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Fast and Robust Image-Based “Scan” System for POS Automation

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***Abstract*— *Current Point-of-Sale processing is complex and time consuming. In this paper, we propose an image-based discount sticker and barcode recognition system for automation. Recognition of discount stickers and barcodes is quite a big challenge, as different shooting conditions can result in different appearances. We design a deep learning classifier of various discount rates and barcodes basing on YOLACT detection network. We also propose a data augmentation to generate various data that are close to real scene to improve the classification performance of deep learning model. Evaluation with our original data set shows that the proposed approach achieves high performance and applicable in the real-world scenario.*

***Keywords*— *Classification, data augmentation, discount sticker, barcode, image-based, deep learning.*

I. INTRODUCTION

Point-of-Sale (POS) system is widely used in the retail industry. It is a general term for systems required to digitize and manage daily sales and sold products. It has various functions such as sales management, inventory management, customer management, headquarters as well as accounting management. Of these, the accounting function is most basic.

A smooth accounting is required without waiting for customers. However, it is necessary to learn how to handle and operate each different cases, which increases the burden on staffs. In normal accounting, a staff registers a product by scanning the barcode one by one with a scanner. However, the operation of discounted products such as time sales is complex. If a discounted “barcode” sticker is affixed on the product, it is easy for staffs to register the discount information just by passing it through the scanner as a normal checkout. If there is a discount sticker such as ○% off, the staffs will need to find and enter a pre-registered discount button on the screen or press a handmade discount rate button to send the discount information to the system.

Based on the various complexity of accounting operations, we aim to provide an automatic image-based “scan” system to facilitate the accounting process of the cash register. The system uses a webcam or digital camera or smart device to capture an image or video stream, and it has function to recognize both discount stickers and barcodes. This system can handle various accounting situations simply by recognizing the discount stickers and barcodes of products, making it easy for non- professionals to get the job done.

II. RELATED WORKS

Recently, research on barcode detection has been conducted, and several effective barcode detection techniques have been proposed. Some approaches take advantage of the feature that barcodes are a set of parallel vertical lines [1]-[4]. Some approaches use different filters to extract barcodes in different orientations and sizes [5]-[7]. Some approaches take measures for moving motion blur or complex backgrounds [8][9]. We have proposed a deep learning-based approach using synthetic-to-real data augmentation to deal with multiple challenges [10].

Some techniques have been integrated into barcode processing systems. In [11], N. M. Z. Hashim et al. propose a system that converts colour images to grayscale images to reduce noise, enhances image contrast between bars and spaces, applies edge detection algorithm to distinguish barcode region, and uses MATLAB toolbox to visualize the image data. In [12], Xia uses a deep learning-based detector of You Only Look Once to design a barcode recognition system for barcode localization and recognition of express delivery. However, there is currently no system that automatically recognizes both discount stickers and barcodes.

Achieving accounting automation requires technology that can recognize both discount stickers and barcodes. In this paper, we propose a deep learning-based approach than can handle both. Currently, we use this technique for accounting automation, it can also be used for inventory and other uses. The remainder of the paper is structured as follows: Section 3 presents the proposed discount stickers and barcodes recognition techniques. Section 4 demonstrates the effectiveness of the proposed method through some experiments. Section 5 draws a conclusion.

III. OUR APPROACH

In this section, we first explain the proposed “scan” system, then explain the proposed discount sticker and barcode classification network, and finally explain our data augmentation for robust classification.

A. System Design

The system architecture is designed as shown in Fig. 1. The part inside the gray frame is the proposed system, and the gray background part shows POS system.

We first reduce the resolution of the camera input. We then use classification network to detect discount sticker region and barcode region and determine the classification category of them. Categories include various discount rates and a barcode. In the case of a discount sticker, the classification result of the discount rate such as 5% discount, 10% discount, 50% discount is output. For barcodes, the barcode category result and segmentation of the barcode region are output. If a

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barcode is detected, we then use its segmentation information and the original high-resolution image to get a high-resolution partial image containing the barcode, then apply an open-source Python package to perform barcode recognition in the region and output decoded information. We finally send the result combining the discount rate and the barcode in the process of linking the “scan” system and the POS system. We set a switch to control the process. If the classification process detects only a barcode, the barcode recognition result is sent to the POS. If the classification process outputs both the discount rate and the barcode, we then use these two pieces of information to generate a discount barcode that reflects the discounted price of the product and send it to the POS.

Our system aims to effectively maintain a balance between processing speed and cognitive performance. To achieve this, we propose the hybrid resolution processing system as one of the solutions. The reason for using low resolution images for classification is to reduce unnecessary computational costs, and it is also possible to train classification from low resolution images. The reason for using high resolution partial images for barcode recognition is that naturally placing the product away from the camera can result in lower resolution and less accurate barcode recognition.

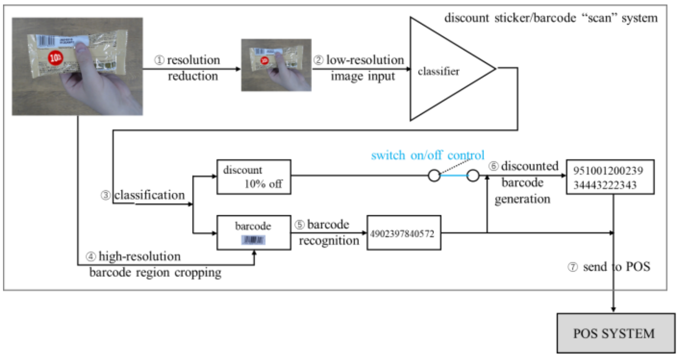

Fig. 1. The proposed “scan” system.

B. *Classifier Network*

Classifier network is the core recognition engine of the “scan” system. The Design of the classifier is our second solution to effectively maintain the balance between processing speed and cognitive performance.

We adopt YOLACT [13] from the existing classifiers. It is a one-step deep learning network that performs independent instances of object detection and mask generation. It provides real-time processing, high-quality masks, and stable detection results. In our system, we design each discount rate and barcode detector / classifier basing on the YOLACT.

In our classifier design, we category all possible discount rates and barcodes. However, the design of discount stickers differs depending on supermarkets, and even with the same design, there are different sizes and colors. Therefore, we collect various designs of discount rates, and group the different design with the same discount rate into the same category. Fig. 2 shows some image samples of 20% discount having different design.

Fig. 2. Image samples of 20% discount.

The network is shown in Fig.3. First, Convolutional Layers apply a convolution operation to the input image, pass the result to the next layer, and result in feature maps, indicating location and strength of detected feature. Second, Feature Pyramid Network extends for efficient multi-scale image feature aggregation. Third, Region Proposal Network learns from feature maps obtained and predicts object boundaries and objectivity scores at each position. Next, Region of Interest Aligns extract feature maps of non-uniform input sizes and output a feature map of a fixed size by utilizing feature similarity. Finally, classification, bounding box of the detected target and instance mask are predicted and output. Here, classification is designed to include various discount rates and a barcode.

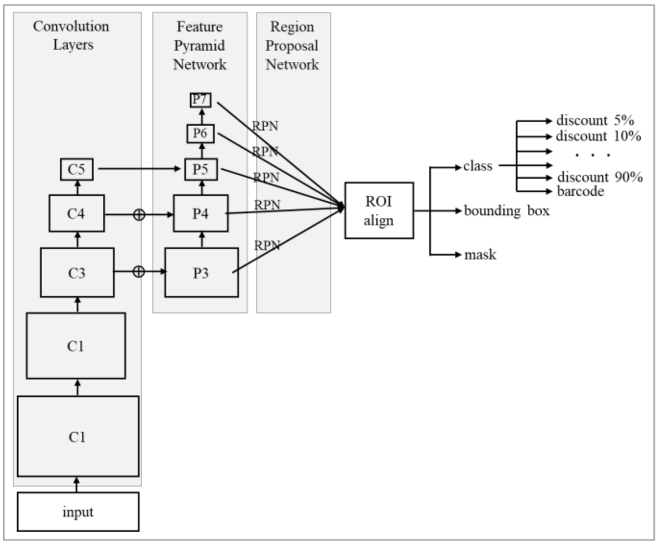

Fig. 3. Classifier network.

C. *Data Augmentation*

Data augmentation is one of the key factors in deep learning performance. In [10], we proposed a synthetic-to-real data augmentation to generate various barcodes that are close to the real scene. This improved the training performance of deep learning model. In this classification task, we propose an effective data augmentation to generate various images that include both discount stickers and barcodes, which achieves coexistence of both data collection cost and data volume and data quality.

The data augmentation is mainly composed of three steps as shown in Fig. 4. We first individually augment discount stickers and barcodes themselves by applying computing vision process to generate a variety of data that is close to the objective states of the real world. We then paste the generated discount stickers and / or barcodes on various background

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images such as product packages. We next augment the images containing the augmented discount stickers and / or barcodes to bring them closer to the actual shooting environments.

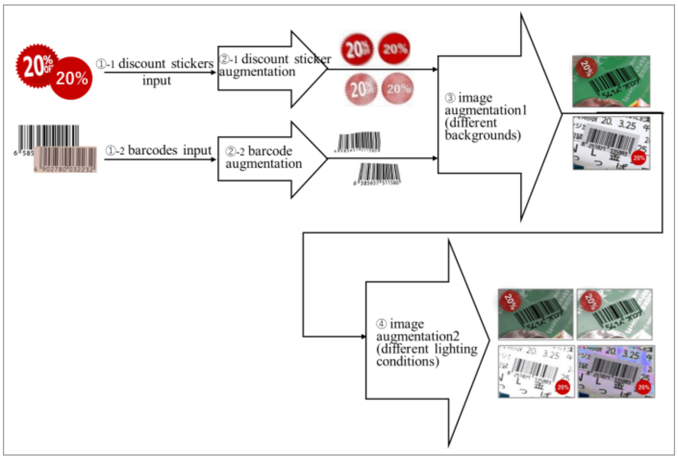

Fig. 4. Processing flow of data augmentation.

The existing augmentation is just for generating images that vary at different angles, horizontal / vertical flips, random cropping, and aspect ratios. However, this usual augmentation is not enough for processing the products of super-market. There are various states on the discount stickers attached to the products and the printed barcodes. Here we give some real samples of discount stickers and barcodes. However, to protect design, we add some markers to the discount stickers. In Fig. 5, (a) shows clear discount stickers and barcodes. (b) shows distortion caused by the shape change of the products' packages, especially in the case of bending of plastic packages or bottles and cans. (c) shows some reflections caused by various lighting conditions. (d) shows motion blur caused by movement of the products. (e) shows some obstruction caused by multiple discount stickers, or peeled off, or by a hand or something while holding the products. (f) shows some discount stickers attached or printed barcodes on complex backgrounds. (g) shows different perspective of images caused by different lighting conditions.

Fig. 5. Real samples of discount stickers and barcodes.

It is obvious that the actual discount stickers and barcodes shown in (b)-(e) are quite different from the clear data shown in (a), and we address the issue with the augmentation of the discount stickers and barcodes themselves. (f)-(g) show various backgrounds and lighting conditions on the images containing the discount stickers and barcodes generated, and we address the problem with the augmentation of the images.

IV. EXPERIMENTS

In this section, we make some experiments to verify the effectiveness of our approach. We first evaluate the performance of discount sticker and barcode recognition, then compare the processing time with the current POS.

A. *Experiment 1*

The purpose of this experiment is to investigate effectiveness of our classification network and our data augmentation in the real-world scenario.

As mentioned in the previous part, existing system for POS automation has not yet been proposed, and there is no data set to evaluate the recognition of both discount stickers and barcodes. Accordingly, we build our own assessment data set including various challenges. In Japanese supermarkets, the discount rates of discount stickers are mainly 10% off, 20% off, 30% off and 50% off, so these discount rates are set to be main evaluation targets. In addition to common products, we also collect natural soft-packed products that are prone to distortion and products with new discount stickers on old ones to include easy to difficult evaluation images. And we shoot them at different shooting angles and lighting conditions to reproduce various distortions, reflections, blurs, etc. The evaluation data set contains some images that are more difficult than the samples shown in Fig. 5.

We set up two evaluation tasks. One task is to evaluate detection performance of discount stickers and barcodes, and the other is to evaluate classification performance. In our detection task, we use mAP evaluation matric, which is a commonly used metric. MAP stands for Mean Average Precision, a method of summarizing the precision-recall curve into a single value that represents the average of all accuracy. On the other hand, we use Accuracy evaluation metric for classification task. Accuracy is the ratio of the number of correct predictions to the total number of predictions made to a data set.

TABLE I. Results of discount stickers and barcode classification with our original data set.

Target	Classification	Number of Images	mAP	Accuracy
Discount stickers	10% off	458	0.998	1.00
	20% off	418	0.998	1.00
	30% off	315	0.997	1.00
	50% off	175	0.997	1.00
barcodes		1366	0.972	0.981
average		-	0.992	0.996

Table I shows detection and classification results of the discount stickers and barcodes. We achieve good performance on them both. The average mAP for detection task is over

0.992, and classification accuracy is over 0.996. The barcodes failed to be detected are those having serious distortion, reflection or having multiple challenges, which is possibly dealt with multiple frames.

Fig. 6 shows a comparison of classification Accuracy WITH and WITHOUT the proposed data augmentation. The latter refers to the basic level data augmentation described in the previous part. Obviously, our approach significantly improves the performance of all kinds of discount stickers and barcode classification.

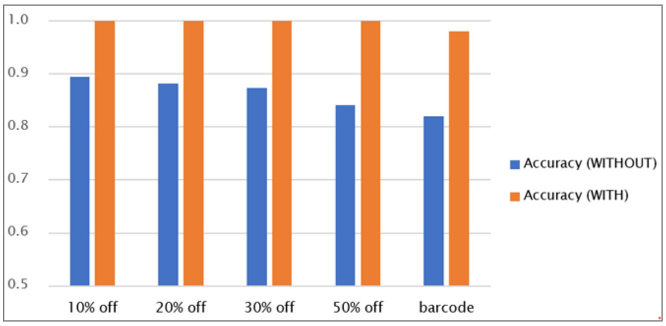

Fig. 6. Classification accuracy comparison WITH and WITHOUT the proposed data augmentation.

B. *Experiment 2*

The purpose of this experiment is to verify the robustness of the proposed approach in various cases.

We test the recognition ability of discount stickers and barcodes in different placement conditions, still status and motion status, etc. Each image includes several challenges.

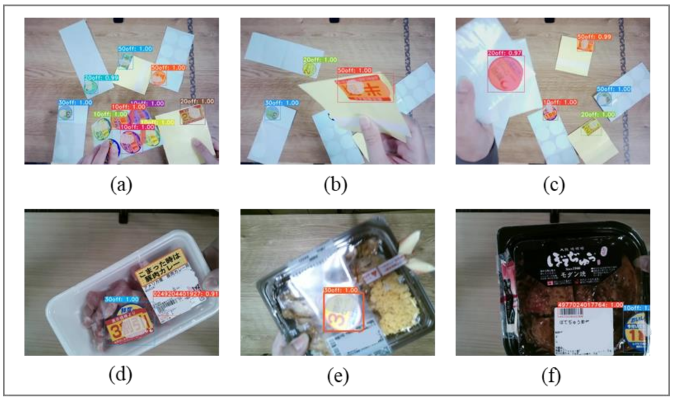

Fig. 7. Some processing results of various cases.

Here we give some recognition results in Fig. 7. We show mask area of the detected target in transparent background color, bounding box with colored frame, and recognition results of the mask region in background color text. Same as Fig. 5, we add some markers to the images to protect the design. In (a), there are multiple discount stickers attached on a reflective paper. In (b), there are multiple discount stickers, and the one in the hassle has a perspective deformation. In (c), there are multiple discount stickers, and the one on the left back has a blur caused by moving. In (d), there is both a barcode and a discount sticker, and the recognition target sticker is pasted on an old one. In (e), the discount sticker has both reflection and motion blur. In (f), there is both a barcode and a discount sicker, and part of the discount sticker is hidden. The results show that our proposed approach works well with multiple recognition targets and multiple challenges, including complex states such as reflection, occlusion, and blur.

C. *Experiment 3*

The purpose of this experiment is to investigate the work efficiency improvement of the proposed system.

We measure and compare the processing time of the current product scanning / manual input method and the proposed method. The PC we use for recognition process is a laptop having GPU.

We first compare the processing time of discounted products only. Fig. 8 shows a comparison result of the average measurement time for processing one discounted product. We measure the operation time of 20 staffs and take the average value of them. The processing time of the current process includes the time to put the product in front of the barcode scanner, the scan time, and the time to manually enter the discount information. The processing time of the proposed method includes the time to place the product under the camera and the recognition time, and the recognition time includes both barcode recognition and discount sticker recognition. The proposed method takes only 1.1 seconds compared to the current processing time of 3.5 seconds for one discounted product. Of these, the proposed process takes only 0.1 seconds for recognition, but the existing method takes 2.5 seconds for barcode scanning and manual input of discount information. The reason for the fast recognition of the proposed approach is that the classification network is simple yet very robust in recognition and can handle the recognition target in any situation using the proposed data augmentation.

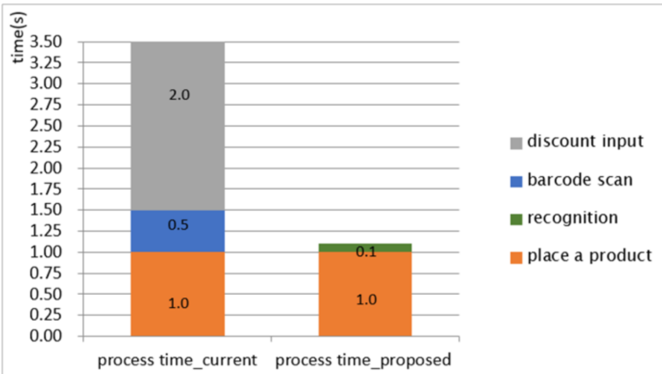

Fig. 8. Processing time comparison for one discounted product.

We then compare the processing time when processing a combination of discounted and non-discounted products. Fig. 9 shows the comparison of increasing the number of discounted products from 1 to 10 out of 10. Same as experiment 2, the measurement time of the proposed method includes the time for placing the product in front of the camera and the recognition time, and the recognition time includes both barcode recognition and discount sticker recognition. In the current process, the processing time increases greatly as

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the number of discount products increases, but the processing time of the proposed method is constant. The reason why the processing time of discounted product and non-discounted product keeps stable is that our network recognizes discount sticker and barcode simultaneous. The proposed method has made it possible to shorten the work time of staffs, reduce their workload, and shorten the waiting time of customers.

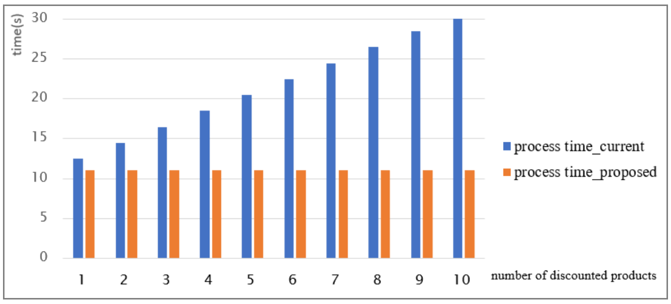

Fig. 9 Processing time comparison for combination of products.

V. CONCLUSION

In this work, we propose a robust deep-based discount stickers and barcodes recognition system. We design the classifier basing on the YOLACT object detection network to simultaneously detect and classify various discount rates and barcodes. To improve the training performance of deep learning model, we propose a novel data augmentation approach to generate various data that is close to the actual scene. The data augmentation consists of three steps. The first step is to individually augment discount stickers and barcodes with different states such as distortion, blur, complex background, etc. The second step is to paste the generated discount stickers or barcodes or both to complex backgrounds. The third step is to augment the images containing the discount stickers or barcodes or both generated in the second step of various real lighting conditions. The evaluation with our original data set shows that our proposed approach is effective and robust in discount sticker recognition and barcode detection. In addition, the processing time evaluation and comparison with the current manual operation with discount information input shows that our system saves a lot of effect of product scanning work.

This approach enjoys practicability, accuracy, and speed. We believe that our approach is applicable and contributable to automation in various fields such as POS processing to improve productivity.

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