Investigating the use of artificial intelligence to process camera trap data

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Abstract:

Wildlife camera traps are an invaluable tool in wildlife biology, but they also pose a major challenge. They can generate millions of photos per year but this data must be processed by researchers in order to be useful. The goal of this project was to attempt the implementation of an artificial intelligence (AI) program that could make it possible to process the large quantity of wildlife data collected by Brookhaven National Laboratory (BNL). The first approach was to implement a free package for R-studio[1] called MLWIC[2] (Machine Learning for Wildlife Image Classification). After challenges, a second alternative was considered called Wildlife Insights Beta[3]. These attempts resulted in the findings that: 1. MLWIC may not be compatible with an updated Windows computer or alternatively that a computer science/coding expert is needed to determine if the program is viable in the future; 2. Wildlife Insights is a useful starting off point which reduces the amount of labor for the user by effectively sorting out blank photos, but is still in beta development and the AI requires more training for accuracy. I have processed 12,426 photos and provided usable wildlife data for potential population estimates for various wildlife species present at the laboratory. This data may assist BNL in deciding whether to invest fund in a better AI program that is accessible, accurate, and easy to use in order to meet the needs of their wildlife monitoring programs.

Introduction:

Wildlife cameras are an excellent tool for more effective wildlife monitoring efforts. Using wildlife cameras provides many benefits including:

- Higher accuracy of sightings without humans
- Large quantities of data for analysis
- Less hands-on time in the field

Artificial Intelligence (AI) is useful in reducing the work-load for sorting wildlife photos; there are many programs available. This project will outline my attempts to implement two AI programs:

1. MLWIC (Machine Learning for Wildlife Image Classification):
   - A free package in R-studio available on GitHub
   - Requires coding and computer science knowledge
   - Can classify images by species
2. Wildlife Insights Beta
   - A free website to upload photos onto
   - Sorts by species

They each have their advantages and drawbacks, but the challenge remains of finding the right program to suit the specific needs and skill levels of specific survey and researchers.

Objectives:

This project aims to find an appropriate solution to hand sorting photos collected by BNL's camera traps and to test the chosen method on photos gathered. The four-poster tick management system which is monitored via camera traps generate approximately one million photos per year, and Brookhaven is looking to expand their other wildlife management programs via camera trap as well.

Figure 1. A Brief Comparison of Photo Sorting Methods

Hand Sorting		MLWIC		Wildlife Insights	
Pros	Cons	Pros	Cons	Pros	Cons
Free	Time consuming	Free	Learning curve	Free	Not very accurate
Reliable accuracy	May require large staff of researchers	97% accurate	Few help resources available	Sorts out blanks photos well (saves time)	Requires more photos and training
Interesting content	Eye and wrist strain; Tedious	Fast rate of sorting	Requires coding knowledge	User friendly; Responsive help team	Uploads can glitch, fail, and be time consuming

Methods:

Experimental setup

- Survey 1: 18 cameras placed from January 19 - March 3
- Survey 2: 14 cameras placed from March 30 - April 9
- Cameras setup in a grid at least .5km distance from one another
- Used scent traps to attract carnivores

MLWIC

- Directions followed from previous intern and GitHub
- Technical difficulties experienced; installation halted

Wildlife Insights

- Approved for use of Beta program
- Created a project
- Uploaded photos, one site at a time
- Reviewed "Computer Vision" (CV) suggestions and changed incorrect ID

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Results:

MLWIC:

- I faced technical difficulties and was unable to implement this program. For a comparison between MLWIC and Wildlife Insights' benefits and challenges, see figure 1.

Wildlife Insights:

- All photos were sorted through the Wildlife Insights interface.
- CV had limited success in providing correct IDs.
- Many blank photos were effectively removed by the CV
- A significant amount of time was dedicated to reviewing CV suggestions and correcting incorrect IDs.

Camera Trap Results:

- A total of 9,168 photos were collected and sorted in survey 1 and 3,258 in survey 2. Proportions of wildlife seen are illustrated in figures 2 and 3.

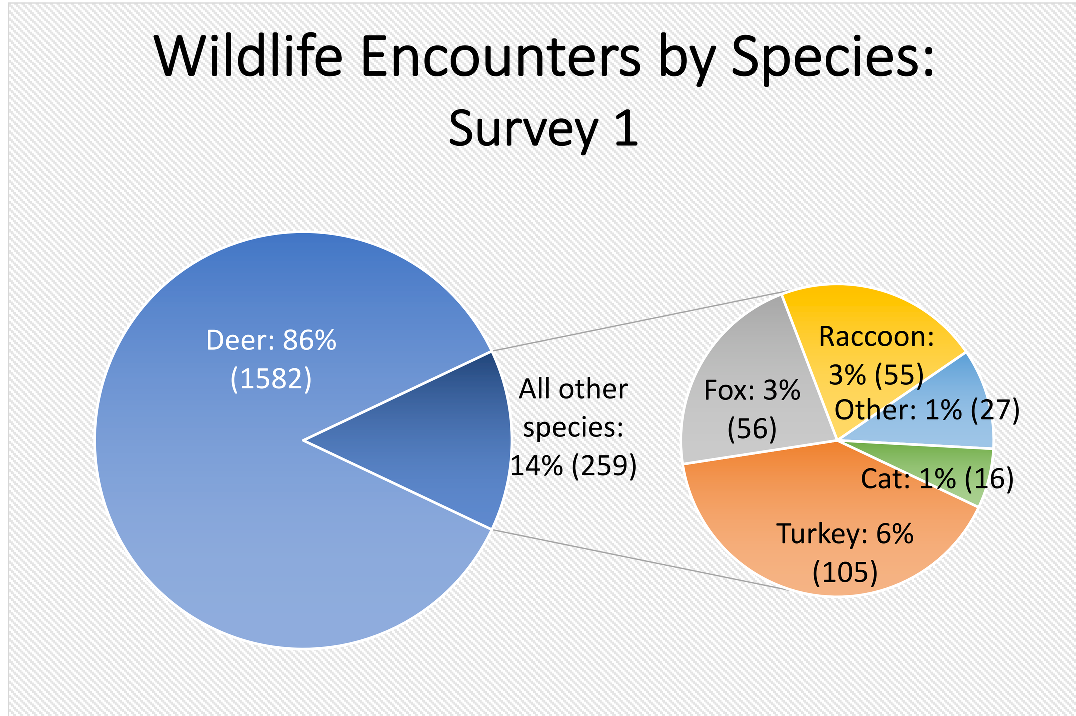

Figure 2. "Wildlife Encounters by Species: Survey 1". Not shown: 7,327 blank photos captured.

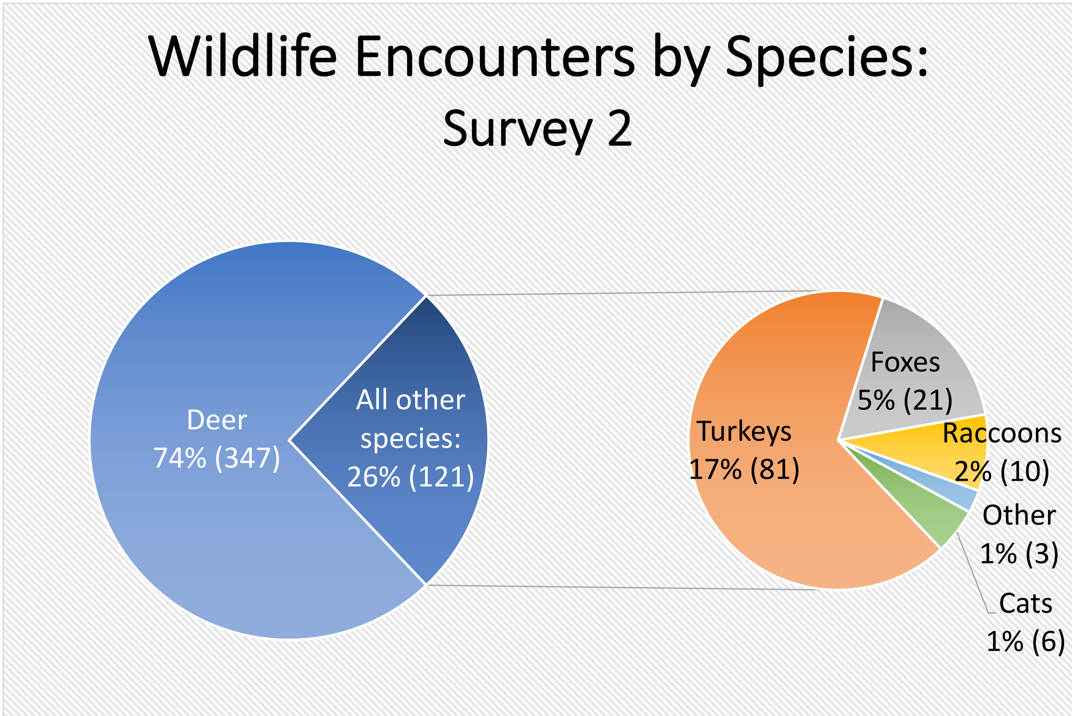

Figure 3. "Wildlife Encounters by Species: Survey 2". Not shown: 2,790 blank photos captured.

Seen above: Top two photos are *Odocoileus virginianus*, white-tailed deer. Second from bottom photo is *Vulpes vulpes*, a red fox. Bottom photo is *Meleagris gallopavo*, wild turkey.

Discussion:

MLWIC:

- The current hypothesis on why MLWIC failed to be implemented is that the BNL computers automatically update, and this program is only compatible with certain versions of operating systems. It also likely faces additional problems because it was not designed for use on Windows Operating Systems.

Wildlife Insights:

- This website is user friendly and very easy to use.
- It saves time by removing many blank photos but will require further AI training to become more regionally accurate for species on Long Island.
- The CV model consistently mistakes some species for others, as shown in figure 4. This likely occurs because the model relies on user data alone to train the AI model, and there are a lack of users and data from this region.
- The CV is retrained every two months, but will require thousands more of species local to BNL in order to be accurate enough to get results without manual review.
- I requested a feature be added to their website in which the AI accesses a database to determine which species it is likely to find based on the user's survey location, which could increase accuracy without requiring thousands of photos to already be in the database.

This survey has some limitations and shortcomings. The camera trap locations utilized scent traps with the goal of attracting carnivores to the sites. There were several major snowfalls during the first survey and rainfall during the second survey which influenced the scent traps and undoubtedly decreased their effectiveness.

Computer Vision suggestion	True species ID
Mule deer	White-tailed deer
Coyote	White-tailed deer
Coyote	Fox
Panther	Domestic cat
Lynx	Domestic cat

Figure 4. Differences between Wildlife Insight's Computer Vision suggestions as compared to true species identification as determined while reviewing survey photos. These inaccuracies can likely be credited to a larger proportion of the CV suggested species within the database as compared to the true species seen.

Looking forward:

This project can be used to inform the laboratory's decision of what method to use for photo sorting in the future and to determine if it may be necessary to invest money into a program that is more accurate and precise than the two methods outlined here. The wildlife data collected from this survey is likely going to be used by the New York State Mammal Survey in their first statewide mammal survey since 1971. This is a great research opportunity for the lab as well as a benefit to wildlife researchers across the state. With this survey information researchers will be able to have a deeper understanding of the extent of wildlife populations and therefore use this knowledge to better inform future management decisions and consequently benefit wildlife species conservation and management.

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