Man versus Machine: an evaluation of the accuracy of AI detection and identification software for processing wildlife camera trap data at Brookhaven National Laboratory

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I. Abstract

Across all disciplines, the process of converting raw data to meaningful information is an arduous task. This task grows even more laborious as the capacity to collect and store vast amounts of data expands, making identifying and evaluating strategies to mitigate the time and effort of transforming data increasingly necessary. In ecology, remotely triggered trail cameras are used to collect valuable information on wildlife such as species richness, diversity, distribution, abundance, behavior, etc. which produce large volumes of raw data (images and/or videos) in need of review, annotation, and analysis. Enormous strides have been made to expedite this timely process, one such being the use of machine learning models and artificial intelligence (AI) to automate detecting and classifying wildlife in images. To further understand the capabilities of AI tools for processing camera trap images, AddaxAI, an AI platform that uses machine learning models and the open-source model MegaDetector for automatic detection and identification, was evaluated using data from an ongoing camera trap study at Brookhaven National Laboratory on Long Island, NY. Compared to image labels determined by manual review using the program Timelapse2, it was found that AddaxAI correctly identified and labeled 93.745% of images from a dataset of 11,862. This is consistent with existing literature on the accuracy of MegaDetector and other AI recognition models. These findings highlight the potential utility of integrating AI recognition into camera trap image processing workflows for many camera trap studies while reinforcing their current limitations and the need for additional human review. This study aligns with Brookhaven's mission in developing next-generation information science and capabilities. In conducting this study, I have developed a thorough understanding of camera trapping, wildlife camera trap image processing, and the capabilities of AI image processing platforms.

II. Introduction

Camera Trapping

Modern camera traps have quickly transformed the methods in which many ecologists and conservation biologists study the distribution of wildlife species, their activity patterns, and interactions among ecological communities. Camera traps, also known as trail or game cameras, are devices that can be deployed in the field for long periods of time to remotely record wildlife activity.[8] The past two decades have seen the rapid expansion of and accessibility to this technology, transforming data collection in the fields of ecology and conservation biology.[4, 8]

Although they provide a more accurate and cost-effective alternative to traditional field surveys, this method of monitoring wildlife over large spatial and temporal scales has the potential to produce enormous volumes of raw data.[3, 7] This timely process of converting large datasets into meaningful information takes away from the efficiency of camera trap surveys and delays progress and actionable insights.[3] A potential solution to the timely issue of processing mega-datasets that has gained significant attention is the use of artificial intelligence (AI) learning models.[3, 7]

AI in Ecology

AI has numerous applications in ecology, in the context of camera trapping, AI is used for its two most basic data processing tasks: determining wildlife presence and location in images and assigning labels to detected animals. Animal detection and classification are used in assessments of species richness, diversity, distribution, etc.[1] Though these tasks appear simple and straightforward, when applied to mega-datasets they quickly become daunting for individual researchers to complete in a timely manner. Camera trap studies often deploy multiple cameras at once for long periods of time, which can quickly generate tens of thousands of images in need of review.[2] To resolve this challenge, ecologists have turned to machine learning and AI image recognition models to help automate the time-consuming task of processing camera trap images.

Models to detect and identify wildlife are created using a subset of data processed by hand to “train” computer algorithms and create a foundation for the model. Models AddaxAI and MegaDetector, can be trained for specific locations and/or species and are ever refining its performance. [6] How well a model performs depends on the characteristics of raw data the model is tasked with processing and the associated challenges they present.[5] Because of this, AI models can overlook and misidentify wildlife when locations change, animals are in motion, smaller species of wildlife, or inanimate objects are in frame.

Project Objective

The purpose of this study was to conduct a sitewide camera trap survey of wildlife at BNL and use a subset of this data to evaluate the accuracy of the AI image recognition model AddaxAI for processing wildlife camera trap images. This survey is a continuation of a much larger, multi-year study to document wildlife diversity, population changes, and coyote (*Canis latrans*) presence at Brookhaven National Laboratory (BNL). The main goal of this study is to report on the accuracy of AI recognition models for processing camera trap footage and provide a better understanding of how these models can be utilized in future camera trap surveys at BNL. A secondary goal of this study is to contribute meaningful data to a multi-year survey of wildlife populations at BNL to aid in the making of future management decisions on the property.

III. Methods & Materials

Study Area

Camera trap surveys spanned the entire Brookhaven National Lab property (approx. 2,153.5 hectares) and lasted for fifteen weeks from late August to early December of 2025; four of which were included in analysis. Surveys were conducted in a grid pattern across the whole property focusing on paths and roads (paved, gravel, sand, etc.). BNL is in the heart of the Central Pine Barrens Region on Long Island, NY. This ecosystem is characterized by sandy soil, minimal understory, and open canopy dominated by pitch pines (*Pinus rigida*). The Lab itself is a mosaic of landscapes including white pine (*Pinus strobus*) dominant stands, oak (*Quercus* spp.) dominant areas, pine barrens restoration stands, manicured lawns, and industrialized buildings.

BNL is host to an abundant diversity of wildlife common to the region. Some of the most common include white-tailed deer (*Odocoileus virginianus*), northern raccoons (*Procyon lotor*), groundhogs (*Marmota monax*), wild turkeys (*Meleagris gallopavo*), Virginia opossums (*Didelphis virginiana*), and red foxes (*Vulpes vulpes*).

Field Surveys

Trail cameras were deployed in a 0.5 km grid consisting of seventy-three locations across the BNL property (Figure 1). This is a pre-existing grid used in an ongoing, multi-year camera trap survey. Out of these seventy-three sites, fifteen were used in the analysis of this study (Figure 1).

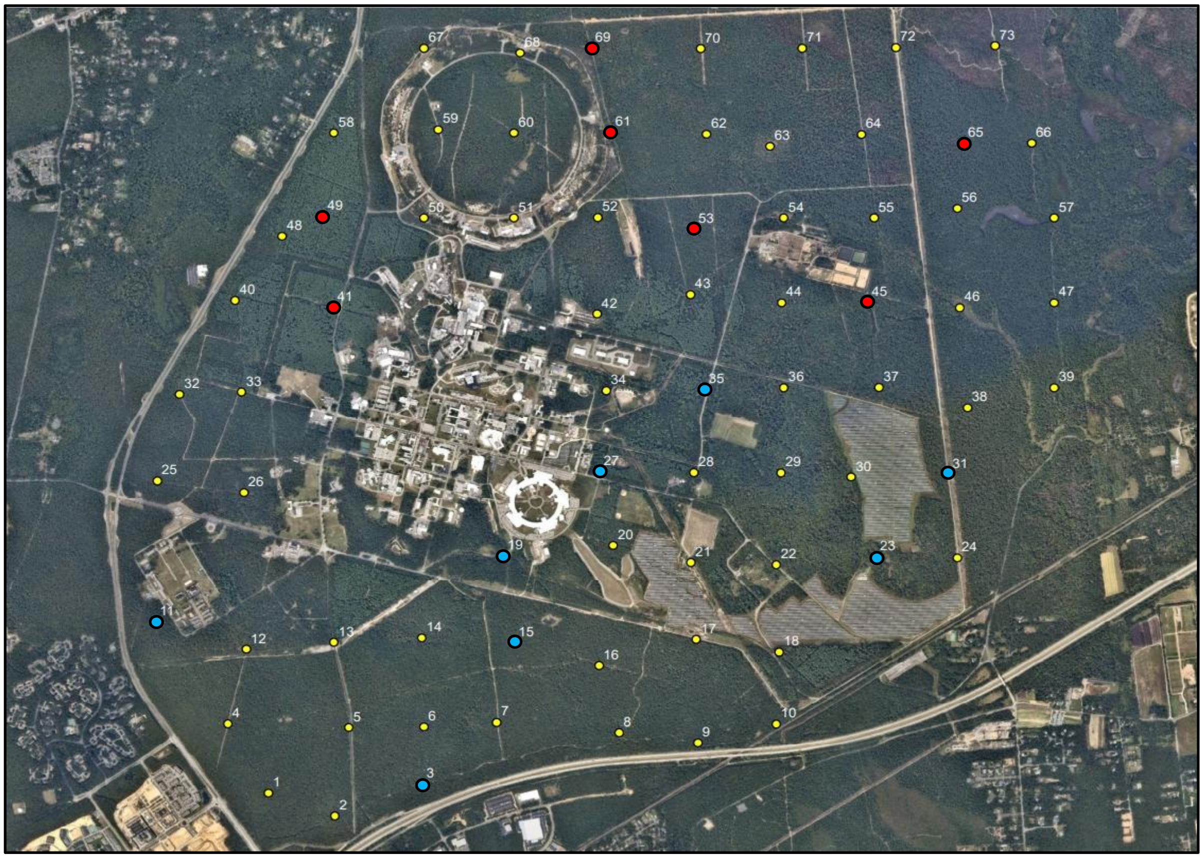

Figure 1. Camera trap locations on Brookhaven National Lab property. Yellow sites encompass site-wide survey, red and blue sites were the subsect used in this study's analysis.

Cameras were deployed in rounds consisting of nine cameras each for two weeks at a time; time frame and number of active cameras were dependent on weather conditions, site accessibility, and vegetation cover. Cameras were deployed every four sites to better cover larger areas at a time per round (e.g. round one consisted of sites 2, 6, 10, 14, 18, 22, 26, 30, and 34 lasting from August 28th to September 11th, 2025). Rounds overlapped, meaning that up to eighteen cameras could be active at one time.

Camera Setup & Deployment

The cameras used in this survey were Moultrie and Browning brand trail cameras. Regardless of brand, camera settings were set to motion trigger, high sensitivity, 10 or 15 second delay, 3-photo burst, and max distance. Cameras operated using alkaline batteries and SD cards; such would be replaced on a need basis with each rotation.

Figure 2. Moultrie camera strapped to oak tree and angled downward using stick (left), fatty-acid tablet baited within range of camera (right).

Cameras were strapped to structurally sound trees along roads and paths. Trees were selected based on proximity to paths, minimal obstructing vegetation, and structural integrity. Cameras were pointed towards paths at approximately knee height, or two feet off the ground, and angled towards the ground as can be seen in Figure 2. Each camera was baited with fatty-acid scent tablets to attract animals to come into view of the camera (Figure 2). Before activation, camera direction and angle were tested using a motion test to ensure correct placement and reduce false triggers caused by vegetation. Information on site number, location, camera number, and dates of deployment and retrieval were recorded using Survey123. Once complete, cameras were set to “custom start” and left active for the full two-week deployment.

Data Analysis

To process camera trap photos, data from SD cards were downloaded after each deployment and processed using the image recognition software AddaxAI and reviewed using image processing program Timelapse2. TimelapseTemplate was used to create a template with which to review camera trap photos in Timelapse2.

All images were uploaded to Timelapse2, processed by MegaDetector through AddaxAI, then were reviewed and analyzed through manual review. MegaDetector labels detections using bounding boxes annotated with the detection's classification and confidence thresholds for the detection itself and in the classification. MegaDetector classifies images into four broad categories: empty (images with $<0.2\%$ confidence), human, vehicle, and animal. Manual review includes mainly recording species ID and count as well as evaluating the accuracy of detections $\geq 0.2\%$.

Image detections and classifications created by MegaDetector were evaluated on true positives (TP; ≥ 1 of bounding boxes were confirmed to contain an animal), true negatives (TN; neither manual review nor MegaDetector detected any animals), false positives (FP; MegaDetector labeled ≥ 1 object in an image which was determined to have no animals present), and false negatives (FN; MegaDetector labeled an image as empty which was confirmed to contain ≥ 1 animal) (Figure 3). In addition to these evaluations, false-true positives (FTP) were determined which were cases when MegaDetector placed bounding box(s) around detected animal(s) that did not contain an animal(s), however, an animal(s) was found elsewhere in the image (Figure 3). For analysis, FTP was combined with FP and FN.

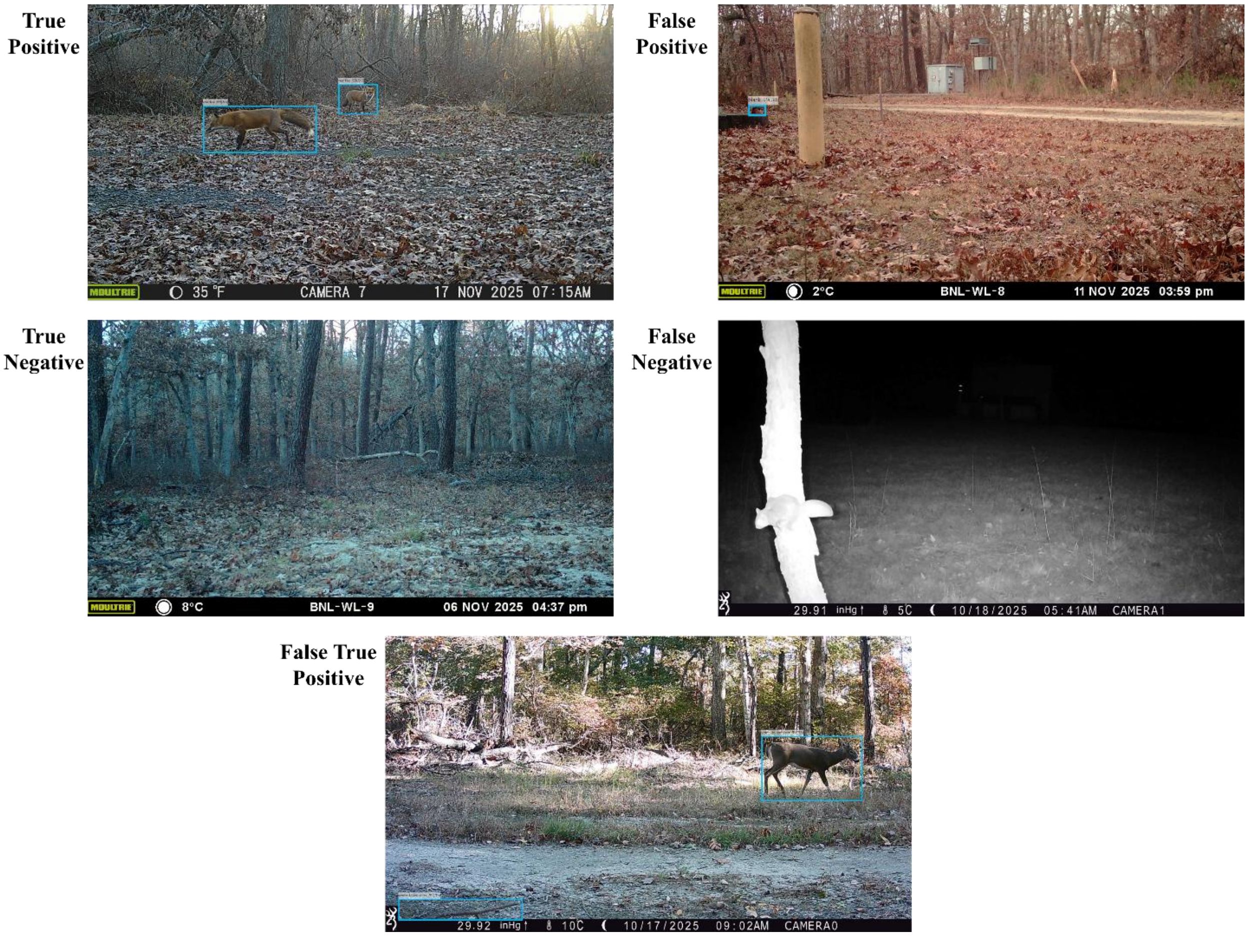

Figure 3. Example of final image results and labels determined by MegaDetector (i.e. blue bounding boxes).

Objects labeled by MegaDetector are influenced by the object detection threshold used (i.e. value indicating the model's confidence in the assigned label). For this study, detections of <0.2% confidence were considered to have been categorized as empty by MegaDetector during manual review.

IV. Results

Camera Trap Data

A total of 11,862 images from fifteen cameras were included in the analysis, with 5,222 images (44.0% of total) determined by manual human review to contain ≥1 object; of these, 4,272 images (81.8% of detections; 36.0% of total) determined by manual human review to contain ≥1 animal. The most photographed animals were white-tailed deer with 3,740 individuals counted in 3,049 images (71.4% of total wildlife images) and red foxes with 304 individuals documented in 301 images (7.0% of total wildlife images) (Table 1).

Species Present	**Number of Images with ≥ 1 Animal Present**	**Count**
White-tailed deer	3049	3740
Wild turkey	296	1268
Bird spp.	297	461
Red fox	301	304
Northern raccoon	133	160
Feral cat	87	89
Virginia opossum	40	40
Eastern cottontail	40	40
Southern flying squirrel	10	10
Groundhog	9	9
Arthropod spp.	3	3
Eastern gray squirrel	1	1
Total	**4272**	**6132**

Table 1. Image set characteristics of wildlife camera trap data from fifteen cameras at BNL.

AddaxAI/MegaDetector Results

AddaxAI, with open-source image recognition software MegaDetector, correctly labeled (i.e. TP and TN) 93.745% and incorrectly labeled (i.e. FP, FN, and FTP) 6.255% of the 11,862 images used in this analysis. A summary of the proportion of MegaDetector's performance after being evaluated by manual human review can be seen below in Figure 4.

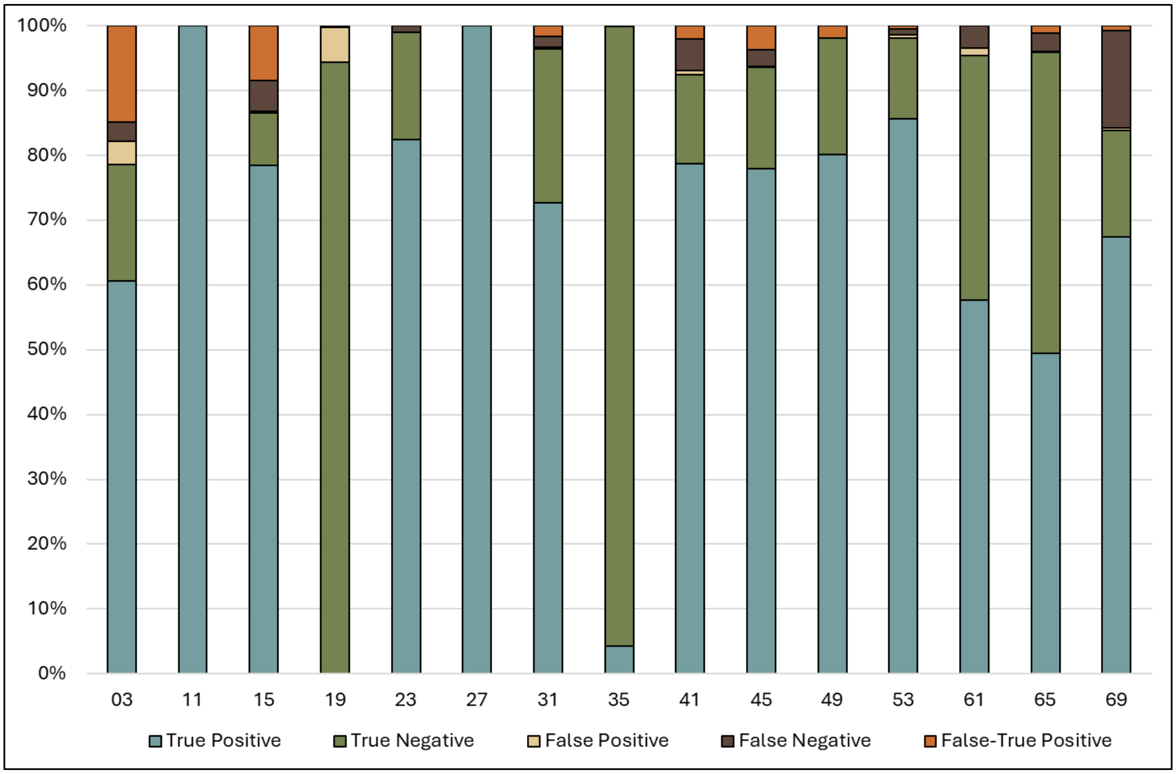

Figure 4. Summary of the proportion of images correctly and incorrectly labeled w/animal presence/absence by Addax AI after manual review.

V. Discussion

It was found that the program AddaxAI, with MegaDetector model incorporated, performed acceptably at detecting wildlife in images collected via motion-triggered camera traps. AddaxAI correctly labeled 93.745% of the 11,862 images processed through the program, a statistic consistent with existing evaluations of MegaDetector's performance.[1] The efficiency of AI processing is entirely dependent on computer hardware and skill of the human reviewer.

Image processing using AI models is likely to be more efficient than processing solely by hand, especially when dealing with mega-datasets.

The accuracy of MegaDetector is heavily influenced by vegetation structure, inanimate objects, objects/animals in motion, partially obscured objects, and smaller species of wildlife such as birds or rodents. Camera studies often survey large areas of land with diverse flora and fauna; this diversity would result in significant incorrect or partially incorrect AI classifications.

These findings highlight the potential utility of integrating AI recognition models in camera trap image processing workflows for many camera trap studies while reinforcing their current limitations and the need for human review in the analysis process.

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