Simple Quality Control Using Deep Learning

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Abstract—Quality control is a fruitful domain for application of deep learning methods. In this paper a simple solution is presented, which shows, that deep neural networks are readily capable of solving quality control problems and their usage isn't limited to a complicated production environment only.

Index Terms—Robot, IEEEtran, Udacity, LATEX, deep learning.

1 Introduction

Quality control have always been such an activity which people excel in. But nowadays we can experience challenges, associated with production volume, speed and complexity where people can't provide necessary pace and precision for examining a final product for imperfections. This is the field where new technologies are establishing their superiority slowly but confidently. While many applications of deep learning have been made already in different industries and a lot of research have been done in this field, the goal of this paper is to show that simple quality assessment tasks don't need a lot of efforts to be powered by deep neural networks.

2 BACKGROUND / FORMULATION

Based on the information from [1], GoogLeNet was chosen as a lightweight yet high quality model to be trained at first on the provided image set and than on collected one. For the model training DIGITS workspace was used. It quickly became clear that the chosen model is suitable for achieving the expected level of accuracy. The only parameter that had to be tuned was the number of epochs. 5 epochs (Fig. 1) gave the best result for accuracy, while 2 and 8 epochs gave slightly worse results.

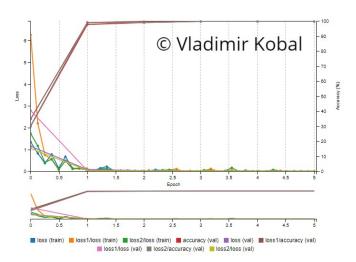


Fig. 1. Model training for provided data set.

The trained model evaluation result was 75.4% which was enough to satisfy the lab requirements (Fig. 2).

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Calculating average inference time over 10 samples...

deploy: /opt/DIGITS/digits/jobs/20180723-151452-28d5/deploy.prototxt
model: /opt/DIGITS/digits/jobs/20180723-151452-28d5/snapshot_iter_1185.caffemodel
output: softmax
iterations: 5
avgRuns: 10
Input "data": 3x224x224
Output "softmax": 3x1x1
name=data, bindingIndex=0, buffers.size()=2
name=softmax, bindingIndex=1, buffers.size()=2
Average over 10 runs is 5.48518 ms.
Average over 10 runs is 5.48563 ms.
Average over 10 runs is 5.485936 ms.
Average over 10 runs is 5.58631 ms.
Calculating model accuacy...

% Total % Received % Xferd Average Speed Time Time Current
Dload Upload Total Spent Left Speed
100 14648 100 12332 100 2316 211 39 0:00:59 0:00:58 0:00:01 2411
Your model accuacy is 75.4098360656 %
```

Fig. 2. Model evaluation for provided data set.

The provided data set has features similar to the ones of the other set which can be collected in a quality assessment task. So the same model can be used for training on a collected data set with great likelihood.

3 DATA ACQUISITION

For quality assessment task apple sorting was chosen. For image collection a simple device was set up. Apples where rolled along a cardboard tray while a web camera was taking pictures. Rolling of apples is essential for exposing every side of each apple. For reducing exposure time and evenly distribute light in addition to ambient lighting two bright lamps where used.

Color information is essential in the apple quality assessment task so using RGB images is the appropriate path. As long as the chosen model input is 256x256 pixels, the web camera was set to 640x360 pixel mode in oder to minimize data size used and computation time when images are being downsampled.

TABLE 1 Collected image number

Good	524
Bad	555
Blank	259

A few iterations where made with available apples to achieve desirable number of shots. Since rolling apples are unlikely to follow the same path, the iterations wouldn't affect the collected image set diversity to a great extent. The final size of the acquired data set is shown in Table 1.

TABLE 2 Collected image samples



4 RESULTS

Collected data was uploaded to the DIGITS workspace and the GoogLeNet model was trained on it. As expected, the model fit the collected data set. Minor tuning was made to the number of epochs. To maximize accuracy 6 epochs where used for the model training (Fig. 3).

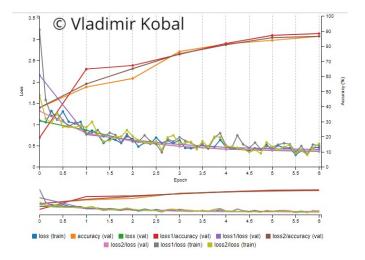


Fig. 3. Model training for collected data set.

5 DISCUSSION

The accuracy achieved for the apple assessment model is not as good as in the case with provided data set but it is explicable since the collected data set is much smaller and the quality of pictures is worse. Anyway, the level of the achieved accuracy is sufficient for sorting apples so this approach is acceptable for some simple quality control tasks. Of course there are applications, where image classification quality is of great importance or inference time is limited by hardware or high demand on FPS. Bus these cases are

out of scope of this paper as only applicability of quick and straightforward deep learning methods to simple tasks is concerned.

6 CONCLUSION / FUTURE WORK

This work shows that modern research in the field of deep networks opened possibilities to use machine learning technologies not only in complex systems with high demand of programming efforts but also in simple quality control tasks where neither quality of captured images nor model fine tuning is needed. Based on these findings it is evident that a cheap programmable sorting device can be developed and commercialized for use in small farming or households.

It is worth doing some additional analysis in the future for further development of the paper subject. Correlation of classification quality and number of images collected/number of classes should be studied. Minimum hardware requirements with respect to desired FPS should be found out.

REFERENCES

[1] A. P. Alfredo Canziani, Eugenio Culurciello, "An analysis of deep neural network models for practical applications," 2017.