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Machine learning for image based species identification

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[file:///home/hduser/Downloads/2021\_Book\_TheScienceOfCitizenScience.pdf](../../../../Downloads/2021_Book_TheScienceOfCitizenScience.pdf) (chapter 10)

https://www.mdpi.com/2071-1050/13/18/10287

Developing a citizen science web portal for manual and automated ecological image detection (get from cct)

[Deep learning-based appearance features extraction for automated carp species identification - ScienceDirect](https://www.sciencedirect.com/science/article/abs/pii/S0144860919302195)

Camera traps not suitable in this environment

*Seratella ignita in nymph stage*

*Testing Git*

Citizen science is the use of interested but non-professionally trained individuals who can be utilised to collect and analyse data. One such citizen science project is the Small Stream Characterisation System (SSCS) being put in place by the East Wicklow Rivers Trust (wicklowrivers.ie, no date), that the author has participated in. This course is designed to train interested individuals in the characterisation and monitoring of small streams by training data on flora, fauna, and hydromorphology. The idea is to create a network of people across the county who regularly assess the condition of a stream or streams local to them. While the participants are trained in the classification of the river fauna, classification is complicated, especially amongst species from the same genus, that nonetheless can indicate opposing river conditions. It is considered that species classification might be improved by applying deep learning techniques to images of fauna that are taken by the volunteers. Some relatively basic classification would need to be done by the volunteers, do exclude species that are not diagnostic of either polluted or pristine rivers, and to reduce the species submitted for classification down to a set of known species which the model has been trained on.

To improve retention of volunteers the method used in gathering the data must be quick and simple, and photographing organisms fits this requirement (Newcomer et al., 2019)

While in-person species diversity measurements are more accurate, it has been found that photographic analyses can accurately capture the relative abundance of species and functional groups (Newcomer et al., 2019). It is relative abundance that is key in determining the … of small streams, so a method that accurately determines the relative abundance of relevant species could be usefully applied to photographic data gathered via citizen science. This would remove the need to train non-scientists to accurately distinguish species. Rather, the citizen scientists would only need to be trained to collect and photograph a sample – as per the current approach – and take pictures of the species present in the sample collected. As the organisms are currently collected in a sample tray for identification and counting, imaging them would be relatively straightforward. These images could then be uploaded and processed by the model, and species’ relative abundance determined. An added benefit would be that the images would be available for later examination by a trained professional, in the cases of outlier streams that were found to be exceptionally poor (or exceptionally good), or to spot check the citizen scientists’ work.

Rajabizadeh and Rezghi (2021) applied both traditional machine learning and deep learning (neural network) techniques to the classification of images of six Iranian snake species. Having found that feature extraction – specifically LDA – significantly improves the performance of traditional classifiers, the SVM classifier was found to give an accuracy of 84%. Of the traditional machine learning algorithms SVM (rbf kernel) performed best out of those tested, namely KNN, Logistic regression, and SVM. The authors note that the most appropriate dimension reduction algorithm to use depends on the dataset and the task, rather than the classifier, so a trial-and-error approach to determining the appropriate approach will be adopted. An accuracy of 93% was achieved using a CNN classifier, and the authors found that it was the colour pattern and shape (the dorsal patterns) that the model used to discriminate between species. The authors determined this by visualising the images after processing by the various hidden layers.

While CNN algorithms tend to perform better than traditional machine learning methods (e.g. Rajabizadeh and Rezghi (2021)) for image-based species classification, the opposite has been reported, notably in the identification of birds by Islam et al. (2019).

Rajabizadeh and Rezghi (2021) note that training a deep CNN algorithm requires a large dataset, but that images of the snakes in question - with at least 50% of the snake’s body visible in the image - were not readily available. They used a final dataset of 594 images in total.

Some researchers have cropped images to focus on particular taxonomic features (James, 2017), but this approach would not be applicable to big data – for a big data processing algorithm the images gathered would need to be processed independent of any human input. The image gathering and processing approach needs to be simple and repeatable. However R-CNN may be applicable in this case, such as identifying the head, tail, or legs of the species in question, before running the classifier algorithm (Thakur, 2020).

The CNN algorithm used by Rajabizadeh and Rezghi (2021) was MobileNetV2 (which can even be used on mobile devices), with 5,147,206 parameters over 150 epochs with an SGD optimizer and a learning rate equal to 0.000 and momentum of 0.9. Images fed to the model were initially resized to 24 x 224 pixels. Their model was pre-trained using images from ImageNet to attain the initial weights and to carry out transfer learning, in order to decrease the training time of the model. However there are no datasets in ImageNet for the species being examined here so this was not replicated. ImageNet would also have been useful in increasing the size of the dataset being used here. The researchers initially trained a model with no initial weights, but this model did not train effectively, indicating the importance of initial weights.

The visualisation of intermediate images by Rajabizadeh and Rezghi (2021) was done using a technique developed by Selvaraju et al. (2020) who extracted visual constructs from the final convolutional (output) layers to determine the class-specific information in the image (in other words, the parts of the image that the model is assigning to each class). They did this by generating a heat map of the most highly weighted feature map activation areas.

This application does not currently fulfil the characteristics of big data, but other citizen science ecology / biodiversity research areas could fulfil the characteristics of big data, with large volumes of varied data rapidly gathered through camera traps, for example.

Rajabizadeh and Rezghi (2021) used accuracy, precision and recall to evaluate the performance of the models (accuracy alone for the traditional algorithms). There will not be enough samples to split the data into train and test here, so precision will not be used.

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