Facial Recognition Technology for Identifying Cercopithecus Hybrid Monkeys

Connor Cane, Kayla Rae Ahlness, Charlene S. Fournier, Kate M. Detwiler, PhD (Faculty Advisor)

Abstract

Implementing innovative technology has become an invaluable resource for wildlife ecology and conservation studies. Recent studies support the use of facial recognition technology in primate species to assist with data collection. The purpose of this project was to develop a facial recognition software to identify individuals in a habituated population of Cercopithecus monkeys, consisting of two species and their hybrids (Cercopithecus ascanius and Cercopithecus mitis). This research is part of a long-term primate study in Gombe National Park, Tanzania. We developed an identification system by combining machine learning, object detection, and image classification. Using 16,226 images of 61 different monkey individuals, we trained an object detection system to detect the face of each monkey and we combined it with a custom-trained fast.ai Convolutional Neural Network (CNN) learning mode for identification. The sequence of these algorithms resulted in an original machine learning model with a 99.44% accuracy rate in detecting and identifying individuals from this population.

Introduction

The recognition of a single individual is critical to long-term studies of animal behavior and ecology (Crouse et al., 2017). Digital and automated technology are gaining more momentum in the fields of wildlife biology and conservation (Arts et al., 2015). The inclusion of efficient processes is crucial in order to capture accurate data on population trends. The Primatology Lab at FAU is conducting ongoing research on hybridization of Cercopithecus monkeys in Gombe National Park, Tanzania (Detwiler, 2019). The goal of the project is to obtain long-term behavioral, ecological, and reproductive data on individual members of the population. The integrity and accuracy of longitudinal research data relies heavily on the ability to identify each individual in the population (Crouse et al., 2017; Clutton-Brock & Sheldon, 2010). Our study population consists of approximately 61 individuals that include blue monkeys (Cercopithecus mitis), red-tailed monkeys (Cercopithecus ascanius), and their hybrids (Figure 1). Multiple researchers work in the field and in the lab to characterize and identify individuals. Currently, identifications are performed manually by trained field assistants and students; however, misidentifications occur. While these monkeys are phenotypically distinct, the differences can sometimes be too negligible for human researchers to reliably distinguish them visually. Data attributed to the wrong individual can mislead or invalidate outcomes of a study, set back researchers within their plan of study, and potentially impact other projects which rely on these data. Additionally, as field assistants and students join and leave the project, they face a substantial learning curve and need to be intensely trained on how to identify each of the individual monkeys (Loos et al., 2013). We addressed these issues by creating innovative techniques in Artificial Intelligence/Machine Learning (AI/ML) to identify individual monkeys that belong to our long-term study population.

Breakthroughs have emerged on multiple fronts in human facial recognition over the last few years (Coşkun et al., 2017). The underlying models and technologies have evolved along with massive improvements to computing power unlocked by modern graphic cards (Steinkraus et al., 2005). In a pilot study, we tested existing human facial recognition programs on monkey pictures generated from the lab. It resulted in failed identifications, which indicated that existing training models were not appropriate for monkey individuals. New models would need to be trained in order to accommodate the unique facial characteristics of the individuals in our population. An earlier study on chimpanzees had success in identifying specific
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individuals by using deep learning techniques on facial profiles (Loos et al., 2013). Capturing accurate individual identifications, regardless of the technique, is difficult, yet important, for long-term ecological, behavioral, and life history studies (Guo et al., 2020). The purpose of our research was to (1) design an AI/ML program that can be utilized to automate the identification process of individuals in our study population and (2) provide an efficient and accurate tool to the research team for current and future projects.

**Figure 1:** Visual examples of *Cercopithecus mitis*, *Cercopithecus ascanius*, and *Cercopithecus mitis* × *Cercopithecus ascanius* hybrids.

Methods

We created an Artificial Intelligence/Machine Learning (AI/ML) model using thousands of photos and trained it in a high-performance computing environment. To effectively train a unique AI/ML model, a large data set of pre-classified images was required at the outset. In this project, we used a dataset consisting of over 16,226 identified images captured and classified by our research team, which profiled 61 individual monkeys (mean = 261 pictures/monkey). From this dataset, we used 12,800 images to train the model and an additional 3,200 images to validate the procedure. We selected the deep learning and computer vision platform FastAI to develop the AI (https://www.fast.ai/) for its ease of use and powerful machine learning capabilities. Initial attempts at training the facial recognition system resulted in 80% identification accuracy. We hypothesized that incidental information (e.g., trees, backgrounds, sky, etc) in the photos resulted in decreased accuracy. Therefore, we addressed these limiting factors for accurate training of the classifier.

To improve the accuracy score, we created a program that cropped images automatically and only displayed the face of the individual, which eliminated confusion from background noise in the image. Object detection is considered one of the most challenging tasks in the computer vision field (Liu et al., 2019; Fischler & Elschlager, 1973). We used YOLOv3 (You Only Look Once, Version 3), a real-time object detection algorithm to identify specific objects in videos, live feeds, or images. YOLO is a Convolutional Neural Network (CNN) (Redmon & Farhadi, 2018), which uses features learned by a deep convolutional neural network to perform object detection in real-time. CNNs are classifier-based systems that can process input images as structured arrays of data and identify patterns between them. We then trained a YOLOv3 (Redmon & Farhadi, 2018) object recognition model using the cropped images and validated its accuracy.
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**Figure 1:** Visual examples of *Cercopithecus mitis*, *Cercopithecus ascanius*, and *Cercopithecus mitis x ascanius* hybrids.

Note. Top Left: *Cercopithecus mitis* (blue monkey); Bottom Left: *Cercopithecus ascanius* (red-tailed monkey); Top Right: *Cercopithecus* hybrid displaying more blue monkey morphological features; Bottom Right: *Cercopithecus* hybrid displaying more red-tailed monkey morphological features. Photo Credits: Maneno Mpongo and Charlene S. Fournier

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A detector with over 4,000 iterations to achieve a 95.9% accuracy rate in identifying and extracting monkey faces from photos. For the image label feature, we used HyperLabel to manually label an initial training set of 1,000 images, which allowed for accelerated ML dataset creation for the computer vision model.

We developed a web application that displays the distribution of probabilities as to the unknown or test monkeys’ possible identification. The computational platforms needed to train a machine learning model are expensive, high-performance, and specialized; however, once a final model is created, it can be exported and used on common CPU-based systems, including basic web-hosted shared and virtual environments. The final web application we created runs on a single CPU processor and utilizes an Apache web server and Python. Both the YOLO object-detection model and the individual prediction model enable any user with access to the application the ability to upload a photo, have the application detect a monkey face, and display a ranked probability of matching. We designed the model as a web-based application for use in the field and optimized it for a mobile-phone-based browser and camera. We tested multiple CNN training models utilizing Google Compute (AI/ML optimized) clusters including Resnet34 and Resnet50, with the latter yielding better accuracy (Figure 2).

![Figure 2: Confusion matrix for our AI model.](image)

Note. Confusion matrix showing prediction, actual loss, and probability (n=61 profiles).

**Results**

We successfully created an AI/ML monkey facial recognition model that can correctly identify an individual from the study population with 99.44% accuracy (Figure 3). The models created were exported and used to create a live website, where researchers can upload photos of the monkeys and get...
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Our results were obtained through the program implementation of FastAI, a deep learning program that allowed for the development of facial recognition through the deep learning library. It provided a layered architecture, which expresses common underlying patterns of many deep learning and data processing techniques in terms of decoupled abstractions. These abstractions can be expressed concisely and clearly by leveraging the dynamism of the underlying Python language and the flexibility of the PyTorch library (Practical Deep Learning for Coders, v3. (n.d.). Retrieved from https://course.fast.ai/). The system is productive and provides a user-friendly interface making it ideal for the implementation of our program. A follow-up study that analyzed photos taken in the field between 2015-2022, showed that our AI/ML application was successful at recognizing 94.9% of the individuals, multiple years before and after their initial classification in 2019 (Ahlness, 2022). Additionally, the web application contains a database of categorized and identified monkey photos for manual reference.

Discussion

We successfully created a two-step Artificial Intelligence/Machine Learning (AI/ML) program that identified a study individual with a 99.44% accuracy rate. Our research program aimed to eliminate costly identification errors to support the ongoing primate research taking place in the Primatology Lab at FAU and our field study site, Gombe National Park, Tanzania.

We created a web application which enables end-users to take or upload a photo of a known member of the group. Using medium and high-resolution cameras, including mobile phones, along with a mobile-friendly web application, researchers have the potential to get instant and highly accurate identifications of monkey individuals over a cellular or Wi-Fi connection. The utilization of the FastAI deep learning program allowed the combination of high-level components through a standard deep learning domain and additionally enabled the use of low-level components that could be combined with other systems for the development of our new program (Howard & Gugger, 2020). During the initial training, we experienced varied results with an 80% accuracy rate for identifications. Other researchers have reported difficulties with challenging lighting, various positions which make facial visibility less than complete, as well as potential partial occlusion by tree branches, leaves, or other monkeys (Loos et al., 2013; Clapham et al., 2020). To overcome the obstacles that decrease accuracy, we used YOLO object detection to find and crop faces before passing the information to the fast AI model for a probability distribution for individual monkey identification. YOLO has the advantage of being much faster than other networks while still maintaining accuracy (Redmon & Farhadi, 2018). Additionally, the YOLO platform allows the researchers to provide contextual feedback, enabling future versions of the application to improve accuracy and functionality. Through this project, we illustrated the power of using AI/ML to assist with deficiencies in long-term population tracking.

For the next step of this project, we will test if the program can be trained to recognize and confidently track individuals from birth to adulthood as they mature within the study group. Training with an expansive set of photos throughout multiple time periods may create more margin for error as previously seen in humans (Rashmi et al., 2017). However, future training models may show improvement for non-human primates as the facial characteristics may be less susceptible to vast changes over an individual lifetime. Additionally, improvements to the web application for better use as a data validation tool and the inclusion of more profiles may increase the effectiveness of this program as a research tool. New methods of training AI/ML also become available each year, which could help in creating more accurate predictive models in the future.
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Data Availability Statement

The facial recognition model (FastAI Notebook) is available from faculty advisor, Dr. Kate M. Detwiler, upon reasonable request. kdetwile@fau.edu

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Figure 3: Loss rate using YOLOv3 object-detector.

Note. Loss rate through >4,000 iterations using YOLOv3 object-detector.

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References


