Convolutional Neural Network for Industrial Egg Classification

Ryota Shimizu, Shusuke Yanagawa, Toru Shimizu, Mototsugu Hamada, Tadahiro Kuroda
Department of Electronics and Electrical Engineering, Keio University
Yokohama, Japan
r_shimizu@kuroda.elec.keio.ac.jp

***Abstract*—CNN (Convolutional Neural Network) is a powerful method for image classifying tasks. CNN's classifying capability is assessed by using large-scale image dataset such as ImageNet in many papers, but few works on CNN with small-scale dataset have been reported. We have been researching application method of Neural Network for classifying tasks in real-world for years [1]. In this work, we applied CNN to a quality inspection of industrial products and assessed its classifying capacity. Our CNN was trained with 2000 images of eggs taken in a factory, classified the images of almost 89,000 eggs into 6 qualities. Our method of combining multi-angle images into 1 image retained the 3-dimensional features of the object, and improved the classification accuracy to 92.3%. It confirmed that CNN is also effective for the quality inspection of industrial products.**

Keywords—Quality Inspection; Image Classificaition; Small-scale Dataset; Convolutional Neural Network

I. INTRODUCTION

CNN has made great successes in image recognition tasks and recorded the lowest error rates as shown in ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) every recent years.

In this work, we applied CNN to a classification task of relatively small-scale dataset: the images of eggs photographed in a factory labeled with 6 qualities, then we assessed the classification accuracy. In other words, we used CNN to inspect the quality of eggs from its photograph.

In this paper, we describe the dataset which we used in section 2. How we applied CNN to the task and the CNN's configurations are described in section 3. The results of the experiment are discussed in section 4, and we conclude this paper in section 5.

II. SMALL-SCALE DATASET

CNN has been applied to classification tasks by some large-scale image dataset like ImageNet so far. However we used the small-scale dataset for CNN training such as egg images photographed in a factory in this work. The dataset is the images from 91711 eggs, and every image is the size of 512×440 pixels. Each image is labeled with one of 6 qualities, as shown in Figure 1: Good Egg, Poor Growth Egg, Wind Egg, Dead Egg, Unusual Air-Chamber Egg, and Reversed Egg. Every egg was taken photos from 4 angles to retain its 3-dimensional features, as shown in Figure 2. Table 1 shows the breakdown of all eggs in 6 qualities.

In this work, we divided the egg image dataset into two categories by a random selection: CNN training data and CNN testing data for evaluation of its classification accuracy.

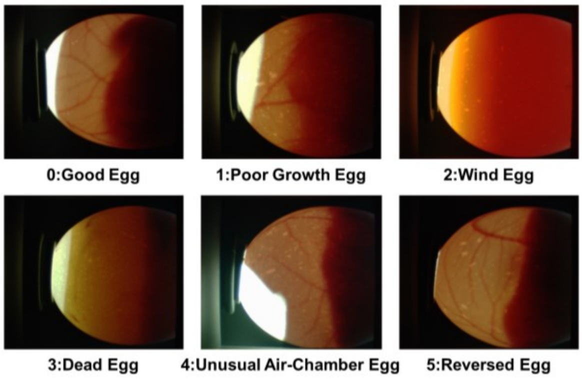

Figure 1. An Example of Egg Dataset

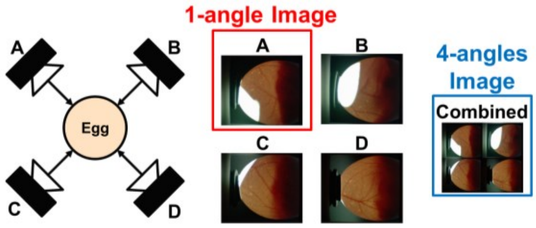

Figure 2. Egg Photograph and Input Images

Table 1. Egg Dataset Breakdown

Quality of Egg	All Data	Training	Test
Good Egg : 0	78445	673	77772
Poor Growth Egg : 1	8138	813	7325
Wind Egg : 2	112	12	100
Dead Egg : 3	1767	177	1590
Unusual Air-Chamber Egg : 4	2998	300	2698
Reversed Egg : 5	251	25	226
Total	91711	2000	89711

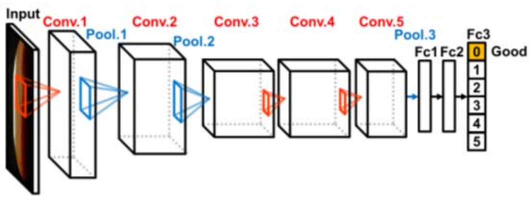

Figure 3. Overall architecture of CNN we used

Table.2 Configuration of CNN We Used

Layers	Input size	Parameters	Strides	Output size
Input	512×440×3	---	---	400×400×3
Conv. 1 + ReLU	400×400×3	11×11×3×96	4	100×100×96
Pooling 1	100×100×96	---	2	50×50×96
Conv. 2 + ReLU	50×50×96	5×5×96×256	1	50×50×256
Pooling 2	50×50×256	---	2	25×25×256
Conv. 3 + ReLU	25×25×256	3×3×256×384	1	25×25×384
Conv. 4 + ReLU	25×25×384	3×3×384×384	1	25×25×384
Conv. 5 + ReLU	25×25×384	3×3×384×256	1	25×25×256
Pooling 3	25×25×256	---	2	12×12×256
Fc1 + ReLU	36864	36864×4096	---	4096
Fc2 + ReLU	4096	4096×4096	---	4096
Fc3 (Output)	4096	4096×6	---	6

III. How to Apply CNN to the Dataset

When we, human, recognize objects from its image, we focus on its some local features then associate what it is, and CNN is the model that modulates this procedure.

We used CNN based on AlexNet as shown in Figure 3, [2], and its configuration is shown in Table 2. First, Input image is resized into 400×400 pixels, then it passes Convolutional layers and Pooling layers. Conv. layers work with the input feature maps for some convolution filters, and with activation function (ReLU) which simulates human neurons reacting to filtered maps, then extracts new feature maps. Pool. layers summarize the feature maps using a max pooling, which provides new feature maps including local features of the input feature maps. Feature maps made from Pool.3 layer are vectorized into feature vectors and inputted to Fully-Connected (Fc) layers. Fc layers reduce the dimensions of feature vector into six, i.e. the number of qualities, by calculating the weighted sum of each feature vector. Finally, the 6-dimensional vector shows the estimation of each six qualities. Filters of Conv. layers and weights of Fc layers are trainable parameters and optimized to minimize the gap between estimation and labels (ground-truth data) through training.

We trained CNN using training data with Adam [3] and learning rate was 1e-04. To avoid an overfitting, we adopted Dropout [4] in Fc1 and Fc2 layers in training and its dropout rate was 0.5. We stopped the training after 100 steps.

Each egg was photographed from four angles as noted above, then we assumed to combine these 4 images into 1 image to save features seen from multi-angles as shown in Figure 2. This modified image contains the features of egg seen from 4 angles and we thought it will work better than 1-angle image because 1-angle image loses the features seen from other 3 angles. We made two dataset from same eggs: 1-angle image and 4-angle combined image. We compared the accuracies of classification between these two dataset.

IV. Results of Experiments

After the training of CNN, we assessed its classification accuracy by using test dataset, its results are shown in Figure 4. Top table is a result using 1-angle images, and the bottom is that of 4-angle images. The accuracy using 4-angle images was 3.3 % higher than that using 1-angle images.

As we see, there is a deviation of accuracies in qualities. One is that classification accuracy of eggs labeled with Good was 93.01 %, which means our CNN loses only 6.99 % of good eggs for products. Other one is that Good and Poor Growth were difficult for the CNN to discriminate because of the label ambiguity. Egg images were labeled by some human inspectors in a factory, but the criterion to discriminate these two qualities varies in each inspector. We think that CNN inherited this ambiguousness and caused such weakness.

1-angle

Quality	Eggs	Classification Result						Accuracy
		0	1	2	3	4	5	
Good : 0	77772	69844	5462	0	10	2455	1	89.81%
P. G. : 1	7325	738	6314	1	72	199	1	86.20%
Wind : 2	100	0	0	90	10	0	0	90.00%
Dead : 3	1590	6	272	8	1268	34	2	79.75%
U. A. : 4	2698	273	149	0	8	2199	69	81.50%
Reversed : 5	226	1	1	0	1	62	161	71.24%
Total	89711	79876						89.0%

4-angles

Quality	Eggs	Classification Result						Accuracy
		0	1	2	3	4	5	
Good : 0	77772	72335	4753	0	1	683	0	93.01%
P. G. : 1	7325	621	6572	2	64	66	0	89.72%
Wind : 2	100	0	0	87	13	0	0	87.00%
Dead : 3	1590	6	168	5	1404	6	1	88.30%
U. A. : 4	2698	249	137	0	2	2275	35	84.32%
Reversed : 5	226	1	11	0	0	48	166	73.45%
Total	89711	82839						92.3%

Figure 4. Classification Results

V. Conclusion and Future Vision

In this work, we employed CNN to inspect the quality of eggs from its image. Classification accuracy was improved by using 4-angle images which include multi-angle features and we achieved 92.3 % accuracy, so we confirmed that image which contains multi-angle feature is effective for the classification of 3-dimensional objects. Our work shows that CNN is effective not only for the classification of large-scale image dataset, but also for that of small-scale dataset.

We are now aiming to improve the classification capacity by making a new dataset with less ambiguousness and the new configuration of CNN that fits to the small-scale image dataset. We also seeking ways to install CNN we used in smaller chips which can be used in the factory easier than now.

Acknowledgment

This work is supported by JST CREST Grant Number JPMJCR1331. The dataset that we used in this work was kindly provided by Shikoku Instrumentation CO. LTD. We thank them all.

References

[1] R. Shimizu, S. Yanagawa, Y. Monde, H. Yamagishi, M. Hamada, T. Shimizu, and T. Kuroda, “Deep Learning Application Trial to Lung Cancer Diagnosis for Medical Sensor Systems,” *13th International SoC Design Conference, Conference Paper,* pp.191-192, 2016.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” *Advances in Neural Information Processing Systems (NIPS)*, pp. 1097-1105, 2012.

[3] D. P. Kingma and J. L. Ba, “Adam: A Method for Stocastic Optimization,” *Proceedings of International Conference of Learning Representations*, 2015.

[4] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: A simple way to prevent neural networks from overfitting,” *Journal of Machine Learning Research*, vol. 15, pp. 1929-1958, 2014.