Expiry-Date Recognition System Using Combination of Deep Neural Networks for Visually Impaired

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Abstract. Many drink packages have expiry dates written in dot matrix characters (digits and non-digits, e.g., slashes or dots). We collected images of these packages and trained two existing deep neural networks (DNNs) to combine and form a system for detecting and recognizing expiry dates on drink packages. One of the DNNs is an object-detection DNN and the other is a character-recognition DNN. The object-detection DNN alone can localize the characters written on a drink package but its recognition accuracy is not sufficient. The character-recognition DNN alone cannot localize characters but has good recognition accuracy. Because the system is a combination of these two DNNs, it improves the recognition accuracy. The object-detection DNN is first used to detect and recognize the expiry date by localizing and obtaining the size of the character. It then scans the expiry-date region and clips the image. The character-recognition DNN then recognizes the characters from the clipped images. Finally, the system uses both DNNs to obtain the most accurate recognition result based on the spacing of the digits. We conducted an experiment to recognize the expiry dates written on the drink package. The experimental results indicate that the recognition accuracy of the object-detection DNN alone was 90%, that of the character-recognition DNN alone was also 90%, and that combining the results of both DNNs was 97%.

1 Introduction

There are various inconveniences for the visually impaired. One such inconvenience is shopping. When shopping, it is essential to obtain product information. However, the visually impaired cannot easily obtain this information. From the results of an interview of 14 visually impaired individuals regarding shopping [1], they can go to the front of the product shelves of the shop where they often visit, because they remember the arrangement of the shelves in the shop. However, they cannot obtain the name, price, or expiry date of perishable foods. In this paper, we focus on automatic recognition of expiry dates.

Tanaka et al. proposed a system for recognizing expiry dates [2]. They used a commercial optical character-recognition software to recognize expiry dates.
They used dilation image processing to recognize dot matrix characters. Such characters are represented by a set of dots, as shown in Fig. 1. Their experimental results indicated that the accuracy of their method for recognizing dot matrix characters was only 43%. Hosozawa et al. proposed an erosion and dilation procedure for dot matrix characters [3]. However, they did not give the recognition accuracy for this procedure. Zaafouri et al. proposed an automated vision approach for recognizing expiry dates using a multilayer NN [4]. Gong et al. proposed a DNN for localizing the expiry date in an image [5]. The last two studies did not consider dot matrix characters.

We propose a system for detecting and recognizing the expiry dates written on drink packages. Many drink packages have expiry dates written in dot matrix characters (digits and non-digits, e.g., slashes or dots). We collected images of such dates and trained two existing DNNs to combine to form our system. With this system, the visually impaired can read expiry dates without the need for assistance. They can also read the expiry date of products they previously bought at home. Our system is not only useful for the visually impaired but also for applications where sighted people manage perishable foods by expiry dates.

2 Expiry-Date Recognition System

2.1 Overview

As mentioned above, our system is a combination of the two DNNs that are object-detection and character-recognition. The object-detection DNN can localize and recognize the characters written on drink packages, but the recognition accuracy is not sufficient. The character-recognition DNN cannot localize the characters but has good recognition accuracy. In our preliminary experiment, the recognition rate of our system was 99%. Figure 2 shows the comparison between the object-detection and character-recognition DNNs.

In our system, the object-detection DNN first detects and recognizes the expiry date by localizing and obtaining the size of the characters. The system then scans the expiry-date region with a raster scan method and clips the image. The character-recognition DNN then recognizes the characters for the clipped image. Finally, the system combines the results of both DNNs to obtain the final result based on the spacing of the digits.
2.2 Object-Detection DNN

We use the Faster R-CNN as the object-detection DNN to localize and recognize the expiry date [6]. We collected 108 images of drink package. Then, we obtained the location and number of digits and dots in the images and created training data. We distorted the images randomly to increase the amount of data. The images were collected in 2011–2019. There was a bias in the frequency of certain digits, i.e. the digit ‘1’ was more common than the others. To make the amount of the digits almost same, we painted more frequent digits white. We increased the amount of the training data to 9,996 and trained the object-detection DNN by using these data.

2.3 Character-Recognition DNN

To create the input data to input to the character-recognition DNN, the system scans the input image and clips a small rectangle of the image. If the system scans and clips the entire image, there will be a huge number of clipped images. The system first limits the scanning area. It scans only the area where the digits were detected with the object-detection DNN. To reduce the number of clipped images, the system first binarizes the image and clips it after satisfying the following criteria.

1. The image edges are white pixels,
2. The center of gravity of the black pixels is at or slightly above the center of the image.

The reason for including above the center of the image is that the center of gravity of digit ‘7’ is slightly higher than that of the image. The system can estimate the size of the digit from the object-detection DNN. However, the size may not match the actual digit size. Therefore, the system repeats clipping by
changing the size of the digit. It adds $-2$ to $2$ pixels to the size of the digits and repeats scanning and clipping five times. Figure 3 shows examples of clipped images from the image of a drink package shown in Fig. 4(e). The system clips digits as well as non-digits.

We use the same training data as those mentioned in Sect. 2.2 and clip the images. Then, we select a total of 1838 clipped images as training data. We use LeNet as the character-recognition DNN [7], which was developed for handwritten digit recognition. We trained this DNN by using the training data.

2.4 Combination of Two DNNs

If the two DNNs output the same expiry date, the system can output the date with high reliability. Due to the errors in recognition, the outputs of two DNNs may differ. In such case, the system needs to select the output from two obtained expiry dates based on the spacing of the digits. For example, when the output of the object-detection DNN was ‘1.11.30’ and that of the character-recognition DNN was ‘19.11.30,’ the system selects ‘19.11.30’ as the final recognition output. When the outputs from two DNNs are inconsistent like ‘20.01.18’ and ‘20.01.13,’ the system determines that recognition failed. In this case, it asks the user to take the image again.

3 Experimental Results

3.1 Object-Detection DNN Alone

We trained the object-detection DNN by using 108 images of drink package and conducted an experiment to localize and recognize the digits in the images. We used 30 other images of drink packages as test images. Figure 4 shows some of the recognition results. We calculated the following recall and precision as the performance index of recognition accuracy.

\[
\text{Recall} = \frac{\text{Number of correct recognitions}}{\text{Number of digits in the image}},
\]

(1)

\[
\text{Precision} = \frac{\text{Number of correct recognitions}}{\text{Number of recognized digits}}.
\]

(2)

Table 1 lists the results of recognizing each character.
Fig. 4. Results from object-detection DNN. Red rectangles in output image show recognized digits. (Color figure online)
Table 1. Recognition results from object-detection DNN

| Character | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 0   | Dot   | Total |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|-------|
| Recall    | 0.988 | 1.000 | 0.900 | 1.000 | 0.875 | 1.000 | 1.000 | 0.857 | 1.000 | 0.895 | 0.933 | 0.961 |
| Precision | 0.963 | 0.979 | 0.818 | 1.000 | 0.875 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.982 | 0.974 |

The system estimated the expiry date by the format “yy.mm.dd.” For example, the results of input images (a), (c), (e), and (g) in Fig. 4 were ‘19.11.26,’ ‘19.12.08,’ ‘19.11.3,’ and ‘2.1.22,’ respectively. The last digit ‘0’ in Fig. 4(f) and the digit ‘0’ in Fig. 4(h) were not detected. Expiry dates were correctly estimated for 27 out of the 30 images; thus, the recognition accuracy was 90%.

3.2 Character-Recognition DNN Alone

We used the same test images mentioned in the Sect. 3.1 and obtained recognition results. The results of input images (a), (c), (e), and (g) in Fig. 4 were ‘19.11.26,’ ‘19.12.0,’ ‘19.11.30,’ and ‘20. .22,’ respectively. The last digit ‘8’ in Fig. 4(c) and digit ‘1’ in Fig. 4(g) were not recognized. Expiry dates were correctly estimated for 27 of the 30 images; thus, the recognition accuracy was 90%.

3.3 Combination of Two DNNs

The system combined the results of both DNNs based on the spacing of the digits. Expiry dates were correctly estimated for 29 of the 30 images; thus, the recognition accuracy was 97%. The only example for which the expiry date could not be estimated was that in Fig. 4(g).

4 Discussion

From the experimental results of the object-detection DNN, 96% of characters were correctly recognized. However, looking at Table 1, precision of 1, 3, and 5 is not sufficient. The digit ‘8’ was recognized as ‘3’. Characters other than the expiry date were also nearby. The character ‘S’ was recognized as ‘5’ and ‘I’ as ‘1’ because the character shapes were similar. This will improve by increasing the amount of training data.

The recognition accuracy of the character-recognition DNN was the same as that of object-detection DNN. The last digit ‘8’ in Fig. 4(c) was recognized as a non-digit. The digit ‘1’ in Fig. 4(g) was not clipped. The reason may be the lack of training data.

Three of the 30 images were not recognized with the object-detection DNN alone. However, two of them were recognized with the character-recognition DNN. Similarly, three of the 30 images were not recognized with the character-recognition DNN alone. However, two of them were recognized with the object-detection DNN. Therefore, the two DNNs complement each other, improving the final recognition accuracy.
5 Conclusion

We proposed a system for recognizing the expiry dates written on drink packages. The system uses two DNNs, one is an object-detection DNN and the other is a character-recognition DNN. The system improved the recognition accuracy by using both DNNs. The experimental results indicate that the recognition accuracy of the object-detection DNN was 90%, that of the character-recognition DNN was 90%, and by using both DNN, the system’s recognition accuracy was 97%.

For a future work, it is necessary to consider a method for improving recognition accuracy by increasing the amount of training data, including the digits that have been incorrectly recognized. It is also necessary for visually impaired people to use the system and give feedback on it. We plan to implement the proposed system in a smartphone application.

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