STAT 479 – Project Proposal

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Introduction

The primary goal of this project is image classification-classifying an image by the object category that it contains. The images we predict from are animal images from more than 10 animal species that we extracted from CALTECH 101 dataset. Each image has a label indicating the species the animal belongs to. Each animal class has about 50 images. We extract the color, texture and shape features from the image and put them into the classifier. KNN, SVM and Random Forest are chosen for this image classification task. KNN and SVM are chosen for image classification since these two classifiers tend to perform well in classifying image based on color, texture and particular shape[1] Random Forest classifier is chosen since it performs better than SVM and can make the training and testing easier[2].

Related Work

Animal image classification. In previous work, different machine learning algorithms have been used to classify animal images into different classes. [3,4,5]. Previous study has shown that KNN, SVM and random forest all performs well in image classification problem.

Caltech 101. Caltech 101 are pictures of objects that belongs to 101 categories. It was collected in September 2003 by Fei-Fei Li, Marco Andreetto and Marc 'Aurelio Ranzato. It is a famous image classification dataset. This problem has been the subject of many recent papers .[6,7,8] In this project, due to the constraint of time and computer ability, we only choose the animal images out of the 101 classes.

Motivation

Wild animals play a vital role in our ecological system, however, according to statistics provided by WWF (World Wildlife Fund) [9], "Populations of vertebrate animals—such as mammals, birds, and fish—have declined by 58% between 1970 and 2012. And we're seeing the largest drop in freshwater species: on average, there's been a whopping 81% decline in that time period". Reasons resulting in decrement of species of wildlife vary--Habitat Loss and Degradation, Human food systems, climate change, species overexploitation—most of them are directly caused by human activities. Though, plenty efforts have been devoted to protecting these species from elimination,

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the limit of conventional measures of animal protection are more and less obvious – loss of efficiency, hard of recruiting enough volunteers etc. There're more we can do with assistance of modern technology. This is the time to offer our close friends on earth more help and this is what we would like to do with Machine Learning, to use the technique of image classification to monitor the living status of wild animals. To be specific, we can use those algorithms to help specialists and volunteers to detect, observe and protect wildlife more efficiently and conveniently.

Besides the practical values of this working, it's also an exciting work that stimulates our interests. We can implement the tools and methods we learnt from the class to make our world better and it's intuitive to make comparison among different algorithms for sake of learning.

Evaluation

The ideal outcome of our project should be a practical classifier that can be applied in real-world wildlife image classification. To be specific, the classifier should have the power to identify specific animals from background and since the conditions vary for different animals, it's also essential to show their species so that we can offer in-time assistance and do real-time observation. To draw a periodical conclusion, the ideal classifier is estimated to have the ability of identify animals' species from given graphic records.

Technically, the index applied to evaluate our models should be the accuracy of classification. Moreover, it should avoid the situation of failure of telling wild animals from the given image (which is known as False Negatives misclassification). To show more details, apart from the conventional misclassification rate (is equal to number of misclassification/ total number of samples), the recall rate and F1 rate should be calculated to evaluate our classifiers, where:

$$Recall\ rate = \frac{TP}{TP + FN}$$

$$F1\ rate = \frac{2TP}{2TP + FP + FN}$$

Where TP stands for True Positive cases, FN stands for False Negative cases, FP stands for False Positive cases. The following figure shows more potential criterions in evaluating our binary (True versus False) classifiers.

		True condition				
	Total population	Condition positive	Condition negative	Prevalence = $\frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$	
Predicted condition	Predicted condition positive	**True positive**, Power	**False positive**, Type I error	Positive predictive value (PPV), Precision = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Predicted condition positive}}$	False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$	
	Predicted condition negative	**False negative**, Type II error	**True negative**	False omission rate (FOR) = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Predicted condition negative}}$	Negative predictive value (NPV) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$	
		True positive rate (TPR), Recall, Sensitivity, probability of detection = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$	Positive likelihood ratio (LR+) = $\frac{TPR}{FPR}$	Diagnostic odds ratio (DOR) = $\frac{LR+}{LR-}$	F_1 score = $\frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$
		False negative rate (FNR), Miss rate = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	Specificity (SPC), Selectivity, True negative rate (TNR) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$	Negative likelihood ratio (LR−) = $\frac{FNR}{TNR}$		

Fig.1: Potential Criterions in evaluating binary classification models

Resources

Dataset: Caltech-101. Animals' Labels [10], This dataset consists of images from 101 object categories and contains from 31 to 800 images per category. Most images are medium resolution, about 300 × 300 pixels. The significance of this database is its large inter-class variability (which also contains lots of animals' labels)

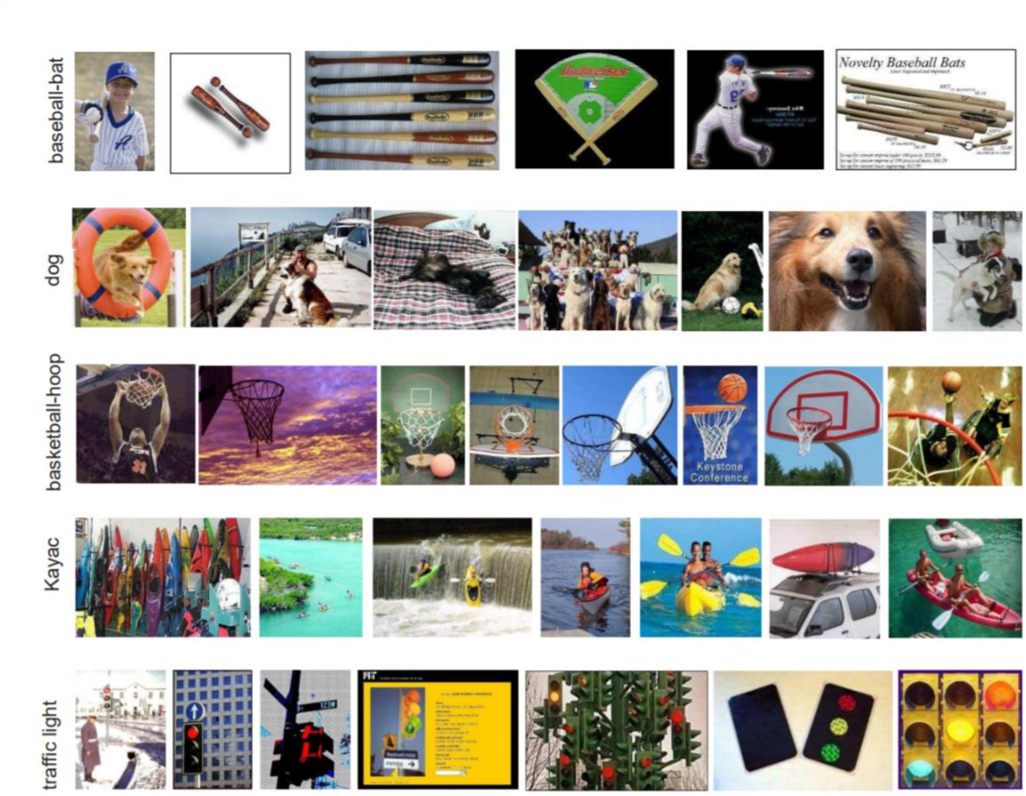

Fig.2[11]: Some images from the dataset, the typical labels we use is those animals' labels, which is similar with the second row's label-dogs, but we focus more on wild animals.

Hardware: Three laptop, containing one Macbook Pro(2 GHz Intel Core i5 /8GB RAM), one Surface Pro (8^{th} Gen i5/8GB RAM/128GB SSD), one Surface Laptop (7^{th} Gen i5/8GB RAM/256GB SSD).

Contributions

Feature Selection: Chen XING& Lingfeng ZHU

Model Building& Tuning: Zhangjie LYU& Lingfeng ZHU

Writing: Zhangjie LYU& Chen XING

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