transmission Sites. *Citizen Science: Theory and Practice*, X(X): X, pp. 1–15. DOI: https://doi.org/10.5334/cstp.724

Submitted: 14 February 2024 **Accepted:** 15 August 2024 **Published:** XX Month 202X

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Citizen Science: Theory and Practice is a peer-reviewed open access journal published by Ubiquity Press.

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