Convolutional Neural Network Image Recognition to Detect Endangered African Animals

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Abstract

Detecting animals for population analysis represents a costly, time intensive and manual process that is built on assumptions (Wilber et al, 2013). Utilizing Inception, a convolutional neural network (CNN) model built for image recognition, we aimed to identify 10 endangered species across Africa from images obtained from ImageNet. Our results show high accuracies of 80% with a pre-trained Inception-v3 model and 98.2% for the re-trained. Lastly, we attempted to better classify images with similar builds, by retraining the model on rhinoceroses and wildebeests. This final component was our most successful model with an accuracy of 99.3%. In conclusion, utilizing Inception, we were able to validate a methodology to better detect endangered species across different terrains of Africa.

1 Introduction

According to the World Wildlife Foundation, between 1970 and 2012, populations of vertebrate animals have declined by 58% (Living Planet Report, 2016). When collecting animal population surveys to generate statistics, it is challenging to accurately count species within a population, given that some reside in unfamiliar terrains, the high costs of conducting field studies and decisions are often based on assumptions (Wilber et al, 2013).

With advances in photography, researchers now capitalize on captured images to identify endangered species in unobservable areas. However, in current practice, image studies of wildlife are reviewed by researchers in a manual approach, involving identifying species in each frame (Yu, 2013).

Recently, the use of wireless sensor networks has become more popular, providing opportunities to observe the unobservable (Porter et al, 2005). These networks capture data spanning from temperature, sound and imagery (Porter et al, 2005).

Applying image recognition to this collected imagery, represents a great opportunity to automatically detect animal species, replacing manual human detection.

With modern advances in image recognition software, we propose a more accurate methodology to identify vulnerable and endangered species using CNN.

2 Related Work

Image recognition has been used in a variety of industries including automotive, medical, and financial. With respect to animal recognition, a handful of researchers have attempted to tackle this problem, but with different objectives.

Similar to our outlined objectives, California-based researchers aimed to address the same issue of endangered species detection, by studying images from the Mojave Desert (Wilber et al, 2013). These researchers utilized a feature-based learning approach, incorporating an LBP-like operator and Support Vector Machines (Wilber et al, 2013). However, their research was specific to a certain terrain and may not be generalizable to detect animals in other terrains.

Other studies have focused on one species in monitoring daily activities, such as courtship. These studies have shown to require significant computing power, making implementation costly (Kembhavi et al, 2008 & Dickson et al, 2008).

Most recently, in a study done by Trnovsky et al, researchers developed an animal recognition system using convolutional neural networks (Trnovszky et al, 2017). However, this 2017 study only used 500 images, representing a small sample size.

3 Problem Definition and Data

Our research objectives are twofold: (1) Validate Inception, a previously trained CNN model currently being utilized for image recognition (Szegedy et al, 2016), and (2) re-train Inception on our own data.

Inception was developed during an ImageNet competition, in hopes of creating a high accurate image recognition tool that is applicable under strict memory constraints and computational budgets (Szegedy et al, 2016). The CNN-based algorithm has been proven successful in multiple applications. Given the high success, we chose to implement this model.

For our study, we limited the target animals to the following 10 species: elephant, zebras, rhinoceros, honeybee, tiger, hippopotamus, chimpanzee, wildebeest, vulture, and frog. These animals were chosen given their endangered status amongst similar terrains in Africa.

For our data source, we collected 15,752 images from ImageNet, an image database commonly used for research applications.

4 Methodology

Validate Inception

We utilized the Image Recognition, Tensor Flow online tutorial (n.d.) to test animals images on Inception-v3.
To begin, we classified 100 images to the respective animal category. With the images as input, the Inception-v3 model predicted the category of each image. We then cross-referenced the correct category versus the predicted category with the highest score for statistical analysis.

Re-train Inception-v3

After testing the model on our 100 images, we retrained its final layer on our 10 animal categories and re-evaluated the results. We performed the same analysis as the first step to compare the performance of our results.

5 Evaluation and Results

As with any predictive modeling, our defined baseline is 50% accuracy.

For our first objective, we used the established model to classify 100 images. Of the 100 images, 80 were correctly classified, resulting in an accuracy of 80%. It failed to classify any of the 10 images correctly for two of our animals: rhinoceroses and wildebeests.

Although the overall accuracy rate of the model is high in comparison to our baseline, the certainty of the classification varied greatly. While the majority of correctly classified images were categorized with a confidence greater than 0.8, many had a confidence level below 0.6. As seen in Figure 1, the accuracy of each individual classification ranged from ~0.1- ~1.0.

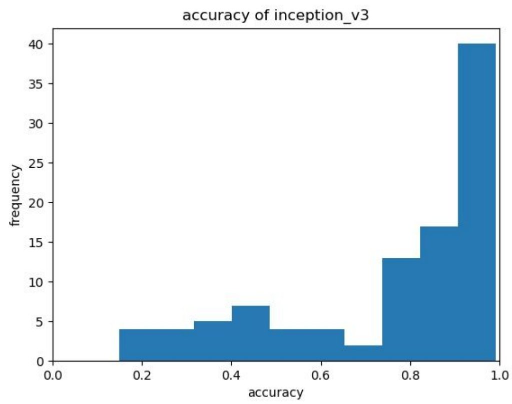

Fig 1. Accuracy of Inception v3 on 100 animal images.

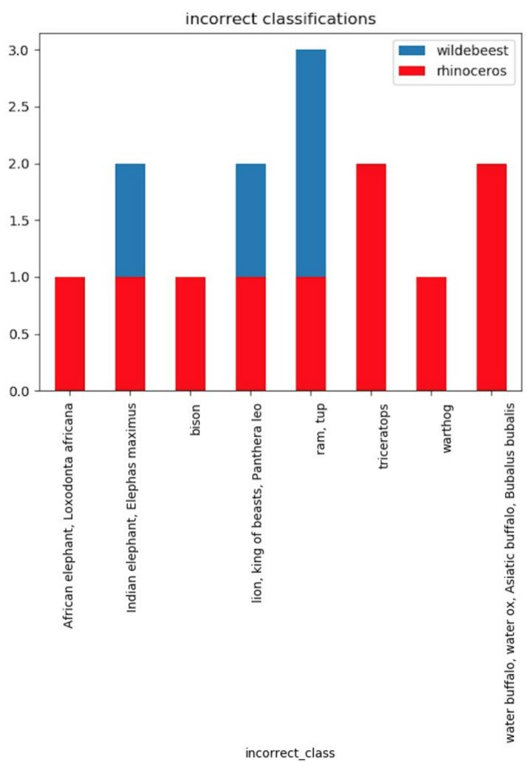

Fig 2. Analysis of Incorrect Classifications.

For our second objective, we retrained the final layer of the Inception v3 model on our ten animal classifiers. The model classified 3,929 of our 4,000 test images correctly. This retrained model has an accuracy rate of 98.2%, a 23% improvement upon the original model. Despite the improvement it has made in accuracy, the model's difficulty in classifying rhinoceroses and wildebeests was still reflected in this objective. Of our 10 categories, rhinoceroses and wildebeests had the lowest accuracy rates.

The confidence of each individual classification also improved. Figure 3 illustrates this change. A strong natural logarithmic trend emerges, indicating that the model has more certainty in the categorizations it has made.

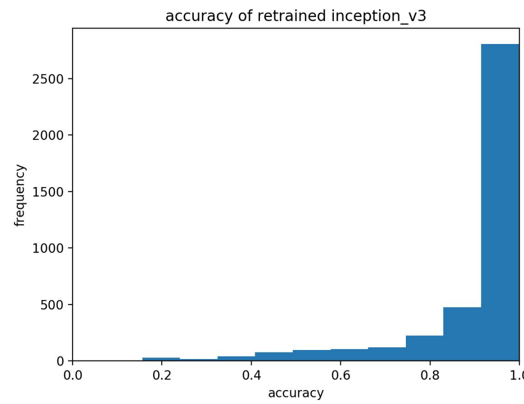

Fig 3. Accuracy of retrained Inception v3 on 15,752 animal images

As discussed prior, during our analysis, we found that the most incorrect classifications were in animals that had similar builds. As shown in figure 2, wildebeests and rhinoceros were commonly misinterpreted to other medium sized, land-dwelling animals.

To improve the classification of these species, we attempted to see if our model could better categorize the commonly misclassified animals: wildebeests and rhinoceros. We tested our new model on 600 images of rhinoceros and wildebeests, in which it performed with an accuracy of 99.3%. The accuracy distribution is illustrated in figure 4. In comparison to figure 2 and figure 3, an even stronger logistic distribution emerges.

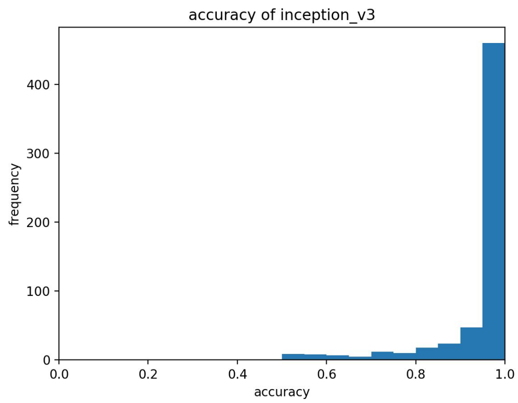

Fig 4. Accuracy of retrained Inception v3 on 1,420 images of Wildebeests & Rhinoceroses

6 Discussion

The results of the first step illustrates the strength of the model we have chosen to use, Inception-v3. In comparison to our baseline accuracy of 50%, Inception-v3 performs very well.

We were able to explore this hypothesis further through the second part of our study. After testing our retrained model, we discovered that it performed even better than our first test. The increased accuracy and confidence of classification indicates the potential for model improvement.

However, our test revealed a flaw in the model's ability to distinguish particular animal species, specifically rhinoceroses and wildebeests. We hypothesize that this may be because both animals are large, same-textured, and share similar colors. To follow up on this observation, we retrained our model to only classify those 2 species. This model performed exceptionally well, representing our highest accuracy of 99.3%.

Our results from both components, strongly support the successful application of the Inception algorithm on our data set.

7 Project Next Steps

As for next steps, we would like to test our framework on other image repositories. For example, Flickr consists of an easy to connect API that could be queried for new animal images.

Representing another opportunity for future development, we could incorporate more complex images. For our first objective, we purposely chose images with one animal present in the frame, but for our second objective we included images with multiple animals of the same species at different times of the day. On those premises, incorporating more complex image frames would further test the capabilities of our models.

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References

Dickinson, P. Freeman, R., Patrick, S., and Lawson, S. (2008). Autonomous Monitoring of Cliff Nesting Seabirds Using Computer Vision. In *Int. Wkshp. on Distributed Sensing and Collective Intelligence in Biodiversity Monitoring*,

Image Recognition, TensorFlow. (n.d.). Retrieved November 03, 2017, from https://www.tensorflow.org/tutorials/image_recognition

Living Planet Report 2016. (n.d.). Retrieved November 10, 2017, from https://www.worldwildlife.org/pages/living-planet-report-2016

Kembhavi, A., Farrell, R., Luo, Y., Jacobs, D., Duraiswami, R. and Davis, L. (2008). Tracking Down Under: Following the Satin Bowerbird. In *IEEE WACV*.

Porter, J., Arzberger, P., Braun, H., Bryant, P., Gage, S., Hansen, T., . . . Williams, T. (2005, July). Wireless Sensor Networks for Ecology. Retrieved November 14, 2017, from http://www.bioone.org/doi/full/10.1641/0006-3568(2005)055%5B0561%3AWSNFE%5D2.0.CO%3B2?prevSearch=

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception Architecture for Computer Vision. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. doi:10.1109/cvpr.2016.308

Trnovszky, T., Kamencay, P., Orjesek, R., Benco, M., & Sykora, P. (2017). Animal Recognition System Based on Convolutional Neural Network. *Advances in Electrical and Electronic Engineering, 15*(3). doi:10.15598/aeee.v15i3.2202

Wilber, M. J., Scheirer, W. J., Leitner, P., Heflin, B., Zott, J., Reinke, D., . . . Boult, T. E. (2013). Animal recognition in the Mojave Desert: Vision tools for field biologists. *2013 IEEE Workshop on Applications of Computer Vision (WACV)*. doi:10.1109/wacv.2013.6475020

Yu, X., Wang, J., Kays, R., Jansen, P. A., Wang, T., & Huang, T. (2013). Automated identification of animal species in camera trap images. *EURASIP Journal on Image and Video Processing,2013*(1). doi:10.1186/1687-5281-2013-52

N/A

A. Supplemental Materials