Deep convolutional neural network and data augamentation for fish detection and classifaction

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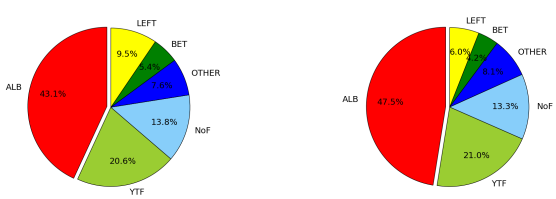
Abstract*—Live fish recognition and fish classification is one of the most parts of fish survey application. Different from the best know and the most well investigated object detection face detection, fish usually occupy a smaller area in a picture than the face of one person, and some pictures are taken under water. So it's a challenge for our pre-trained model to detect the fish and classify. In this paper, We introduced two methods to improve our accuracy for the fish classification. In the western and central pacific, where 60% of the world's tuna is caught, illegal, unreported , and unregulated fishing practices are threatening marine ecosystems. The Nature Conservancy is inviting the Kaggle community to develop the algorithms to automatically detect and classify species of tunas. The Kaggle competition aims to detect and classify the species of fish. The competition provides a train dataset which contains six species of tuna fish. Eight target categories are available in the dataset:Albacore tuna, Bigeye tuna, Yellowfin tuna, Mahi, Opah, Shark, Other(meaning that there are fish present but not in the above six categories), and No Fish(meaning that no fish in the picture). Each image has only one fish category. The dataset is critically imbalanced, the Albacore tuna has thousands of images while the Opah has only sixty images. We apply the Alexnet, GoogleNet, VggNet neural network for the classification. As a result of the small dataset, the VggNet architecture performs worse than AlexNet. In this paper we proposed a local region based the fish area modelling approch so that the local feature can be modelled. In the futrue, we will use the py-faster-rcnn to do the detection and classifacation.



(a) Training database (b) Testing database

Fig. 1. Data distribution of Kaggle

I. Introduction

In this paper, we introduced two methods to improve the accuracy. On the one hand, in consideration of the imbalance of the dataset, we get a new picture by rotating the images. Through this method, we can increase the number of some species of fish images, which can help avoid the over-fitting. And the detection of rotation angle of the fish has a certain degree of robustness. We doubled the datasets by this way and

TABLE I
Kaggle Database

classes	Total	Training	Valiation
ALB	45.5%	43.1%	47.5%
YFT	19.4%	20.6%	21.0%
NoF	12.3%	13.8%	13.3%
OTHER	7.9%	7.6%	8.1%
BET	5.2%	5.4%	4.2%
Sum	90.3%	90.5%	94.0%

TABLE II
Singal model result on full data

database	model	iteration	accuracy
full	alexnet	70k	0.94
full	googlenet	40k	0.942
full	vgg16	34k	0.44

TABLE III
Kaggle Database

database	model	iteration	accuracy
full+rotating	alexnet	78k	0.9673
full+rotating	googlenet	80k	0.964
full+rotating	vgg16	20k	0.45

TABLE IV
Kaggle Database

database	model	iteration	accuracy
full+rotating+mosaic	alexnet	60k	0.9703
full+rotating+mosaic	googlenet	56k	0.954

the accuracy increases two percent. On the other hand, we use the faster-rcnn to achieve the detection and classification. There have been less efforts made on solving fish detection and classification simultaneously. The second method is to pick up some pictures to do some image processing. We make a mosaic of the area where the fish are located, and we used the processed image and the raw images to train our model. this illustrates the difference between the two images.This method can force our neural network to concentrate on the area where the fish present. The features are learned from comparing the raw pictures with the pictures with mosaic. In this method, We modified the Caffe to get the pooled image data to find the area that contributes to the classification most. Through comparing the pooling gray image with the picture, we find the area fish presents is brighter than other areas, which proves that the fish area contributes to the classification most. In addition, we use the prossesing images to finetune our pre-trained model and it performs better when testing.

(a) the image (b) the pooling image

Fig. 2. We make a mosaic of the area where the fish are located,and the mosaic can help our model detect the fish area.

(a) the raw image (b) image with mosaic

Fig. 3. We make a mosaic of the area where the fish are located

II. Related Work

Recently, several papers have brought some methods for fish detection and fish classifaction. Spatial constraints are are introduced by dividing the image to regions and learning the feature region. In our method, we use the image processing method to dividing the image to feature regions and background regions. The feature regions contribute to the fish classification most.

III. Experiments

IV. Conclusion

We have used two methods to help our model to detect the fish and avoid the over fitting.

References