

Machine Learning Engineer Nanodegree

Capstone Proposal

Identify Monkey

Domain Background:

I'm interested in image classification, so now I'm making more projects in Image processing using CNN, it's more important to make image classification because it'll be more accurate and save more time. Monkey classification is to classify major types of monkeys based on biometric cues. Usually facial images are used to extract features and then a classifier is applied to the extracted features to learn a type of monkey recognizer. That's in Computer Vision and Biometrics fields. The monkey classification result is often a type of monkey.

Problem Statement:

The goal is to create a monkey classification based on monkeys' image so it's a binary classification problem; the tasks involved are the following:

- 1) Set up an image generator
- 2) Next, use the pre-trained model to extract features from the test images.
- 3) Finally, use the model to make predictions based on those test image features.

Datasets and Inputs:

My dataset from kaggle.

The dataset consists of two files, training and validation. Each folder contains 10 subfolders labeled as n0~n9, each corresponding a species form [Wikipedia's monkey cladogram](#). Images are 400x300 px or larger and JPEG format (almost 1400 images). Images were downloaded with help of the [googliser](#) open source code.

Label mapping:

- > Label, Latin Nama
- > n0, alouatta_palliata
- > n1, erythrocebus_patas
- > n2, cacajao_calvus
- > n3, macaca_fuscata
- > n4, cebuella_pygmea
- > n5, cebus_capucinus
- > n6, mico_argentatus
- > n7, saimiri_sciureus
- > n8, aotus_nigriceps
- > n9, trachypithecus_johnii

•For more information on the monkey species and number of images per class make sure to check monkey_labels.txt file.

monkey_labels.txt

Text (first 100 rows)

Label,	Latin Name	, Common Name	, Train Images	, Validation Images
n0	, alouatta palliata	, mantled howler	, 131	, 26
n1	, erythrocebus patas	, patas monkey	, 139	, 28
n2	, cacajao calvus	, bald uakari	, 137	, 27
n3	, macaca fuscata	, japanese macaque	, 152	, 30
n4	, cebuella pygmea	, pygmy marmoset	, 131	, 26
n5	, cebus capucinus	, white headed capuchin	, 141	, 28
n6	, mico argentatus	, silvery marmoset	, 132	, 26
n7	, saimiri sciureus	, common squirrel monkey	, 142	, 28
n8	, aotus nigriceps	, black headed night monkey	, 133	, 27
n9	, trachypithecus johnii	, nilgiri langur	, 132	, 26

<https://www.kaggle.com/slothkong/10-monkey-species/data>

Cladogram with extinct families

Below is a cladogram with some extinct monkey families. Generally, extinct non-hominoid simians, including early Catarrhines are discussed as monkeys as well as simians or anthropoidea which **cladistically** means that Hominoidea are monkeys as well, restoring monkeys as a single grouping. It is indicated approximately how many million years ago (Mya) the clades diverged into newer clades. It is thought the New World monkeys started as drifted "Old World monkey" group from the old world (probably Africa) to the new world (South America).



Japanese macaque (*Macaca fuscata*)



Goeldi's marmoset (*Callimico goeldii*)



Common squirrel monkey (*Saimiri sciureus*)



Bonnet macaque (*Macaca radiata*)



Crab-eating macaque (*Macaca fascicularis*)

Solution Statement

I will use deep learning toward the final solution. The reason for this is that a deep learning model may be more effective at determining the important features in a given image than a monkey being using manual gradient and color thresholds in typical computer vision techniques, as well as other manual programming needed within that process. Specifically, I will use convolutional neural networks (CNN), which are very effective at finding patterns within images by using filters to find specific pixel groupings that are important. My aim is to have an output both more effective at detecting the lines as well as faster at doing so than common computer vision techniques

And this the way to help and people to know which type of monkey.

Benchmark Model

I used Inception V3 model and VGG16 Convolutional Network. Inception V3 model, with weights pre-trained on ImageNet. Convolutional networks are at the core of most state-of-the-art computer vision solutions for a wide variety of tasks. Although increase of model size and computational cost tend to immediate increase in accuracy for most tasks (as long as enough labeled data is provided for training), computational efficiency and low parameter count are still enabling factors for various use cases such as mobile vision and big-data scenarios. Here we explore ways to scale up networks in ways that aim at utilizing the added computation as efficiently as possible by suitably factorized convolutions and aggressive regularization. And VGG16 Convolutional Network “evaluation of networks of increasing depth using an architecture with very small (3x3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16-19 weight layers”. The default input size for this model is 224x224.

Evaluation Metrics

I am going to work with Transfer learning w/ VGG16 Convolutional Network, Inception V3 model and accuracy_score from sklearn.metrics for classification problems.

Project Design

- My libraries :[Keras](#),[Tensorflow](#),[Scikit-learn](#),[Opencv](#),[os](#),[glob](#),[matplotlib](#),[random](#),[pandas](#),[numpy](#),[seaborn](#),[zlib](#),[itertools](#),[scipy](#),[RandomUnderSampler](#)
- My workflow :
 - 1- Load Data
 - 2- Visualize the dataset. The min/max pixel values are already scaled between 0 and 1.
 - 3- Define Helper Functions :- Helper Functions Learning Curves and Confusion Matrix
 - 4- Evaluate Classification Models :- Transfer learning w/ VGG16 Convolutional Network. Add top layer, Train top layer, Fit model, Evaluate model .