

1 **Machine learning to classify animal species in camera trap images: applications in ecology**

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44

45 **Abstract**

46 1. Motion-activated cameras (“camera traps”) are increasingly used in ecological and  
47 management studies for remotely observing wildlife and have been regarded as among the most  
48 powerful tools for wildlife research. However, studies involving camera traps result in millions  
49 of images that need to be analyzed, typically by visually observing each image, in order to  
50 extract data that can be used in ecological analyses.

51 2. We trained machine learning models using convolutional neural networks with the ResNet-18  
52 architecture and 3,367,383 images to automatically classify wildlife species from camera trap  
53 images obtained from five states across the United States. We tested our model on an  
54 independent subset of images not seen during training from the United States and on an out-of-  
55 sample (or “out-of-distribution” in the machine learning literature) dataset of ungulate images  
56 from Canada. We also tested the ability of our model to distinguish empty images from those  
57 with animals in another out-of-sample dataset from Tanzania, containing a faunal community  
58 that was novel to the model.

59 3. The trained model classified approximately 2,000 images per minute on a laptop computer  
60 with 16 gigabytes of RAM. The trained model achieved 98% accuracy at identifying species in  
61 the United States, the highest accuracy of such a model to date. Out-of-sample validation from  
62 Canada achieved 82% accuracy, and correctly identified 94% of images containing an animal in  
63 the dataset from Tanzania. We provide an R package (Machine Learning for Wildlife Image  
64 Classification; MLWIC) that allows the users to A) implement the trained model presented here  
65 and B) train their own model using classified images of wildlife from their studies.

66 4. The use of machine learning to rapidly and accurately classify wildlife in camera trap images  
67 can facilitate non-invasive sampling designs in ecological studies by reducing the burden of  
68 manually analyzing images. We present an R package making these methods accessible to  
69 ecologists. We discuss the implications of this technology for ecology and considerations that  
70 should be addressed in future implementations of these methods.

71 Keywords: artificial intelligence, camera trap, convolutional neural network, deep neural  
72 networks, image classification, machine learning, R package, remote sensing

## 73 **Introduction**

74 An understanding of species' distributions is fundamental to many questions in ecology  
75 (MacArthur, 1984; Brown, 1995). Observations of wildlife can be used to model species  
76 distributions and population abundance and evaluate how these metrics relate to environmental  
77 conditions (Elith, Kearney, & Phillips, 2010; Tikhonov et al., 2017). However, developing  
78 statistically sound data for species observations is often difficult and expensive (Underwood,  
79 Chapman, & Connell, 2000) and significant effort has been devoted to correcting bias in more  
80 easily collected or opportunistic observation data (Royle & Dorazio, 2008; MacKenzie et al.,  
81 2017). Recently, technological advances have improved our ability to observe animals remotely.  
82 Sampling methods such as acoustic recordings, images from crewless aircraft (or “drones”), and  
83 motion-activated cameras that automatically photograph wildlife (i.e., “camera traps”) are  
84 commonly used (Blumstein et al., 2011; O’Connell et al., 2011; Getzin et al., 2012). These tools  
85 offer great promise for increasing efficiency of observing wildlife remotely over large  
86 geographical areas with minimal human involvement and have made considerable contributions  
87 to ecology (Rovero et al., 2013; Howe et al., 2017). However, a common limitation is these  
88 methods lead to a large accumulation of data – audio and video recordings and images – which  
89 must be first classified in order to be used in ecological studies predicting occupancy or  
90 abundance (Swanson et al., 2015; Niedballa et al., 2016). The large burden of classification, such  
91 as manually viewing and classifying images from camera traps, often constrains studies by  
92 reducing the sampling intensity (e.g., number of cameras deployed), limiting the geographical  
93 extent and duration of studies. Recently, machine learning has emerged as a potential solution for  
94 automatically classifying recordings and images.

95 Machine learning methods have been used to classify wildlife in camera trap images with  
96 varying levels of success and human involvement in the process. One application of a machine  
97 learning approach has been to distinguish empty and non-target animal images from those  
98 containing the target species to reduce the number of images requiring manual classification.  
99 This approach has been generally successful, allowing researchers to remove up to 76% of  
100 images containing non-target species (Swinnen et al., 2014). Development of methods to identify  
101 several wildlife species in images has been more problematic. Yu et al. (2013) used sparse  
102 coding spatial pyramid matching (Lazebnik, Schmid, & Ponce, 2006) to identify 18 species in  
103 images, achieving high accuracy (82%), but their approach necessitates each training image to be  
104 manually cropped, requiring a large time investment. Attempts to use machine learning to  
105 classify species in images without manual cropping have achieved far lower accuracies: 38%  
106 (Chen et al., 2014) and 57% (Gomez Villa, Salazar, & Vargas, 2017). However, more recently  
107 Norouzzadeh et al. (2018) used convolutional neural networks with 3.2 million classified images  
108 from camera traps to automatically classify 48 species of Serengeti wildlife in images with 95%  
109 accuracy.

110 Despite these advances in automatically identifying wildlife in camera trap images, the  
111 approaches remain study specific and the technology is generally inaccessible to most ecologists.  
112 Training such models typically requires extensive computer programming skills and tools for  
113 novice programmers (e.g., an R package) are limited. Making this technology available to  
114 ecologists has the potential to greatly expand ecological inquiry and non-invasive sampling  
115 designs, allowing for larger and longer-term ecological studies. In addition, automated  
116 approaches to identifying wildlife in camera trap images have important applications in detecting  
117 invasive species or sensitive species and improving their management.

118 We sought to develop a machine learning approach that can be applied across study sites and  
119 provide software that ecologists can use for identification of wildlife in their own camera trap  
120 images. Using over three million identified images of wildlife from camera traps from five  
121 locations across the United States, we trained and tested deep learning models that automatically  
122 classify wildlife. We provide an R package (Machine Learning for Wildlife Image Classification;  
123 MLWIC) that allows researchers to classify camera trap images from North America or train  
124 their own machine learning models to classify images. We also address some basic issues in the  
125 potential use of machine learning for classifying wildlife in camera trap images in ecology.  
126 Because our approach nearly eliminates the need for manual curation of camera trap images we  
127 also discuss how this new technology can be applied to improve ecological studies in the future.

128

## 129 **Materials and Methods**

### 130 *Camera trap images*

131 Species in camera trap images from five locations across the United States (California, Colorado,  
132 Florida, South Carolina, and Texas) were identified manually by researchers (see Appendix S1  
133 for a description of each field location). Images were either classified by a single wildlife expert  
134 or evaluated independently by two researchers; any conflicts were decided by a third observer  
135 (Appendix S1). If any part of an animal (e.g., leg or ear) was identified as being present in an  
136 image, this was included as an image of the species. This resulted in a total of 3,741,656  
137 classified images that included 28 species or groups (see Table 1) across the study locations. We  
138 present these images and their classifications for other scientists to use for model development as  
139 the North American Camera Trap Images (NACTI) dataset. Images were re-sized to a resolution

140 of 256 x 256 pixels using a custom Python script before running models to increase processing  
141 speed. A subset of images (approximately 10%) was withheld using conditional sampling to be  
142 used for testing of the model (described below). This resulted in 3,367,383 images used to train  
143 the model and 374,273 images used for testing.

144

#### 145 *Machine learning process*

146 Supervised machine learning algorithms use training examples to “learn” how to complete a task  
147 (Mohri, Rostamizadeh, & Talwalkar, 2012; Goodfellow, Bengio, & Courville, 2016). One  
148 popular class of machine learning algorithms is artificial neural network, which loosely mimics  
149 the learning behavior of the mammalian brain (Gurney, 2014; Goodfellow et al., 2016). An  
150 artificial neuron in a neural network has several inputs, each with an associated weight. For each  
151 artificial neuron, the inputs are multiplied by the weights, summed, and then evaluated by a non-  
152 linear function, which is called the activation function (e.g., Sigmoid, Tanh, or Sine). Usually  
153 each neuron also has an extra connection with a constant input value of 1 and its associated  
154 weight, called a “bias,” for neurons. The result of the activation function can be passed as input  
155 into other artificial neurons or serve as network outputs. For example, consider an artificial  
156 neuron with three inputs ( $I_1$ ,  $I_2$ , and  $I_3$ ); the output ( $\theta$ ) is calculated based on:

$$157 \quad \theta = \text{Tanh}(w_1 I_1 + w_2 I_2 + w_3 I_3 + w_4 I_b) \text{ (eqn 1),}$$

158 where  $w_1$ ,  $w_2$ ,  $w_3$  and  $w_4$  are the weights associated with each input,  $I_b$  is the bias, and  $\text{Tanh}(x)$   
159 is the activation function (Fig. 1). To solve complex problems multiple neurons are needed, so  
160 we put them into a network. We arrange neurons in a hierarchical structure of layers; neurons in  
161 each layer take input from the previous layer, process them, and pass the output to the next layer.

162 Then, an algorithm, called backpropagation (Rumelhart, Hinton, & Williams, 1986), tunes the  
163 parameters of the neural network (weights and bias values) enabling it to produce the desired  
164 output when we feed an input to the network. This process is called training. To adjust the  
165 weights, we define a loss function as a measure of the difference between the predicted (current)  
166 output of the neural network and the correct output ( $Y$ ). The loss function ( $L$ ) is the mean  
167 squared error:

$$168 \quad L = \frac{1}{n} \sum_{i=1}^n (Y - \theta)^2 \text{ (eqn2).}$$

169 We compute the contribution of each weight to the loss value ( $\frac{dL}{dW}$ ) using the chain rule in  
170 calculus. Weights are then adjusted so the loss value is minimized. In this “weight update” step,  
171 all the weights are updated to minimize  $L$ :

$$172 \quad w_i = w_{i \text{ initial}} - \eta \frac{dL}{dW} \text{ (eqn 3),}$$

173 where  $\eta$  is the learning rate and is chosen by the scientist. A higher  $\eta$  indicates larger steps are  
174 taken per training sample, which may be faster, but a value that is too large will be imprecise and  
175 can destabilize learning. After adjusting the weights, the same input should result in an output  
176 that is closer to the desired output. For more details of backpropagation and training, see  
177 Goodfellow et al., 2016.

178 In fully connected neural networks, each neuron in every layer is connected to (provides input to)  
179 every neuron in the next layer. Conversely, in convolutional neural networks, which are inspired  
180 by the retina of the human eye, several convolutional layers exist in which each neuron only  
181 receives input from a small sliding subset of neurons (“receptive field”) in the previous layer. We  
182 call the output of a group of neurons the “feature map,” which depicts the response of a neuron



183 to its input. When we use convolutional neural networks to classify animal images, the receptive  
184 field of neurons in the first layer of the network is a sliding subset of the image. In subsequent  
185 layers, the receptive field of neurons is a sliding subset of the feature map from previous layers.  
186 We interpret the output of the final layer as the probability of the presence of species in the  
187 image. A softmax function is used at the final layer to ensure that the outputs sum to one. For  
188 more details on this process, see Simonyan & Zisserman, 2014.

189 Deep neural networks (or “deep learning”) are artificial networks with several ( $> 3$ ) layers of  
190 structure. In our example, we provided a set of animal images from camera traps of different  
191 species and their labels (species identifiers) to a deep neural network, and the model learned how  
192 to identify species in other images that were not used for training. Once a model is trained, we  
193 can use it to classify new images. The trained model uses the output of the final layer in the  
194 network to assign a confidence to each species or group it evaluates, where the total confidence  
195 assigned to all groups for each image sums to one. Generally, the majority of the confidence is  
196 attributed to one group, the “top guess.” For example, for 90% of the images in our test dataset,  
197 the model attributed  $> 95\%$  confidence to the top guess. Therefore, for the purpose of this paper,  
198 we mainly discuss accuracy with regard to the top guess, but our R package presents the five  
199 groups with the highest confidence, the “top five guesses,” and the confidence associated with  
200 each guess.

201 Neural network architecture refers to several details about the network including the type and  
202 number of neurons and the number of layers. We trained a deep convolutional neural network  
203 (ResNet-18) architecture because it has few parameters, but performs well; see He et al. (2016)  
204 for full details of this architecture. Networks were trained in the TensorFlow framework (Adabi  
205 et al., 2016) using Mount Moran, a high performance computing cluster (Advanced Research

206 Computing Center, 2012). First, since invasive wild pigs (*Sus scrofa*) are a subject of several of  
207 our field studies, we developed a “Pig/no pig” model, in which we determined if a pig was either  
208 present or absent in the image. In the “Species Level” model, we identified images to the species  
209 level when possible. Specifically, if our classified image dataset included < 2,000 images for a  
210 species, it was either grouped with taxonomically similar species (by genera, families, or order),  
211 or it was not included in the trained model (Table 1). In the “Group Level” model, species were  
212 grouped with taxonomically similar species into classifications that had ecological relevance  
213 (Appendix S2). The Group Level model contained fewer groups than the Species Level model,  
214 so that more training images were available for each group. We used both models because if the  
215 Species Level model had poor accuracy, we predicted the Group Level model would have better  
216 accuracy since more training images would be available for several groups. As it is the most  
217 broadly applicable model and is the one implemented in the MLWIC package, we will mainly  
218 discuss the Species Level model here, but show results from the Group Level to demonstrate  
219 alternative approaches.

220 For each of the three models, 90% of the classified images for each species or group were used  
221 to train the model and 10% of the images were used to test it in most cases. However, we wanted  
222 to evaluate the model’s performance for each species present at each study site, so we altered  
223 training-testing allocation for the rare situations where there were few classified images of a  
224 species at a site. Specifically, with 1-9 classified images for a species at a site, we used all of  
225 these images for testing and none for training; for site-species pairs with 10-30 images, 50%  
226 were used for training and testing; and for > 30 images per site for each species, 90% were  
227 allocated to training and 10% to testing (Appendices S3 - S7 show the number of training and  
228 test images for each species at each site).

229

230 *Evaluating model accuracy*

231 Model testing was conducted by running the trained model on the withheld images that were not  
232 used to train the model. Accuracy ( $A$ ) was assessed as the proportion of images in the test dataset  
233 ( $N$ ) that were correctly classified ( $C$ ) by the top guess ( $A = C/N$ ). Top 5 accuracy ( $A5$ ) was  
234 defined as the proportion of images in the test dataset that were correctly classified by any of the  
235 top 5 assignments ( $C5$ ;  $A5 = C5/N$ ). For each species or group we calculated the rate of false  
236 positives ( $FP$ ) as the proportion of images classified as this species or group ( $N_{model\ group}$ ) by  
237 the model's top guess that contained a different species according to human observers  
238 ( $N_{true\ other}$ ;  $FP = N_{true\ other}/N_{model\ group}$ ). We calculated the rate of false negatives for each  
239 species ( $FN$ ) as the proportion of images observers classified as a specific species or group  
240 ( $N_{true\ group}$ ) that the model's top guess classified differently ( $N_{model\ other}$ ;  $FN =$   
241  $N_{model\ other}/N_{true\ group}$ ). This assumes the observers were correct in their classification of  
242 images. We fit generalized additive models (GAMs) to the relationship between accuracy and the  
243 logarithm (base 10) of the number of images used to train the model. We also calculated the  
244 accuracy and rates of error specific to each of the five data sets from which images were  
245 acquired.

246 To evaluate how the model would perform for a completely new study site in North America, we  
247 used a dataset of 5,900 classified images of ungulates (moose, cattle, elk, and wild pigs) from  
248 Saskatchewan, Canada by running the Species Level model on these images. We also evaluated  
249 the ability of the model to operate on images with a completely different species community  
250 (from Tanzania) to determine the model's ability to correctly classify images as having an animal

251 or being empty when encountering new species that it has not been trained to recognize. This  
252 was done using 3.2 million classified images from the Snapshot Serengeti dataset (Swanson et  
253 al., 2015).

254

## 255 **Results**

256 Our models performed well, achieving  $\geq 97.5\%$  accuracy of identifying the correct species with  
257 the top guess (Table 2). The model determining presence or absence of wild pigs had the highest  
258 accuracy of all of our models (98.6%; Pig/no pig; Table 2). For the Species Level and Group  
259 Level models, the top 5 accuracy was  $> 99.9\%$ . The model confidence in the correct answer  
260 varied, but was mostly  $> 95\%$ ; see Fig. 2 for confidences for each image for three example  
261 species. Supporting a similar finding for camera trap images in Norouzzadeh et al. (2018), and a  
262 general trend in deep learning (Goodfellow et al., 2016), species and groups that had more  
263 images available for training were classified more accurately (Fig. 3, Table 1). GAMs relating  
264 the number of training images with accuracy predicted 95% accuracy could be achieved when  
265 approximately 71,000 training images were available for a species or group. However, these  
266 models were not perfect fits to the data, and for several species and groups, 95% accuracy was  
267 achieved with fewer than 70,000 images (Fig. 3). We found there was not a large effect of  
268 daytime vs. nighttime on accuracy in the Species Level model as daytime accuracy was 98.2%  
269 and nighttime accuracy was 96.6%. The top 5 accuracies for both times of day were  $\geq 99.9\%$ .  
270 When we subsetted the testing dataset by study site, we found that site-specific accuracies ranged  
271 from 90-99% (Appendices S3 - S7). The model performed poorly (0 – 22% accuracy) for species  
272 in the four instances when the model did not include training images from that site (when  $< 10$   
273 classified images were available for the species/study site combination; Appendices S3 - S7).

274 Upon further investigation, we found these images were difficult to classify manually. For  
275 example, striped skunks in Florida were misclassified in both of the images from this study site  
276 (Appendix S5). These images both contained the same individual at the same camera, and most  
277 wildlife experts would not classify it as a skunk (Appendix S8).

278 When we conducted out-of-sample validation by using our model to evaluate images of  
279 ungulates from Canada, we achieved an overall accuracy of 81.8% with a top 5 accuracy of  
280 90.9%. When we tested the ability of our model to accurately predict presence or absence of an  
281 animal in the image using the Serengeti Snapshot dataset, we found that 85.1% were classified  
282 correctly as empty, while 94.3% of images containing an animal were classified as containing an  
283 animal. Our trained model was capable of classifying approximately 2,000 images per minute on  
284 a Macintosh laptop with 16 gigabytes (GB) of RAM.

285

## 286 **Discussion**

287 To our knowledge, our Species Level model achieved the highest accuracy (97.5%) to date in  
288 using machine learning for wildlife image classification (a recent paper achieved 95% accuracy;  
289 Norouzzadeh et al., 2018). This model performed almost as well during the night as during the  
290 day (accuracy = 97% and 98%, respectively). We provide this model as an R package (MLWIC),  
291 which is especially useful for researchers studying the species and groups available in this  
292 package (Table 1) in North America, as it performed well in classifying ungulates in an out-of-  
293 sample test of images from Canada. The model can also be valuable for researchers studying  
294 other species by removing images without any animals from the dataset before beginning manual  
295 classification, as we achieved high accuracy in separating empty images from those containing

296 animals in a dataset from Tanzania. This R package can also be a valuable tool for any  
297 researchers that have classified images, as they can use the package to train their own model that  
298 can then classify any subsequent images collected.

299

### 300 *Optimizing camera trap use and application in ecology*

301 The ability to rapidly identify millions of images from camera traps can fundamentally change  
302 the way ecologists design and implement wildlife studies. Camera trap projects amass large  
303 numbers of images which require a sizable time investment to manually classify. For example,  
304 the Snapshot Serengeti project (Swanson et al., 2015) amassed millions of images and employed  
305 28,000 volunteers to manually classify 1.5 million images (Swanson et al., 2016; Palmer et al.,  
306 2017). We found researchers can classify approximately 200 images per hour. Therefore, a  
307 project that amasses 1 million images would require 10,000 hours for each image to be doubly  
308 observed. To reduce the number of images that need to be classified manually, ecologists using  
309 camera traps often limit the number of photos taken by reducing the size of camera arrays,  
310 reducing the duration of camera trap studies, and imposing limits on the number of photos a  
311 camera takes (Kelly et al., 2008; Scott et al., 2018). This constraint can be problematic in many  
312 studies, particularly those addressing rare or elusive species that are often the subject of  
313 ecological studies (O'Connell et al., 2011), as these species often require more effort to detect  
314 (Tobler et al., 2008). Using deep learning methods to automatically classify images essentially  
315 eliminates one of the primary reasons camera trap arrays are limited in size or duration. The  
316 Species Level model in our R package can accurately classify 1 million images in less than nine  
317 hours with minimal human involvement.

318 Another reason to limit the number of photos taken by camera traps is storage limitations on  
319 cameras (Rasambainarivo et al., 2017; Hanya et al., 2018). When classifying images manually,  
320 we might try to use high resolution photos to improve technicians' abilities to accurately classify  
321 images, but higher resolution photos require more storage on cameras. Our results show a model  
322 can be accurately trained and applied using low-resolution (256 x 256 pixel) images, but many of  
323 these images were re-sized from a higher resolution, which might contain more information than  
324 those which originated at a low resolution. Nevertheless, we hypothesize a model can be  
325 accurately trained using images from low resolution cameras, and our R package allows users  
326 who have such images to test this hypothesis. If supported, this can make camera trap data  
327 storage much more efficient. Typical cameras set for 2048 x 1536 pixel resolution will run out of  
328 storage space when they reach approximately 1,250 photos per GB of storage. Taking low  
329 resolution images instead can increase the number of photos stored per GB to about 10,000 and  
330 thus decrease the frequency at which researchers must visit cameras to change storage cards by a  
331 factor of eight. Minimizing human visitation also will reduce human scents and disturbances that  
332 could deter some species from visiting cameras. In the future, it may be possible to implement a  
333 machine learning model on a game camera (Elias et al., 2017) that automatically classifies  
334 images as empty or containing animals so that empty images are discarded immediately and not  
335 stored on the camera. This type of approach could dramatically reduce the frequency with which  
336 technicians need to visit cameras. Furthermore, if models effectively use low-resolution images,  
337 it is not necessary for researchers to purchase high resolution cameras. Instead, researchers can  
338 purchase lower cost, lower resolution cameras and allocate funding toward purchasing more  
339 cameras and creating larger camera arrays.

340

341 *Applications to management of invasive and sensitive species*

342 By removing some of the major burdens associated with the use of camera traps, our approach  
343 can be utilized by ecologists and wildlife managers to conduct more extensive camera trapping  
344 surveys than were previously possible. One potential use is in monitoring the distribution of  
345 sensitive or invasive species. For example, the distribution of invasive wild pigs in North  
346 America is commonly monitored using camera traps. Humans introduce this species into new  
347 locations that are often geographically distant from their existing range (Tabak et al., 2017),  
348 which can quickly lead to newly-established populations. Camera traps could be placed in areas  
349 at risk for introduction and provide constant surveillance. An automated image classification  
350 model that simply ‘looks’ for pigs in images could monitor camera trap images and alert  
351 managers when images with pigs are found, facilitating removal of animals before populations  
352 establish. Additionally, after wild pigs have been eradicated from a region, camera traps could be  
353 used to monitor the area to verify eradication success and automatically detect re-colonization or  
354 reintroduction events. Similar approaches can be used in other study systems to more rapidly  
355 detect novel invasive species arrivals, track the effects of management interventions, monitor  
356 species of conservation concern, or monitor sensitive species following reintroduction efforts.

357

358 *Limitations*

359 Using out-of-sample model validation on a dataset from Canada revealed a lower accuracy  
360 (82%) than at study sites from which our model was trained. Additionally, when we did not  
361 include images of species/site combinations in training the model, due to low sample sizes, the  
362 model performed poorly (Appendices S3 - S7; but these images were often difficult to classify



363 even by wildlife experts, Appendix S8). One potential explanation is the model evaluated both  
364 the animal and the environment in the image and these are confounded in the species  
365 identification (Norouzzadeh et al., 2018). Therefore, the model may have lower accuracies in  
366 environments that were not in the training dataset. Ideally, the training dataset would include  
367 training images representing the range of environments in which a species exists. Our model  
368 includes training images from diverse ecosystems, making it relevant for classifying images from  
369 many locations in North America. A further limitation is in our reported overall accuracy, which  
370 is reported across all of the images that were available for testing, and we had considerable  
371 imbalance in the number of images per species (Table 1). We provide accuracies for each  
372 species, so the reader can more directly inspect model accuracy. Finally, our model was trained  
373 using images that were classified by human observers, which are capable of making errors  
374 (O'Connell et al., 2011; Meek, Vernes, & Falzon, 2013), meaning some of the images in our  
375 training dataset were likely misclassified. Supervised machine learning algorithms require such  
376 training examples, and therefore we are unaware of a method for training such models without  
377 the potential for human classification error. Instead, we must acknowledge that these models will  
378 make mistakes due to imperfections in both human observation and model accuracy.

379

### 380 *Future directions*

381 As this new technology becomes more widely available, ecologists will need to decide how it  
382 will be applied in ecological analyses. For example, when using machine learning model output  
383 to design occupancy and abundance models, we can incorporate accuracy estimates that were  
384 generated when conducting model testing. The error of a machine learning model in identifying a  
385 species is similar to the problem of imperfect detection of wildlife when conducting field

386 surveys. Wildlife are often not detected when they are present (false negatives) and occasionally  
387 detected when they are absent (false positives); ecologists have developed models to effectively  
388 estimate occupancy when data have these types of errors (Royle & Link, 2006; Guillera-Arroita  
389 et al., 2017). We can use Bayesian occupancy and abundance models where the central  
390 tendencies of the prior distributions for the false negative and false positive error rates are  
391 derived from testing the machine learning model (e.g., values in Table 1). While we would  
392 expect false positive rates in occupancy models to resemble the false positive error rates for the  
393 machine learning model, false negative error rates would be a function of the both the machine  
394 learning model and the propensity for some species to avoid detection by cameras when they are  
395 present (Tobler et al., 2015).

396 Another area in need of development is how to group taxa when few images are available for the  
397 species. We grouped species when few images were available for model training using an  
398 arbitrary cut off of approximately 2,000 images per group (Table 1). We had few images of  
399 horses (*Equus* spp.), but the model identified these images relatively well (93% accuracy),  
400 presumably because they are phenotypically different from other species in our dataset. We also  
401 had few images of opossums (*Didelphis virginiana*), but we did not group this species because it  
402 is phenotypically different from other species in our dataset and was of ecological interest in our  
403 studies; we achieved lower accuracy for this species (78%). We also included a group for rodents  
404 from species for which we only had few images (*Erethizon dorsatum*, *Marmota flaviventris*,  
405 *Genomys* spp., *Mus* spp., *Neotoma* spp., *Peromyscus* spp., *Tamias* spp., and *Rattus* spp.). The  
406 model achieved relatively low accuracy for this group (79%), presumably because there were  
407 few images for training (3,279) and members of this group are phenotypically different, making  
408 it difficult for the model to train on this group. When researchers develop new machine learning

409 models, they will need to consider the available data, the species or groups in their study, and the  
410 ecological question that the model will help address.

411 Here, we mainly focused on the species or class that the model predicted with the highest  
412 confidence (the top guess), but in many cases researchers may want to incorporate information  
413 from the model's confidence in the guess and additional model guesses. For example, if we are  
414 interested in the highest overall accuracy, we could only consider images where the confidence  
415 in the top guess is  $> 95\%$ . If we subset the results from our model test in this manner, we remove  
416 10% of the images, but total accuracy increases to 99.6%. However, if the objective of a project  
417 is to identify rare species, researchers may want to focus on all images in which the model  
418 predicts that species to be in the top 5 guesses (the 5 species or groups that the model predicts to  
419 have the highest confidence). In our model test, the correct species was in the top 5 guesses in  
420 99.9% of the images, indicating that this strategy may be viable.

421 We expect the performance of machine learning models to improve in the future (Jordan &  
422 Mitchell, 2015), allowing ecologists to further exploit this technology. Our model required  
423 manual identification of many images to obtain high levels of accuracy (Table 1). Our model was  
424 also limited in that we were only able to classify the presence or absence of species; we were not  
425 able to determine the number of individuals, their behavior, or demographics. Similar machine  
426 learning models are capable of including the number of animals and their behavior in  
427 classifications (Norouzzadeh et al., 2018), but we could not include these factors because they  
428 were rarely recorded manually in our dataset. As machine learning techniques improve, we  
429 expect models will require fewer manually classified images to achieve high accuracy in  
430 identifying species, counting individuals, and specifying demographic information. Furthermore,  
431 as scientists begin projects intending to use machine learning to classify images, they may be

432 more willing to spend time extracting detailed information from fewer images instead of  
433 obtaining less information from all images. This development would create a larger dataset of  
434 information from images that can be used to train models. As machine learning algorithms  
435 improve and ecologists begin considering this technology when they design studies, we think  
436 that many novel applications will arise.

437 As camera trap use is a common approach to studying wildlife worldwide, there are likely now  
438 large datasets of classified images. If scientists work together and share these datasets, we can  
439 create large image libraries that span continents (Steenweg et al., 2017); we may eventually be  
440 able to train a machine learning model that can identify many global species and be used by  
441 researchers globally. Further, effectively sharing images and classifications can potentially be  
442 integrated with a web-based platform, similar to that employed by Camera Base  
443 (<http://www.atrium-biodiversity.org/tools/camerabase>) or eMammal (<https://emammal.si.edu/>).

444

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453

454 **Data Accessibility**

455 The trained Species Level model is available in the R package MLWIC from github  
456 (<https://github.com/mikeyEcology/MLWIC>). We provide the 3.7 million classified images as the  
457 North American Camera Trap Images (NACTI) dataset in a digital repository.

458

459 **Author Contributions**

460 MAT, RSM, KCV, NPS, SJS, and DWW conceived of the project; DWW, JSL, MAT, RKB,  
461 BW, PAD, JCB, MDW, BT, PES, NPS, KCV, JMH, ESN, JSI, EAO, RKB, PML, and AKM  
462 oversaw collection and manual classification of wildlife in camera trap images from the study  
463 sites; MSN and JC developed and programmed the machine learning models; MAT led the  
464 analyses and writing of the R package; EGM assisted with R package development and  
465 computing; MAT and RSM led the writing. All authors contributed critically to drafts and gave  
466 final approval for submission.

467

468 **References**

469 Adabi, M., Barhab, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... Zheng, X. (2016). TensorFlow:  
470 a system for large-scale machine learning (Vol. 16, pp. 265–283). Presented at the 12th  
471 USENIX Symposium on Operating Systems Design and Implementation, USENIX  
472 Association.  
473 Advanced Research Computing Center. (2012). *Mount Moran: IBM System X cluster*. Laramie,  
474 WY: University of Wyoming. <https://arcc.uwyo.edu/guides/mount-moran>

- 475 Blumstein, D. T., Mennill, D. J., Clemins, P., Girod, L., Yao, K., Patricelli, G., ... Kirschel, A.  
476 N. G. (2011). Acoustic monitoring in terrestrial environments using microphone arrays:  
477 applications, technological considerations and prospectus: Acoustic monitoring. *Journal*  
478 *of Applied Ecology*, 48(3), 758–767. doi:10.1111/j.1365-2664.2011.01993.x
- 479 Brown, J. H. (1995). *Macroecology*. University of Chicago Press.
- 480 Chen, G., Han, T. X., He, Z., Kays, R., & Forrester, T. (2014). Deep convolutional neural  
481 network based species recognition for wild animal monitoring (pp. 858–862). IEEE  
482 International Conference on Image Processing (ICIP). doi:10.1109/ICIP.2014.7025172
- 483 Elias, A. R., Golubovic, N., Krintz, C., & Wolski, R. (2017). Where’s the bear?: automating  
484 wildlife image processing using IoT and Edge Cloud Systems (pp. 247–258). ACM  
485 Press. doi:10.1145/3054977.3054986
- 486 Elith, J., Kearney, M., & Phillips, S. (2010). The art of modelling range-shifting species.  
487 *Methods in Ecology and Evolution*, 1(4), 330–342. doi:10.1111/j.2041-  
488 210X.2010.00036.x
- 489 Getzin, S., Wiegand, K., & Schöning, I. (2012). Assessing biodiversity in forests using very  
490 high-resolution images and unmanned aerial vehicles. *Methods in Ecology and Evolution*,  
491 3(2), 397–404. doi:10.1111/j.2041-210X.2011.00158.x
- 492 Gomez Villa, A., Salazar, A., & Vargas, F. (2017). Towards automatic wild animal monitoring:  
493 Identification of animal species in camera-trap images using very deep convolutional  
494 neural networks. *Ecological Informatics*, 41, 24–32. doi:10.1016/j.ecoinf.2017.07.004
- 495 Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning* (1st ed.). Cambridge,  
496 Massachusetts: MIT Press.

- 497 Guillera-Arroita, G., Lahoz-Monfort, J. J., van Rooyen, A. R., Weeks, A. R., & Tingley, R.  
498 (2017). Dealing with false-positive and false-negative errors about species occurrence at  
499 multiple levels. *Methods in Ecology and Evolution*, 8(9), 1081–1091. doi:10.1111/2041-  
500 210X.12743
- 501 Gurney, K. (2014). *An Introduction to Neural Networks* (1st ed.). London: CRC Press. Retrieved  
502 from <https://www.taylorfrancis.com/books/9781482286991>
- 503 Hanya, G., Otani, Y., Hongo, S., Honda, T., Okamura, H., & Higo, Y. (2018). Activity of wild  
504 Japanese macaques in Yakushima revealed by camera trapping: Patterns with respect to  
505 season, daily period and rainfall. *PLOS ONE*, 13(1), e0190631.  
506 doi:10.1371/journal.pone.0190631
- 507 He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. In  
508 *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp.  
509 770–778). IEEE. doi:10.1109/CVPR.2016.90
- 510 Howe, E. J., Buckland, S. T., Després-Einspenner, M.-L., & Kühl, H. S. (2017). Distance  
511 sampling with camera traps. *Methods in Ecology and Evolution*, 8(11), 1558–1565.  
512 doi:10.1111/2041-210X.12790
- 513 Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: trends, perspectives, and prospects.  
514 *Science*, 349(6245), 255–260. doi:10.1126/science.aaa8415
- 515 Kelly, M. J., Noss, A. J., Di Bitetti, M. S., Maffei, L., Arispe, R. L., Paviolo, A., ... Di Blanco,  
516 Y. E. (2008). Estimating Puma Densities from Camera Trapping across Three Study  
517 Sites: Bolivia, Argentina, and Belize. *Journal of Mammalogy*, 89(2), 408–418.  
518 doi:10.1644/06-MAMM-A-424R.1

- 519 Lazebnik, S., Schmid, C., & Ponce, J. (2006). Beyond bags of features: spatial pyramid matching  
520 for recognizing natural scene categories. In *Computer vision and pattern recognition*  
521 (Vol. 2, pp. 2169–2178). New York: IEEE.
- 522 MacArthur, R. H. (1984). *Geographical ecology: patterns in the distribution of species*.  
523 Princeton, New Jersey: Princeton University Press.
- 524 MacKenzie, D. I., Nichols, J. D., Royle, J. A., Pollock, K. H., Bailey, L. L., & Hines, J. E.  
525 (2017). *Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of*  
526 *Species Occurrence* (2nd ed.). London, UK: Academic Press.
- 527 Meek, P. D., Vernes, K., & Falzon, G. (2013). On the reliability of expert identification of small-  
528 medium sized mammals from camera trap photos. *Wildlife Biology in Practice*, 9(2).  
529 doi:10.2461/wbp.2013.9.4
- 530 Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2012). *Foundations of Machine Learning*. MIT  
531 Press.
- 532 Niedballa, J., Sollmann, R., Courtiol, A., & Wilting, A. (2016). camtrapR : an R package for  
533 efficient camera trap data management. *Methods in Ecology and Evolution*, 7(12), 1457–  
534 1462. doi:10.1111/2041-210X.12600
- 535 Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., &  
536 Clune, J. (2018). Automatically identifying, counting, and describing wild animals in  
537 camera-trap images with deep learning. *Proceedings of the National Academy of*  
538 *Sciences*, 201719367. doi:10.1073/pnas.1719367115
- 539 O’Connell, A. F., Nichols, J. D., & Karanth, K. U. (Eds.). (2011). *Camera traps in animal*  
540 *ecology: methods and analyses*. Tokyo ; New York: Springer.



- 541 Palmer, M. S., Fieberg, J., Swanson, A., Kosmala, M., & Packer, C. (2017). A ‘dynamic’  
542 landscape of fear: prey responses to spatiotemporal variations in predation risk across the  
543 lunar cycle. *Ecology Letters*, 20(11), 1364–1373. doi:10.1111/ele.12832
- 544 Rasambainarivo, F., Farris, Z. J., Andrianalizah, H., & Parker, P. G. (2017). Interactions between  
545 carnivores in Madagascar and the risk of disease transmission. *EcoHealth*, 14(4), 691–  
546 703. doi:10.1007/s10393-017-1280-7
- 547 Rovero, F., Zimmermann, F., Bersi, D., & Meek, P. (2013). ‘Which camera trap type and how  
548 many do I need?’ A review of camera features and study designs for a range of wildlife  
549 research applications. *Hystrix, the Italian Journal of Mammalogy*, 24(2), 1–9.
- 550 Royle, J. A., & Dorazio, R. M. (2008). *Hierarchical modeling and inference in ecology*. New  
551 York: Academic Press.
- 552 Royle, J. A., & Link, W. A. (2006). Generalized site occupancy models allowing for false  
553 positive and false negative errors. *Ecology*, 87(4), 835–841.
- 554 Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-  
555 propagating errors. *Nature*, 323(6088), 533–536. doi:10.1038/323533a0
- 556 Scott, A. B., Phalen, D., Hernandez-Jover, M., Singh, M., Groves, P., & Toribio, J.-A. L. M. L.  
557 (2018). Wildlife presence and interactions with chickens on Australian commercial  
558 chicken farms assessed by camera traps. *Avian Diseases*, 62(1), 65–72.  
559 doi:10.1637/11761-101917-Reg.1
- 560 Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image  
561 recognition. *ArXiv:1409.1556 [Cs]*. Retrieved from <http://arxiv.org/abs/1409.1556>
- 562 Steenweg, R., Hebblewhite, M., Kays, R., Ahumada, J., Fisher, J. T., Burton, C., ... Rich, L. N.  
563 (2017). Scaling-up camera traps: monitoring the planet’s biodiversity with networks of

- 564 remote sensors. *Frontiers in Ecology and the Environment*, 15(1), 26–34.
- 565 doi:10.1002/fee.1448
- 566 Swanson, A., Kosmala, M., Lintott, C., & Packer, C. (2016). A generalized approach for  
567 producing, quantifying, and validating citizen science data from wildlife images.  
568 *Conservation Biology*, 30(3), 520–531. doi:10.1111/cobi.12695
- 569 Swanson, A., Kosmala, M., Lintott, C., Simpson, R., Smith, A., & Packer, C. (2015). Snapshot  
570 Serengeti, high-frequency annotated camera trap images of 40 mammalian species in an  
571 African savanna. *Scientific Data*, 2, 150026. doi:10.1038/sdata.2015.26
- 572 Swinnen, K. R. R., Reijniers, J., Breno, M., & Leirs, H. (2014). A novel method to reduce time  
573 investment when processing videos from camera trap studies. *PLoS ONE*, 9(6), e98881.  
574 doi:10.1371/journal.pone.0098881
- 575 Tabak, M. A., Piaggio, A. J., Miller, R. S., Sweitzer, R. A., & Ernest, H. B. (2017).  
576 Anthropogenic factors predict movement of an invasive species. *Ecosphere*, 8(6),  
577 e01844. doi:10.1002/ecs2.1844
- 578 Tikhonov, G., Abrego, N., Dunson, D., & Ovaskainen, O. (2017). Using joint species  
579 distribution models for evaluating how species-to-species associations depend on the  
580 environmental context. *Methods in Ecology and Evolution*, 8(4), 443–452.  
581 doi:10.1111/2041-210X.12723
- 582 Tobler, M. W., Carrillo-Percegué, S. E., Leite Pitman, R., Mares, R., & Powell, G. (2008). An  
583 evaluation of camera traps for inventorying large- and medium-sized terrestrial rainforest  
584 mammals. *Animal Conservation*, 11(3), 169–178. doi:10.1111/j.1469-1795.2008.00169.x

585 Tobler, M. W., Zúñiga Hartley, A., Carrillo-Percastegui, S. E., & Powell, G. V. N. (2015).  
586 Spatiotemporal hierarchical modelling of species richness and occupancy using camera  
587 trap data. *Journal of Applied Ecology*, 52(2), 413–421. doi:10.1111/1365-2664.12399  
588 Underwood, A. ., Chapman, M. ., & Connell, S. . (2000). Observations in ecology: you can't  
589 make progress on processes without understanding the patterns. *Journal of Experimental*  
590 *Marine Biology and Ecology*, 250(1–2), 97–115. doi:10.1016/S0022-0981(00)00181-7  
591 Yu, X., Wang, J., Kays, R., Jansen, P. A., Wang, T., & Huang, T. (2013). Automated  
592 identification of animal species in camera trap images. *EURASIP Journal on Image and*  
593 *Video Processing*, 2013(1). doi:10.1186/1687-5281-2013-52  
594  
595

## Tables and Figures

**Table 1:** Accuracy of the Species Level model

Species or group name	Scientific name	Number		Accuracy	Top 5 accuracy	False positive rate	False negative rate
		of training images	Number of test images				
Moose	<i>Alces alces</i>	8,967	997	0.98	1.00	0.02	0.02
Cattle	<i>Bos taurus</i>	1,817,109	201,903	0.99	1.00	0.01	0.01
Quail	<i>Callipepla californica</i>	2,039	236	0.90	0.96	0.11	0.10
Canidae	Canidae	20,851	2,321	0.89	0.99	0.08	0.11
Elk	<i>Cervus canadensis</i>	185,390	20,606	0.98	1.00	0.01	0.02
Mustelidae	Mustelidae	1,991	223	0.76	0.98	0.12	0.24
Corvid	Corvidae	4,037	452	0.79	1.00	0.15	0.21
Armadillo	<i>Dasypus novemcinctus</i>	8,926	993	0.87	0.99	0.08	0.13
Turkey	<i>Meleagris gallopavo</i>	3,919	447	0.88	1.00	0.12	0.12
Opossum	<i>Didelphis virginiana</i>	1,804	210	0.78	0.96	0.15	0.22

Horse	<i>Equus spp.</i>	2,517	281	0.93	0.99	0.05	0.07
Human	<i>Homo sapiens</i>	88,667	9,854	0.96	1.00	0.03	0.04
Rabbits	Leporidae	17,768	1,977	0.96	1.00	0.06	0.04
Bobcat	<i>Lynx rufus</i>	22,889	2,554	0.90	0.99	0.05	0.10
Striped skunk	<i>Mephitis mephitis</i>	10,331	1,154	0.95	0.99	0.03	0.05
Unidentified							
deer	<i>Odocoileus spp.</i>	86,502	9,613	0.96	1.00	0.02	0.04
Rodent	Rodentia	3,279	366	0.79	0.98	0.17	0.21
Mule deer	<i>Odocoileus hemionus</i>	76,878	8,543	0.98	1.00	0.03	0.02
White-tailed							
deer	<i>Odocoileus virginianus</i>	12,238	1,360	0.81	1.00	0.22	0.19
Raccoon	<i>Procyon lotor</i>	42,948	4,781	0.88	1.00	0.10	0.12
Mountain lion	<i>Puma concolor</i>	13,272	1,484	0.93	0.98	0.03	0.07
Squirrel	<i>Sciurus spp.</i>	59,072	6,566	0.96	1.00	0.05	0.04
Wild pig	<i>Sus scrofa</i>	287,017	31,893	0.97	1.00	0.02	0.03

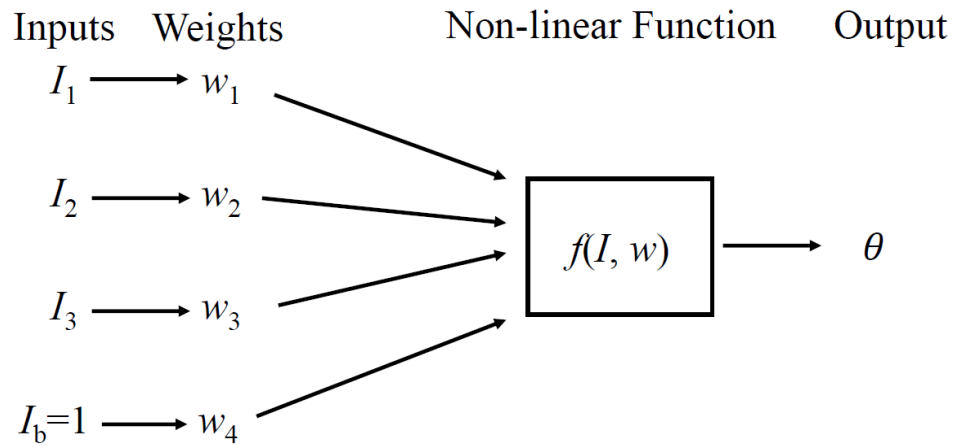
*Vulpes vulpes* and *Urocyon*

Fox	<i>Cinereoargentus</i>	10,749	1,204	0.91	0.99	0.07	0.09
Black Bear	<i>Ursus americanus</i>	79,628	8,850	0.94	1.00	0.02	0.06
Vehicle		23,413	2,602	0.93	1.00	0.04	0.07
Bird	Aves	61,063	6,787	0.94	1.00	0.05	0.06
Empty		414,119	46,016	0.96	1.00	0.06	0.04
Total		3,367,383	374,273	0.98	1.00		

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**Table 2:** Accuracy (across all images for all species) of the three deep learning tasks analyzed

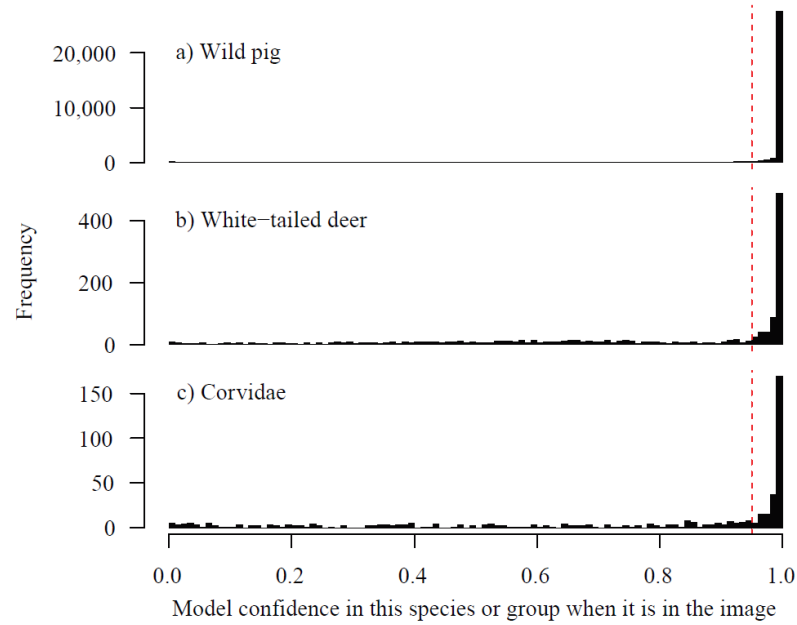
Model	Accuracy (%)
Pig/no pig	98.6
Species Level	97.5
Group Level	97.8



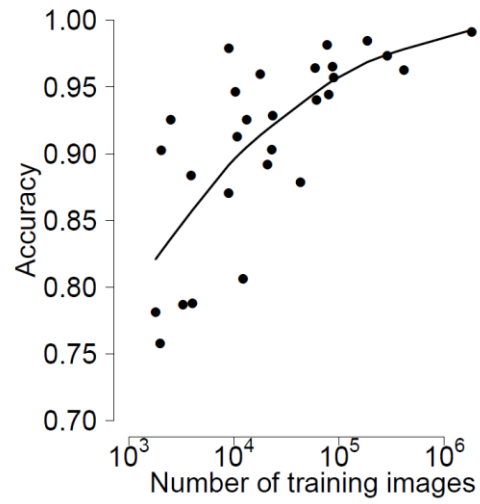
**Figure 1:** Within an artificial neural network, inputs ( $I$ ) are multiplied by their weights ( $w$ ), summed, and then evaluated by a non-linear function, which also accounts for bias ( $I_b$ ). The output ( $\theta$ ) can be passed as input into other neurons or serve as network outputs.

Backpropagation involves adjusting the weights so that a model can provide the desired output.





**Fig. 2:** Histograms represent the confidence assigned by all of the top five guesses by the Species Level model for each of these three example species when it was present in an image. The dashed line represents 95% confidence; the majority of model-assigned confidences were greater than this value.



**Fig. 3:** Machine learning model accuracy increased with the size of the training dataset. Points represent each species or group of species. The line represents the result of generalized additive models relating the two variables.

## **Supporting Information**

**Appendix S1.** Site descriptions for each of the study locations

**Appendix S2.** Accuracy of the Group Level for each species

**Appendix S3.** Accuracy of the Species Level model at the Tejon research site in California.

**Appendix S4.** Accuracy of the Species Level model in Colorado

**Appendix S5.** Accuracy of the Species Level model at Buck Island Ranch in Florida

**Appendix S6.** Accuracy of the Species Level model at the Camp Bullis Military Training Center in Texas

**Appendix S7.** Accuracy of the Species Level model at the Savannah River Ecology Laboratory in South Carolina

**Appendix S8.** Image classified as a striped skunk by humans, but cattle by the Species Level model