



Machine learning to classify animal species in camera trap images

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Agenda

- Introduction
- Data
- Machine learning process
- Result
- My opinion



Introduction

- ▶ Camera traps are increasingly used to remotely observe wildlife over large geographical areas with minimal human involvement and Have made considerable contributions to ecology.
- ▶ A common limitation is these methods lead to a large accumulation of images which must be first classified in order to be used in ecological studies.
- ▶ The burden of manually viewing and classifying images often constrains studies by reducing the sampling intensity



Data

- Species in camera trap images from six different locations across the United States and Canada.
- If any part of an animal (e.g., ear) was identified as being present in an image, this was included as an image of the species.



Data

- If an image did not contain any animals, it was classified as empty.
- This resulted in a total of 3,741,656 classified images that included 27 species or groups.
- They randomly selected 90% of the classified images for each species or group to train the model and 10% of the images to test it.



Machine learning process

- They trained a deep convolutional neural network using the TensorFlow framework.
- They used the ReLU activation function, 55 epochs, a backpropagation algorithm of Stochastic Gradient Descent with Momentum and the learning rate (η) and weight decay varied by epoch number.



RESULTS

- ▶ the model performed well, achieving 97.6% accuracy of identifying the correct species with the top guess.
- ▶ The top-5 accuracy was >99.9%.
- ▶ The model confidence in the correct answer varied, but was mostly >95%
- ▶ there was not a large effect of daytime versus night-time on accuracy in the model, as daytime accuracy was 98.2% and night-time accuracy was 96.6%.



Cont.

- using the model to evaluate images of ungulates from Canada the overall accuracy was 81.8% .
- For discover if the image is empty or not, 85.1% were classified correctly as empty, while 94.3% of images containing an animal were classified correctly.
- the trained model was capable of classifying approximately 2,000 images per minute on a Macintosh laptop with 16 gigabytes of RAM.

(a) Correct classification by model



Model Guess	Confidence (%)
Wild pig	96.11
Cattle	2.38
Empty	1.49
White-tailed deer	<0.1
Moose	<0.1

Answer from human classifiers: Wild pig

(b) Incorrect classification by model



Model Guess	Confidence (%)
Wild pig	48.82
Cattle	31.27
Moose	16.93
Black bear	2.51
Bobcat	0.51

Answer from human classifiers: Cattle

FIGURE 1 Examples of images that could be difficult to classify. The model correctly identifies a wild pig (a) by seeing only its hindquarters and tail (right side of image). The model incorrectly classifies a cattle as a wild pig (b), as only an ear is visible in the image; note that the model has relatively low confidence in the top guess for this image. Nevertheless, cattle are within the top-5 guesses for this image, so while it is incorrect, it counts towards the top-5 recall for cattle



TABLE 1 Model performance for each species or group

Species or group name	Scientific name	Number of training images	Number of test images	Recall	Top-5 recall	Precision	False-positive rate	False-negative rate
Moose	<i>Alces alces</i>	8,967	997	0.98	1.00	0.98	0.02	0.02
Cattle	<i>Bos taurus</i>	1,817,109	201,903	0.99	1.00	0.99	0.01	0.01
Quail	<i>Callipepla californica</i>	2,039	236	0.91	0.96	0.93	0.07	0.09
Canidae	Canidae	20,851	2,321	0.89	0.99	0.93	0.07	0.11
Elk	<i>Cervus canadensis</i>	185,390	20,606	0.99	1.00	0.99	0.01	0.01
Mustelidae	Mustelidae	1,991	223	0.77	0.99	0.87	0.13	0.23
Corvid	Corvidae	4,037	452	0.84	1.00	0.80	0.20	0.16
Armadillo	<i>Dasypus novemcinctus</i>	8,926	993	0.89	0.99	0.93	0.07	0.11
Turkey	<i>Meleagris gallopavo</i>	3,919	447	0.90	1.00	0.90	0.10	0.10
Opossum	<i>Didelphis virginiana</i>	1,804	210	0.79	0.96	0.88	0.12	0.21
Horse	<i>Equus spp.</i>	2,517	281	0.94	0.99	0.94	0.06	0.06
Human	<i>Homo sapiens</i>	88,667	9,854	0.96	1.00	0.97	0.03	0.04
Rabbits	Leporidae	17,768	1,977	0.95	1.00	0.96	0.04	0.05
Bobcat	<i>Lynx rufus</i>	22,889	2,554	0.91	0.99	0.94	0.06	0.09
Striped skunk	<i>Mephitis mephitis</i>	10,331	1,154	0.95	0.98	0.96	0.04	0.05
Rodent	Rodentia	3,279	366	0.79	0.98	0.88	0.12	0.21
Mule deer	<i>Odocoileus hemionus</i>	87,700	8,543	0.98	1.00	0.98	0.02	0.02
White-tailed deer	<i>Odocoileus virginianus</i>	87,900	1,360	0.94	1.00	0.95	0.05	0.06
Raccoon	<i>Procyon lotor</i>	42,948	4,781	0.90	1.00	0.89	0.11	0.10
Mountain lion	<i>Puma concolor</i>	13,272	1,484	0.92	0.98	0.97	0.03	0.08
Squirrel	<i>Sciurus spp.</i>	59,072	6,566	0.97	1.00	0.95	0.05	0.03
Wild pig	<i>Sus scrofa</i>	287,017	31,893	0.98	1.00	0.98	0.02	0.02
Fox	<i>Vulpes vulpes</i> and <i>Urocyon cinereoargenteus</i>	10,749	1,204	0.91	0.99	0.94	0.06	0.09
Black bear	<i>Ursus americanus</i>	79,628	8,850	0.95	1.00	0.98	0.02	0.05
Vehicle		23,413	2,602	0.93	1.00	0.95	0.05	0.07
Bird	Aves	61,063	6,787	0.94	1.00	0.95	0.05	0.06
Empty		414,119	46,016	0.96	1.00	0.94	0.06	0.04
Total		3,367,365	364,660	0.98	1.00	0.98		



My opinion

- I think this application will be so helpful for remotely observing wildlife.
- The paper was too simple and didn't mention many details about the work I think this is good and bad point at the same time.
- The authors ignore some important points (e.g., pervious work in this field and compare their result by the current models in that field),
- The paper need more graphs and figures.



Any questions ?