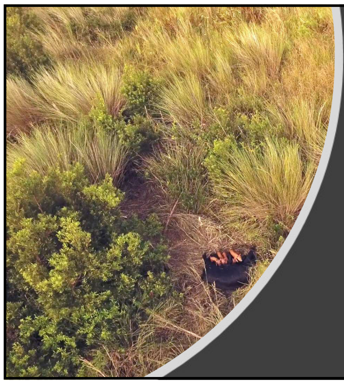


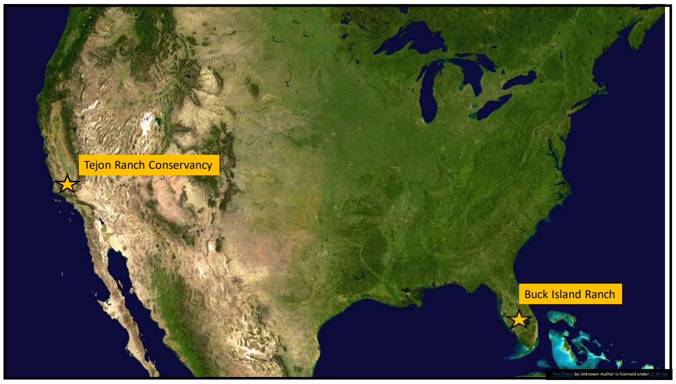
Wild Hogs and Big Data: How to deal with 7 million game camera images to answer questions on hog biology and management

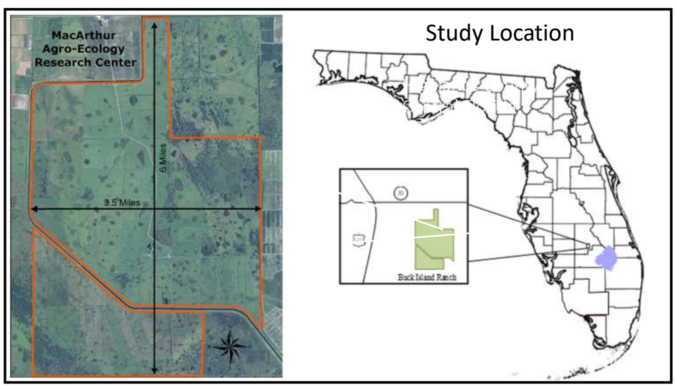
University of Florida
Range Cattle Research and Education Center
Webinar 11 December, 2018

Presented by: Dr Raoul Boughton
rboughton@ufl.edu

5 year study (USDA): 2014-2019

1. **Density and demography, reproduction and survival.**
   - Uniquely marked individuals (captures)
   - Capture-Resight Spatial Models (game cameras)
2. **Spatial Ecology, movement, resource selection models and interactions with livestock and at point sources**
   - GPS collars
   - UHF proximity collar studies among cattle, hogs and point sources
3. **Population control BACI design**
   - Does this change interactions, space use by hogs?
   - What effort is needed to remove hogs?
   - What is the time to population recovery?
4. **Disease sampling and identification**
   - Blood, feces, nasal, buccal, genital
   - Focus on ARMs and viruses (torque teno and circovirus to use in epidemiological models)
5. **Aerial assessment of rooting damage**
   - Drone flights and analyses of rooting damage





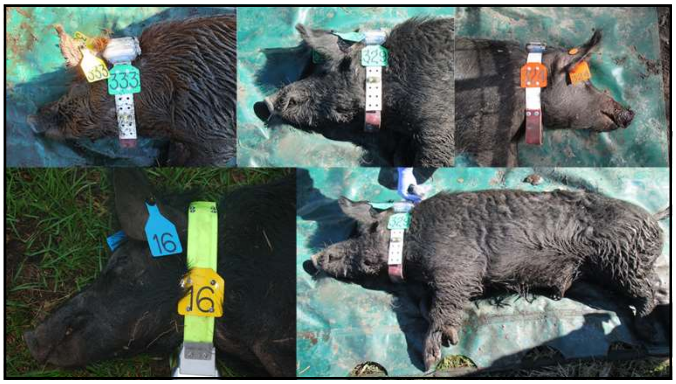
Game Camera Deployment

- 44 Game Cameras, 1/km2
- Deployed August 2015
- Continuously running since ~3.5 years
- Maintained monthly
- ~ 100,000 images processed a month

Trailer build for hog study

Needed for reduced use of anesthetics, ease of handling, and access for taken samples from awake hogs

Lots of help and hard work



Data Summary Information

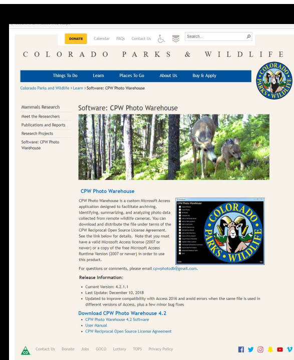
- **772 Feral Hog Captures**
  - 302 unique marks deployed (~100 per year)
  - 260 non-marked hogs removed during removals
  - 121 marked hogs removed during removals
  - 89 recaptures, resampled and released
- **> 4 million images taken (*in Florida*)**
  - ~ 276,975 of wild hogs
- **111 GPS units deployed (30 minute fixes)**
  - 546,060 fixes obtained.
  - Many early failures, short retention, water damage

Wild Hogs and Big Data

Image Management

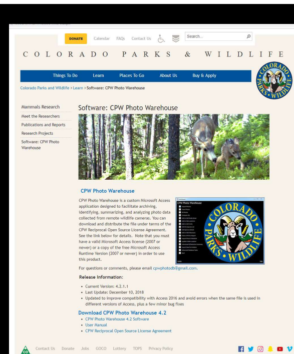
CPW Photo Warehouse

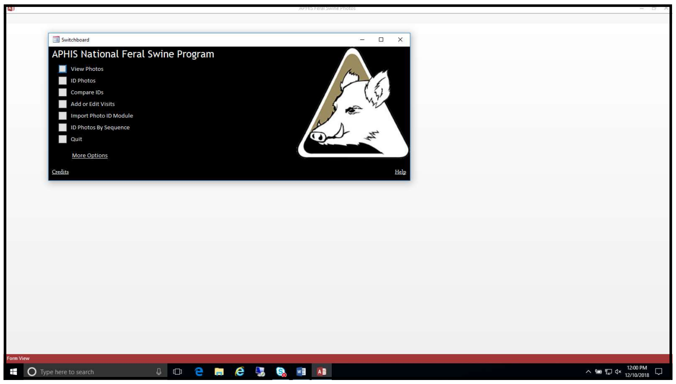
- Microsoft Access Application
- Archiving, summarizing, analyzing photos
- Double blind entry
- Third party verification
- Module creation and management for out of database identification (many uses at once)
- Tried and tested with many research projects
- Automated query functions to allow for data management
- Automated query functions to allow for data manipulation and format for analyses
  - Occupancy tables
  - Capture-recapture tables
- Excellent data management tool

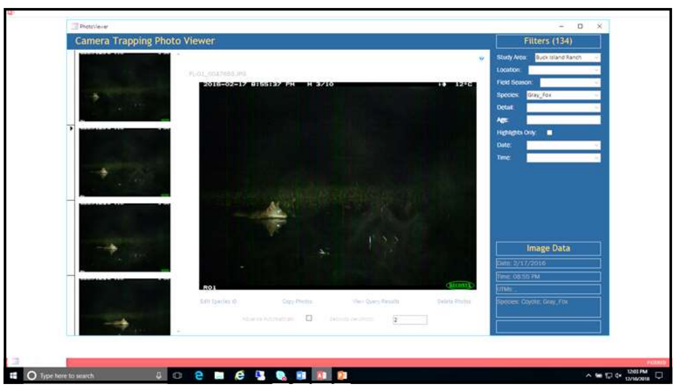


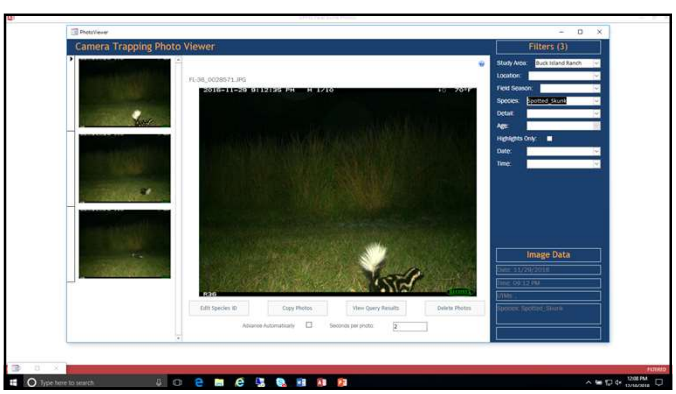
CPW Photo Warehouse - Problems

- Too many photos for MS Access
  - Overburdened within 1-3 months of data collection
- Moved to SQL server platform requiring some changes in code. ***Issue solved***
  - housed on USDA server access by secure login only
- Unable to keep up with image classification
  - 100,000 images/month
  - 200,000 IDs needed/month (double blind)
  - Plus verification
  - ~ 80hrs/wk fulltime
  - 1.5 million images identified and verified over 3.5years. ***Not Enough***




Switchboard
APHIS National Feral Swine Program
View Photos
ID Photos
Compare IDs
Add or Edit Visits
Import Photo ID Module
ID Photos By Sequence
Quit
More Options
Credits
Help


PhotoViewer
Camera Trapping Photo Viewer
Filters (134)
Study Area:
Buck Island Ranch
Location:
Field Season:
Species:
Gray_Fox
Detail:
Age:
Highlights Only:
Date:
Time:
Image Data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Camera Trapping Photo Viewer
Filters (3)
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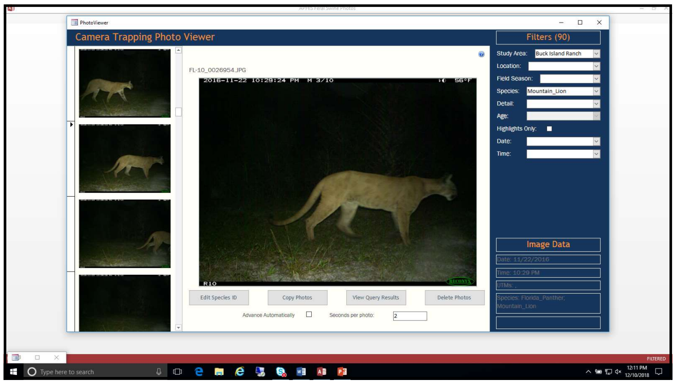
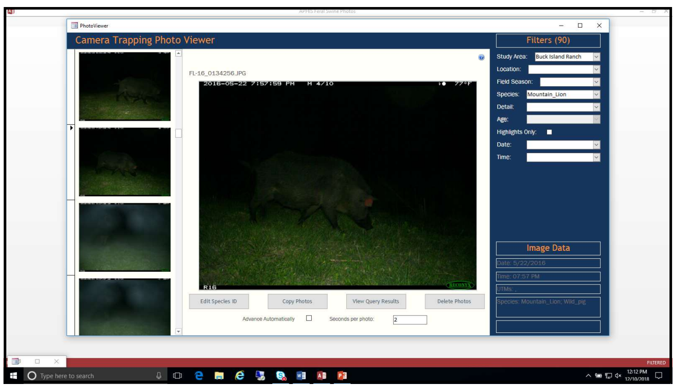
Buck Island Ranch
Location:
Field Season:
Species:
Spotted_Skunk
Detail:
Age:
Highlights Only:
Date:
Time:
Image Data


PhotoViewer
Camera Trapping Photo Viewer
Filters (90)
Study Area:
Buck Island Ranch
Location:
Field Season:
Species:
Mountain_Lion
Detail:
Age:
Highlights Only:
Date:
Time:
FL-10_0026954.JPG
2016-11-22 10:29:24 PM M 3/10 56°F
R10
Image Data
Date: 11/22/2016
Time: 10:29 PM
UTMs: ,
Species: Florida_Panther; Mountain_Lion
Edit Species ID
Copy Photos
View Query Results
Delete Photos
Advance Automatically
Seconds per photo:
2
FILTERED
Type here to search
12:11 PM
12/10/2018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Camera Trapping Photo Viewer
Filters (90)
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Buck Island Ranch
Location:
Field Season:
Species:
Mountain_Lion
Detail:
Age:
Highlights Only:
Date:
Time:
FL-16_0134256.JPG
2016-05-22 7:57:59 PM M 4/10 77°F
R16
Image Data
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Time: 07:57 PM
UTMs: ,
Species: Mountain_Lion; Wild_pig
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Copy Photos
View Query Results
Delete Photos
Advance Automatically
Seconds per photo:
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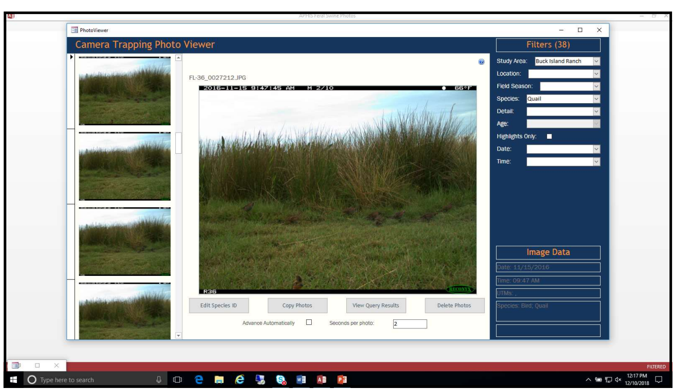
FILTERED
Type here to search
12:12 PM
12/10/2018


PhotoViewer
Camera Trapping Photo Viewer
Filters (38)
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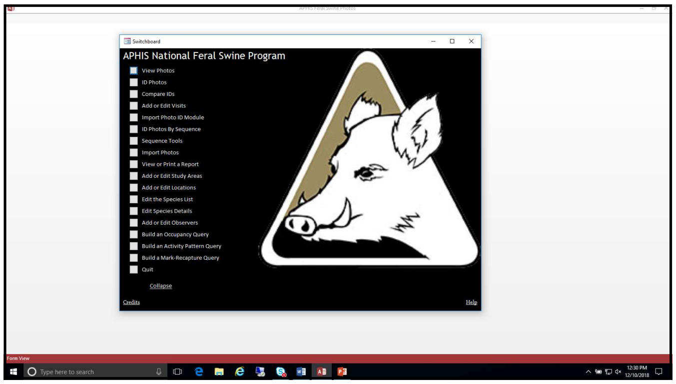
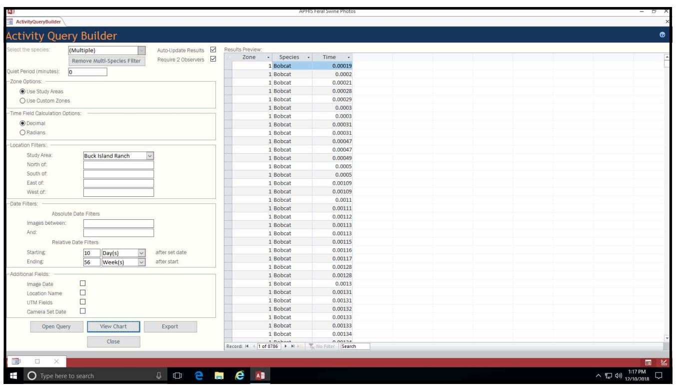
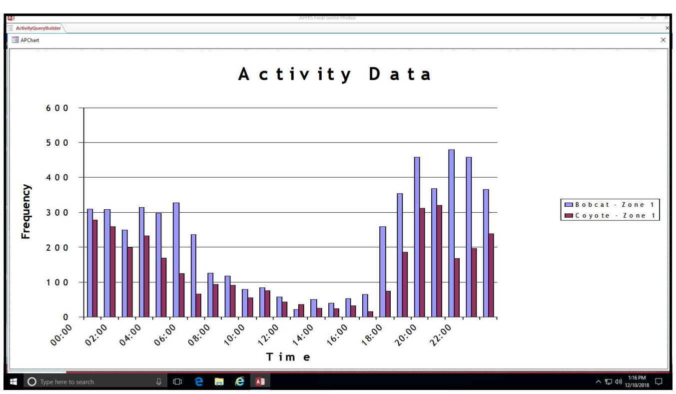
Buck Island Ranch
Location:
Field Season:
Species:
Quail
Detail:
Age:
Highlights Only:
Date:
Time:
FL-36_0027212.JPG
2016-11-15 9:47:45 AM M 2/10 66°F
R36
Image Data
Date: 11/15/2016
Time: 09:47 AM
UTMs: ,
Species: Bird; Quail
Edit Species ID
Copy Photos
View Query Results
Delete Photos
Advance Automatically
Seconds per photo:
2
FILTERED
Type here to search
12:17 PM
12/10/2018

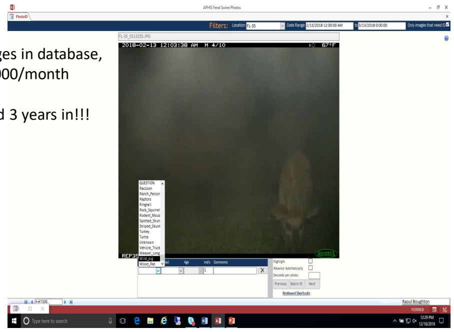

Switchboard
APHIS National Feral Swine Program
View Photos
ID Photos
Compare IDs
Add or Edit Visits
Import Photo ID Module
ID Photos By Sequence
Sequence Tools
Import Photos
View or Print a Report
Add or Edit Study Areas
Add or Edit Locations
Edit the Species List
Edit Species Details
Add or Edit Observers
Build an Occupancy Query
Build an Activity Pattern Query
Build a Mark-Recapture Query
Quit
Collapse
Credits
Help


Activity Query Builder
Remove Multi Species Filter
Zone
Species
Time
Buck Island Ranch
Open Query
View Chart
Export
Close


Activity Data
600
500
400
300
200
100
0
Frequency
00:00
02:00
04:00
06:00
08:00
10:00
12:00
14:00
16:00
18:00
20:00
22:00
Time
Bobcat - Zone 1
Coyote - Zone 1

Stalled by ID process

- Currently 6.9 million images in database, continual growth at 100,000/month
- Only, 1.5 million identified 3 years in!!!

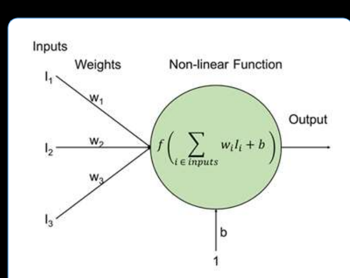


Machine Learning Process

- Supervised machine learning algorithms use training examples to “learn” how to complete a task.
- In our setting, we provided a set of animal images already identified (1.5million) from camera traps of different species and their labels (species identifiers) to a deep neural network.
- We trained the model to identify species in training images.
- Once a model is trained, it learns how to classify new images that were not used for training.

Image classification neuron

- I1 to I3 are inputs in our case Red, Blue, Green
- In our species classification setting, the inputs to the network are ***normalized Red, Green, Blue (RGB) values of raw pixels*** of image
- We then interpret the output of the final layer as the probability of the presence of species in the image.



The math you should know but don't have to

- $\boldsymbol{\theta = ReLu(w_1 I_1 + w_2 I_2 + w_3 I_3 + b)}$ **(eqn 1),**

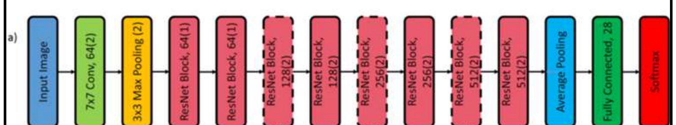
  Output of neuron calculated based on red, green, blue

- $\boldsymbol{L(P,Y) = -\sum_i P_i \log(Y_i)}$ **(eqn2)**

  Loss calculated = predicted result compared to actual identification

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

  Weights adjusted to improve loss (**L, eqn2**) to best case scenario



ResNET multi-neuron deep learning network

This has been set-up for you as an R package, available in GitHub.
"***Machine Learning for Wildlife Image Identification in R***"

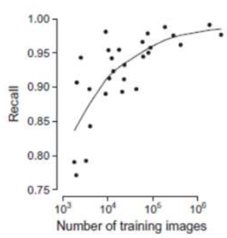
Images used from across the USA

- We used 3,741,656 classified images to train and assess neural model
  - California, Colorado, Florida, South Carolina, Texas and Canada
- 10% of each species retained for testing model (374,273 images)
- 27 Species or groups able to trained

TABLE 1 Model performance for each species or group

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

Recall – ability of model to recognize species in training dataset for that species



(a) Correct classification by model

(b) Incorrect classification by model

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

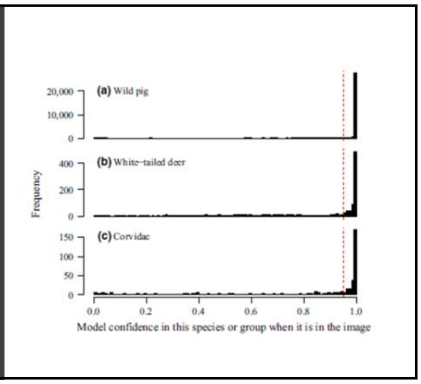
Answer from human classifiers: Wild pig

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

Answer from human classifiers: Cattle

Model Confidence Assignment

- Very high confidence achieved for most species
- But not every image is high
- Use confidence to assess what you will accept or need further verification



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APPLICATION

Methods in Ecology and Evolution

Machine learning to classify animal species in camera trap images: Applications in ecology

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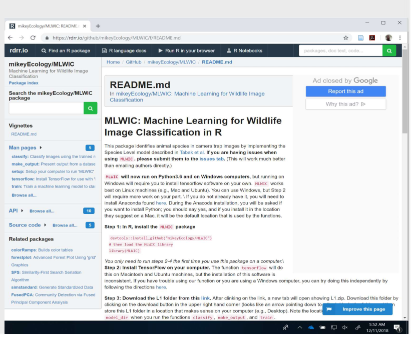
You don't need to understand neural network mathematics and architecture to run the machine learning module.
Go to github
https://rdrr.io/github/mikeyEcology/MLWIC/f/README.md



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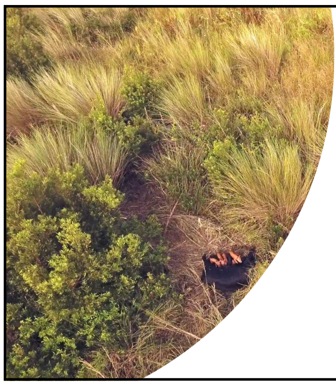
Brittany Bankovich (MS)
Phillipe Hernandez (PhD)

Technicians:
Bethany Wight
Brandon Parker

30+ UF and CSU undergraduate student species identification experts

UF|IFAS
UNIVERSITY of FLORIDA



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Presented by: Dr Raoul Boughton
rboughton@ufl.edu