

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

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

173 where η is the learning rate and is chosen by the scientist. A higher η 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 subsetting 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

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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		

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

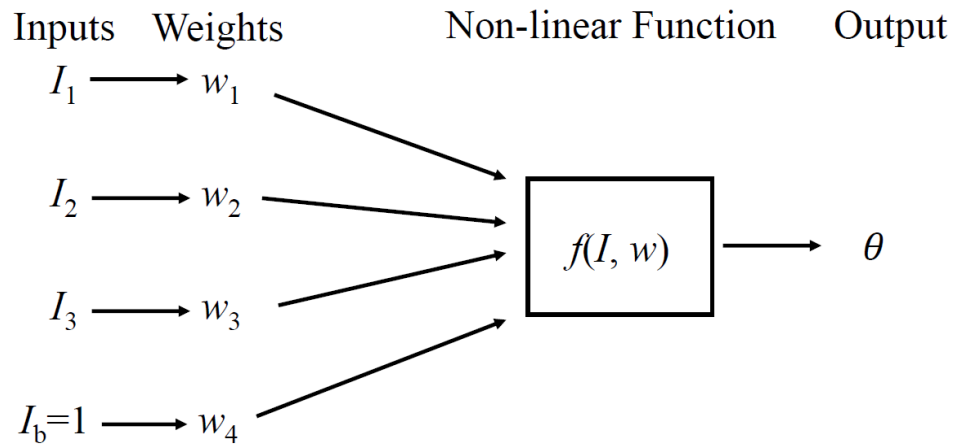


Figure 1: Within an artificial neural network, inputs (I) are multiplied by their weights (w), summed, and then evaluated by a non-linear function, which also accounts for bias (I_b). The output (θ) can be passed as input into other neurons or serve as network outputs.

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

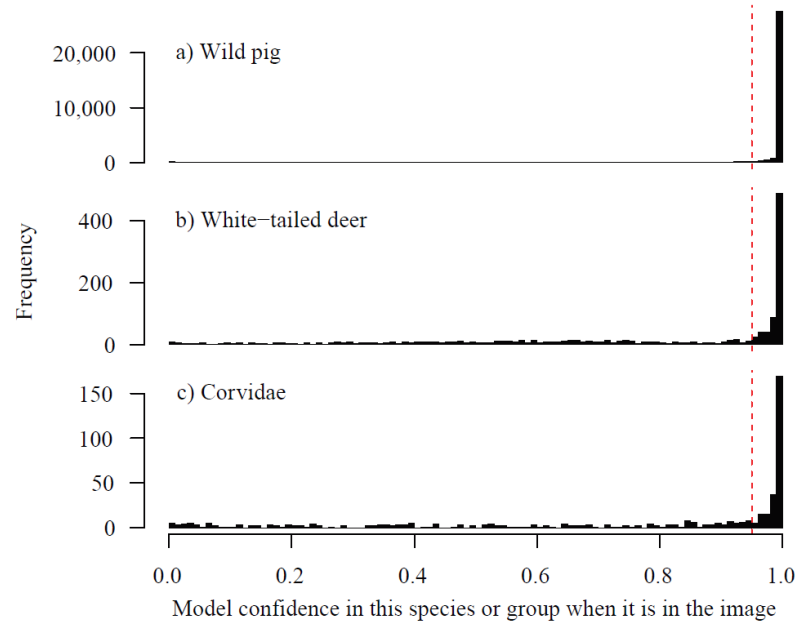


Fig. 2: Histograms represent the confidence assigned by all of the top five guesses by the Species Level model for each of these three example species when it was present in an image. The dashed line represents 95% confidence; the majority of model-assigned confidences were greater than this value.

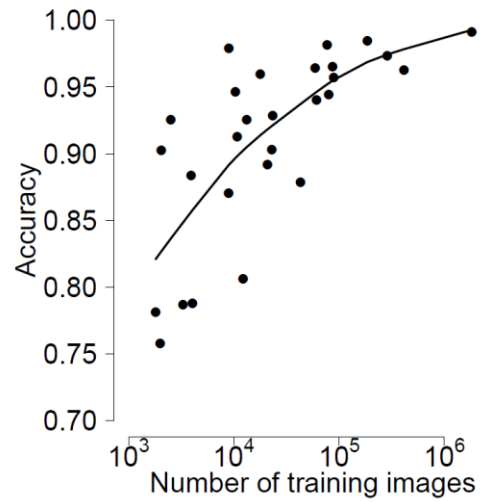


Fig. 3: Machine learning model accuracy increased with the size of the training dataset. Points represent each species or group of species. The line represents the result of generalized additive models relating the two variables.

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