Item number	Title/reference *(academic style) name initials (year) title, publisher, volume, pages*	Name of reviewer
10	Willi, M., Pitman, R.T., Cardoso, A.W., Locke, C., Swanson, A., Boyer, A., Veldthuis, M. and Fortson, L., 2019. Identifying animal species in camera trap images using deep learning and citizen science. Methods in Ecology and Evolution, 10(1), pp.80-91.	CESIE

Review of findings / main outcome

The paper investigates how citizen scientists can benefit from *deep learning* in classifying camera trap data, and to what extent citizen science projects incorporating machine predictions can have a significant impact on the project's success, quality, and number of annotations.

Dickinson, Zuckerberg, & Bonter, (2010), Silvertown (2009), Swanson et al., (2015) claim that citizen scientists have become valuable contributors to general science, ecology, and camera trap projects. Indeed, Swanson et. Al. (2015) outline that the manual processing and classification of millions of images produced through camera traps would be too much work for research teams to be completed within a reasonable timeframe. In such cases, the collective effort of volunteers is of pivotal importance, as demonstrates Zooniverse, the largest online citizen science platform, with the aim of providing citizen scientists with guidelines, additional information, classification data, and annotation tools.
However, camera trap projects might face challenges such as the need to remove sensitive images before the publication phase on citizen science platforms, as well as the high number of empty images to be removed.

With the aim of differentiating among images of different animal species or humans or empty images, LeCun et al., (1989) describe convolutional neural networks (CNNs) which consist of two linked main components, a convolutional part extracting local features from images, and a fully connected part mapping the learned spatial features respectively.
It is relevant to note that ecology researchers can significantly reduce image classification time and manual effort by combining citizen scientists and CNNs, enabling faster processing of data from large camera trap studies.
Furthermore, it is important to highlight that the transfer-learning technique aims to leverage models trained on a large camera trap datasets to smaller datasets, as well as its potential to support citizen science platforms (e.g., Zooniverse) to train and use models for new datasets with few labelled images more quickly.

In regards with image classification, researchers built project-specific workflows by identifying different options for tasks to assign to the citizen scientists. One of the tasks, "the survey-task", included showing the capture events to citizen scientists along with all possible classifications to choose from. The following step for volunteers consisted of annotating each capture event, and if the majority of volunteers identified more than one species in a single capture event, the procedure to follow was to exclude it from the study. This happened due to the additional complexity involved in modelling such images, and the low occurrence of such situations. Instead, for the remaining images, the most frequent occurrences of annotated species were the ones selected as the final label.

Finally, the paper explored the impact of applying a trained model on newly collected images in a live project on Zooniverse. The purpose was to reduce the number of volunteer annotations required by considering the output of a trained model for a camera trap project on Zooniverse. In order to evaluate the experiment, the efficiency gain and the impact on the quality of the final aggregated labels were assessed.
The study reported the accuracy as the percentage of correct model predictions for camera trap events compared to the aggregated volunteer opinion (ground truth).

Swanson et al. (2016) comment that citizen scientists classified species images from Serengeti National Park reaching an aggregated accuracy of 96,6% as compared to expert opinion.

Overall, the paper shows the results gained, such as CNNs reaching high accuracies in camera trap classification on dataset labelled by citizen scientists, even though classification accuracy demonstrated to be low for rare species. However, the study widely showed the great potential of powerful machine learning algorithms to reinforce citizen scientist analysis of large camera trap studies.

Quotes / very useful statements

"Citizen scientists have become essential contributors to general science, ecology, and camera trap projects" (Dickinson, Zuckerberg, & Bonter, (2010), Silvertown (2009), Swanson et al., (2015)

Key references *(academic style) name initials (year) title, publisher, volume, pages*

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