Surface Water Quality Classification Based on MobileNetV2

Jingbo Hao and Yang Tao

College of Artificial Intelligence, Nanchang Institute of Science & Technology, 998 Gezaoshan Ave., Honggutan New District, Nanchang, China.
Email: jbhao@126.com

Abstract. Water quality detection is important for water resources protection. There is an urgent need for convenient and precise water quality detection methods. In this paper a deep learning based detection method is proposed. A MobileNetV2 classifier is constructed and tested aiming at surface water quality classification. The experimental results show that the classifier has excellent performance and can also be deployed on edge devices conveniently.

1. Introduction
Water is the vital source of life and water resources protection is a critical task for all the world. For that purpose, water quality detection is important and necessary. However, traditional detection methods are usually complicated or imprecise. With the rise of deep learning modelling technology, deep neural networks (DNN) have achieved state-of-the-art performance in many scenarios, which is very inspiring for water quality detection.

![Five-level quality rating system](image)

**Figure 1.** Five-level water quality rating system

Surface water quality can be rated as five classes [5]: (1) Good for drinking, (2) Usable for drinking after treatment, (3) Usable for drinking after processing, (4) Usable for industrial purposes, (5) Usable for irrigation, as shown in Figure 1 [1]. Water quality can be directly impacted by human development, climate change, and energy and land use. Nowadays many lakes and reservoirs is suffering from eutrophication. Their water quality is worrying and needs periodic detection.
This paper focuses on the classification of surface water images for simple and accurate water quality detection. A MobileNetV2 [3] based DNN classifier is constructed and trained to do the job. The classifier’s construction is first explained. The experimental results are then presented and discussed. Finally the conclusions are drawn.

2. Classifier Construction

2.1. Classifier Structure
MobileNets are a family of DNN architectures released by Google which are intended to be used on machines with limited computing power to provide state-of-the-art accuracy. MobileNetV2 builds upon the ideas from MobileNetV1 [2] and introduces a novel network module: bottleneck residual block (Figure 2). MobileNetV2 uses linear bottlenecks between the layers and shortcut connections between the bottlenecks. Linear bottlenecks prevent destroying information while shortcut connections enable faster training and better accuracy.

![Figure 2. Bottleneck residual block.](image)

The output of the MobileNetV2 backbone is typically a 7x7 feature map. The classifier first uses a global pooling layer to reduce the size from 7x7 to 1x1 and is followed by a classification layer and a softmax layer (Figure 3).

![Figure 3. MobileNetV2 based classifier.](image)
2.2. Model Training
The training process was executed on a computer with an Intel i7-8700 CPU and an NVIDIA GeForce GTX 1070 GPU. The training script is mainly implemented in the TensorFlow framework, especially the TF-Slim library which provides common abstractions enabling users to define models quickly and concisely, while keeping the model architecture transparent and its hyper parameters explicit [4]. Five thousand of lake/reservoir water images are collected and rated into five classes (Figure 4) by hand as the training set. These images are resized into 224×224 and augmented in a random manner during training. The final model was trained with a batch size 64 and a depth multiplier 0.5 for 27000 steps. After training and model transformation, a frozen TensorFlow model was generated successfully.

![Figure 4. Five classes of surface water.](image)

3. Experimental Results
The test set consists of two hundred water images without any overlap with the training set. The running result on the model shows an excellent accuracy 99.5%. Then the original model was transformed into a TFLite model and tested in a pure CPU mode. The accuracy value doesn’t deteriorate and the execution speed is quite fast (within 30ms per image). The experimental results show that the classifier has excellent performance and can also be easily deployed on edge devices with limited computing power.

4. Conclusions
Water quality detection is important for water resources protection. Traditional detection methods are usually complicated or imprecise. Recent breakthroughs in deep learning are bringing DNN classifiers into the center of computer vision. A MobileNetV2 classifier is constructed here for surface water quality classification. The experimental results show that the classifier behaves very well and is quite suitable for edge devices. It is believed that in the near future a portable device or even an Android app supporting such a water quality classifier can be developed and widely used.

5. Acknowledgments
The authors would like to thank Mr. Shaoyi Li for his support to this work and are also grateful to those article providers for their selfless help.

6. References
[1] Feng X 2015 Five-level water quality rating system China Daily http://english.www.gov.cn/policies/infographics/2015/04/17/content_281475090571594.htm
[2] Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, Andreetto M and Adam H 2017 MobileNets: Efficient convolutional neural networks for mobile vision applications arXiv Preprint arXiv:1704.04861
[3] Sandler M, Howard A, Zhu M, Zhmoginov A and Chen L 2018 MobileNetV2: Inverted residuals and linear bottlenecks Proc. IEEE Conf. on Computer Vision and Pattern Recognition 2018 pp 4510–4520
[4] Silberman N and Guadarrama S 2016 TF-Slim: A high level library to define complex models in TensorFlow Google AI Blog https://ai.googleblog.com/2016/08/tf-slim-high-level-library-to-define.html
[5] State Environmental Protection Administration of China 2002 *Environmental Quality Standards for Surface Water* (Beijing: Standardization Administration of China)