TL-Tensorflow CNN model and dataset for electronic equipment

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ABSTRACT

This paper proposes a solution for classification of electronics laboratory equipment with emphasis on the electronic laboratory tools / equipment. It uses transfer-learning applied to the pretrained Inception-V3 network model. A study regarding the impact of small retrain dataset is conducted to see its impact in transfer-learning over Inception-V3 network model.

INTRODUCTION

Transfer learning is a technique where an pretrained network is repurposed by retraining only a small part of its layers (therefore retraining is fast) with a different, smaller set of samples. The advantages would be the speed of retraining and the smaller set of data needed for retraining: the latter of utmost importance, as dataset is most times insufficient. It is commonly used in deep learning applications, when a new task needs to be served by an old pre-trained network. In a sentence, the "knowledge" (most layers' weights, except the few last) is transferred from a source domain, to a target domain.

Transfer learning has been used before on Inception-V3 for various purposes, including: pulmonary image classification[4], Terry's nail detection [5], traffic sign recognition [6], breast cancer image classification[7], civil engineering [8], animal classification[9] or flower classification [10] with very good results, in the range of 90+ % accuracy.

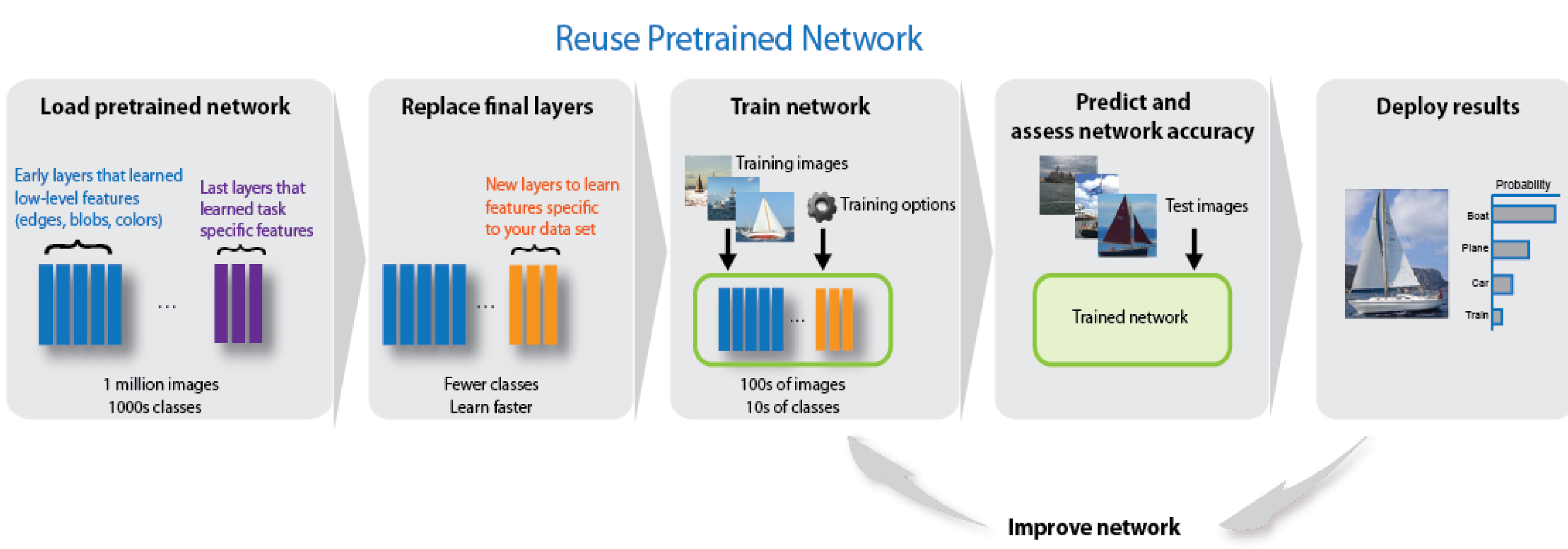

Figure 1. A visual explanation of the transfer learning process, by MathWorks[1]

APPROACH

We have TL-trained the inception-V3 network using Tensorflow's[11] retrain script, with about 700 images split in 4 classes:

- Benchtop digital multimeter (BENCHDMM): 199 images
- Benchtop power supply (BENCHPSU): 187 images
- Handheld digital multimeter (DMM): 219 images
- Benchtop oscilloscope (OSCILLOSCOPE): 95 images

Another 10% images out of each category were kept separately for test (for a total of 78 images) and tested at the end of each training. A python script looped over the test images, and hit and misses were counted. We have downloaded and manually cured all images. Then, we have used Geeqie[12] linux tool to cleanup possible duplicates.

Figure 2. Some of the images from the DMM dataset

RESULTS

We have TL-trained the TensorFlow inception-v3 model, with the 700+ images, receiving a train accuracy of 97% and final test accuracy of 90.9%. Independently, we have tested other hand-picked images and we observed 69 hits and 9 misses (that is, about 85% hit-rate, which almost matches the final test accuracy value)

All the code, dataset and models can be found at URL [3].

BENCHDMM (images)	BENCHPSU (images)	DMM (imgs)	OSCILLOSCOPE (images)	Train accuracy (%)	Validation accuracy (%)	Final test accuracy (%)
199	187	219	95	97	92	90.3
100	98	108	50	100	98	91.9
50	49	54	25	100	85	88.9
40	39	43	20	100	100	92.3
32	31	35	20	100	100	92.3
25	25	25	25	100	100	90.9

Table 1. Impact of dataset size when doing transfer learning on 4 classes, on training / validation accuracy.

CONCLUSIONS

- We have created an annotated image dataset of 700 images split across four categories of electronic equipment.
- We have performed transfer learning using an Inception v3 architecture model, and retrained it on the aforementioned dataset.
- We have achieved 88.5 % … 92.3 % top accuracy results, in line with the reported accuracies reported in other Inception-V3 transfer-learning papers
- Training progressively with less and less data (down to 25 images per category), had marginal effect on accuracy. For 4 classes, 25 images per class will suffice for 88+ percent accuracy.

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