JCSE Journal of Computing Science and Engineering

Regular Paper

Journal of Computing Science and Engineering,
Vol. 12, No. 4, December 2018, pp. 149-156

CNN-Based Drug Recognition and Braille Embosser System for the Blind

Soyeong Lee, Sunhae Jung, and Hyunjoo Song*
Department of IT Media Engineering, Duksung Women's University, Seoul, Korea
{dtddtd3987, alrnrdls15, hjsong0001}@duksung.ac.kr

Abstract

Visual impairments reduce one's ability to perform daily tasks such as taking medicine. While the sighted can use their vision to effortlessly locate and identify drugs, the blind must rely on external assistance to complement their visual sense. Thus, receiving appropriate aid at the right time is crucial to avoid the misuse of drugs. We conducted interviews regarding medicine intake with 30 partially or completely blinded persons registered at three supporting facilities. Participants reported limitations of their current methods in finding their medication which led to them taking unintentional irregular doses caused by the lack of aid. Based on the results of the interview, we developed a drug recognition model and braille embosser system for Android smartphones. Using a picture of a medicine taken with a built-in camera, the CNN-based recognition model can classify 11 types of medicines with 99.6% accuracy. In addition, a low-cost braille embosser, which can connect to one's smartphone via Bluetooth, can print the classification results as a braille label for future identification without a smartphone.

Category: Human-Computer Interaction

Keywords: Human-computer interaction; Deep learning; Drug recognition; Braille embosser

I. INTRODUCTION

Taking medicine is one of the most challenging tasks for visually impaired people, since they must locate the correct medicine without visual sense. People with low vision can compensate by using a variety of assistive devices, such as glasses or magnifiers. By contrast, completely blind people must rely on braille printing on the medicine package in order to find the right one. However, according to a survey conducted in 2017 [1], only 0.2% of drugs on the market have braille printing on them. As a result, the blind must rely on the sighted to find the correct medicines, although such assistance may not be available every time it is needed.

In order to remedy this problem, a number of smartphone applications [2, 3] employ object recognition and OCR (optical character recognition) techniques to help the blind recognize objects. Furthermore, advances in deep learning techniques have led to higher object recognition accuracy and integration with other techniques such as text-to-speech (TTS). For instance, recognized results can be narrated to the user in real time through a smartphone camera. However, general-purpose commercial object recognition applications such as Aipoly [2] may not be able to distinguish between various types of domestically available medication or prescribed pills. In addition, one must use the smartphone application every time they have to take medicines.

Therefore, the most effective way to aid the blind in taking medicine would be to enact laws regarding braille

Open Access http://dx.doi.org/10.5626/JCSE.2018.12.4.149 http://jcse.kiise.org

This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (http://creativecommons.org/licenses/by-nc/3.0/) which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

Received 11 October 2018; **Revised** 12 November 2018; **Accepted** 15 November 2018
*Corresponding Author

Copyright © 2018. The Korean Institute of Information Scientists and Engineers pISSN: 1976-4677 eISSN: 2093-8020

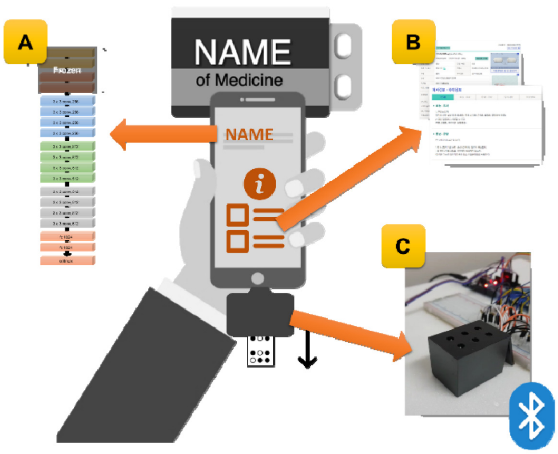

Fig. 1. Overview of proposed system. (A) Convolutional neural network for drug recognition. (B) Efficacy and safety information of the drug. (C) Braille embosser.

labels on medicines. However, in Korea, Article 69 of the regulation on safety of medicine and drugs leaves braille printing to the pharmaceutical company's discretion, and a revision to mandate it is still underway. Furthermore, prescribed medicines are being packaged in powder paper or bottles in pharmacies, so the efficacy of revision may still be limited to over-the-counter drugs. In order to remedy this problem, one can print out braille labels for each of their medicines, but the price of a commercial braille labeler is not affordable for personal use.

In this paper, we propose a system with a drug recognition model and a braille embosser to aid the blind in taking medicine (Fig. 1). The recognition model is based on prior work on deep learning and was loaded onto a smartphone application. We then built an Arduino-based low-cost braille label embosser and linked it to the application. Section II summarizes previous studies related to this work, and Section III summarizes the results from interviews with the visually impaired. Sections IV and V cover our convolutional neural network (CNN)-based drug recognition model and braille embosser, which were designed according to the interview results. Section VI describes the smartphone application and is followed by discussion, conclusion, and future work.

II. RELATED WORK

A. CNN-Based Object Recognition

CNN-based models have been used for object classification. LeNet [4] introduced a CNN-like structure for character recognition, and many prior works were inspired by this structure. Since 2010, a number of classification algorithms have competed to achieve higher accuracy in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). In 2012, AlexNet [5] showed drastic improvements with a deep CNN by achieving a 16% error rate, which had been reported as approximately 25% in 2011. Since then, CNN has been recognized as a promising solution for image classification. In 2014, GoogLeNet [6] and VGGNet [7] took first and second places in ILSVRC, respectively. Between them, VGGNet showed competitive performance, even with much simpler structures, compared to GoogLeNet. In this work, we also built a CNN-based algorithm to identify drugs based on their images.

However, CNN-based design has a shortcoming: it is difficult to train the network if the number of images is insufficient. For instance, VGGNet consists of 138 million parameters, and it not only requires a huge dataset, but also takes hours to optimize the parameters. Similar limitations also exist in the bioinformatics field [8], and transfer learning [9] was used to solve this problem. The concept was also proven to be effective in image classification research. It used the parameters optimized in prior work and only trained additional layers in order to solve specific problems of interest. Since ImageNet [10] provided an image database large enough to train the feature extraction layers, follow-up studies were able to adopt the trained models from prior work. Since drug recognition also handles a classification problem with a small dataset, we adopted transfer learning in this study as well.

B. Applications to Aid the Blind

The advances in and prevalence of smartphones have introduced a new way to aid the blind. Kramer et al. [11] proposed a smartphone-based facial recognition tool to aid in identifying persons. However, the user had to maintain a wireless connection to the server, which was responsible for facial recognition. Our system also used a recognition model, but we mounted it on a smartphone application so as to allow for usage without an internet connection. Rodrigues et al. [12] studied smartphone usage of the blind by conducting an 8-week study. This research investigated how users respond to a TalkBack (i.e., screen reading accessibility features in the Android operating system) tutorial and reported that the tutorial was not sufficient to become comfortable with the feature. Thus, we began by providing an external TTS service. However, we learned that our interviewees were accustomed to using TalkBack and preferred the consistent user experience provided by its default accessibility feature (Section VI).

In terms of object recognition applications, ThirdEye [3] provided object recognition and OCR with auditory feedback. It could recognize everyday objects and even some well-known medication packages such as ibuprofen. Another approach to recognizing an object is provided by the application named 'Be My Eyes' [13]. It randomly connects the blind with sighted volunteers via video call. These volunteers help the visually impaired with more sophisticated needs, such as checking the expiry dates of foods. According to the interviews in Section III, both smartphone applications are widely used and accepted. However, the former application could not successfully identify domestic drugs in Korea, while the latter necessarily involves the exposure of private information to volunteers. Song et al. [14] worked on the classification of seven domestic prescribed pills, but the system was not designed for the visually impaired. It relied on features extracted from hue, shape, and text on a pill. This work aims to support the blind in Korea in taking medicines without any external help.

III. INTERVIEWS WITH THE BLIND

We conducted interviews with 30 visually impaired people (4 partially blind and 26 completely blind) in order to investigate difficulties associated with taking medicine. All of them were registered at three different supporting facilities for visually impaired people. We wanted to make the interview environment as comfortable as possible, so we consulted an expert at one of the facilities. Consequently, we asked instructors at the facility, who met with the participants regularly, to conduct interviews on our behalf. Thus, we designed and revised questions for the proxy interview. We prepared 15 questions (Table 1) about taking medicines (Q1–Q5), prior experience with smartphone applications (Q6-8), using a braille embosser (Q9–Q11), using a smartphone camera with a paired braille embosser for drug identification (Q12–Q14), and other general comments (Q15). Each participant received about $10 for participation.

Of the 30 participants, 23 reported difficulties when taking medicines. Of the 21 completely blind participants, the majority (15 participants) expressed difficulties with identifying drugs, while the others mentioned frustration with searching for efficacy and safety information. Two partially blind participants expressed difficulties with reading small labels on the package. Regarding the identification of drugs, 16 participants relied on memory; they kept their drugs in memorable places or used distinguishable containers. Eight participants asked family members or acquaintances to identify the drugs. However, they reported that they eventually had to find a person to help them when their strategy had failed. This was inevitable, considering the response to question 5; 20 participants reported that they had never seen any medicine boxes with braille writing on them, and 3 of the participants who had seen such medicine still complained that it was illegible.

Next, we investigated personal experience with smartphone applications. Participants complimented an OCR-capable object recognition application [3] and a crowd-sourced object recognition application [13]. However, one of the participants was still concerned about the insufficient accuracy of OCR applications. In addition, screen reading capability (e.g., in VoiceOver or TalkBack) was another reported obstacle to daily use: some applications neglected alternative text, and part of the text was not discoverable.

Regarding a braille embosser, approximately two-thirds of participants had used one. They expressed that while it was useful (9 participants), the commercial product was too expensive (9 participants). As a result, 25 participants answered that they were willing to purchase a portable braille embosser for an affordable price. We also received positive feedback from 24 participants about linking the recognition application with the embosser. In addition,

Table 1. List of interview questions

	Questions
Q1	Have you ever experienced difficulties when taking medicines? If so, please describe your experience.
Q2	How do you recognize your medicines when you take them?
Q3	What do you do if your method is unavailable?
Q4	How often do you use braille? (5-pt Likert scale)
Q5	Have you ever seen any medicine with braille printed on it? If so, please describe your experience.
Q6	What was the most comfortable experience of using your smartphone application?
Q7	What was the most uncomfortable experience of using your smartphone application?
Q8	What are your concerns about a smartphone application for the visually impaired?
Q9	Have you ever used a braille embosser?
Q10	Please describe your thoughts about using a braille embosser.
Q11	Are you willing to buy a portable braille embosser? If so, how much are you willing to pay for it?
Q12	Are you willing to use a smartphone application that uses a camera for drug identification?
Q13	What are your concerns about drug identification using a smartphone camera?
Q14	Are you willing to use a braille embosser that can print the name of an identified medicine?
Q15	Are there any other general comments about the application?

Fig. 2. Image samples of 11 domestic drugs for drug recognition model.

participants wanted the embosser to be a general-purpose device that could print out texts other than the names of medicines. Based on the responses from the interviews, we designed a drug recognition and braille embosser system.

IV. DRUG RECOGNITION MODEL

A number of object classification models have proven effective. However, to the best of our knowledge, these models were not trained to distinguish Korean domestic medications. For instance, ImageNet [10] contains only general terms, such as pill, pill bottle, or multivitamin. As a result, interviewees had to use an OCR application to identify drugs, but they were concerned about accuracy and also expressed difficulties in finding the side of the medicine with the name on it.

In order to remedy this problem, we built a domestic drug image dataset and trained a classification model with it. The drug identification model was built with Keras [15] and converted into a TensorFlow [16] model to mount on an Android application. We used a system with AMD Ryzen5 2400G CPU and NVIDIA GTX1080 8GB GPU to build and train the model.

A. Drug Image Dataset

In the early stages of this research, we worked on crawling images of domestic household medicines on Internet websites. However, only a few images were available for each drug, and the numbers were even smaller after removing the duplicates. Therefore, we manually took pictures of 11 domestic drugs (4 antipyretic drugs, 2 digestive medicine, 2 cold medicines, 1 stomach medicine, 1 anti-diarrhea, and 1 contraceptive in Fig. 2), which were suggested by a local pharmacist based on popularity. We excluded prescription drugs for safety, as instructed by the pharmacist. As a result, we collected 640 images for each drug, resulting in a total of 7,040 images with various lighting conditions and compositions, as shown in Fig. 3. Since the target users of our system are blind, we assumed that the user might not be able to take a clear picture, and we intentionally included rotated and partially visible pictures in the dataset.

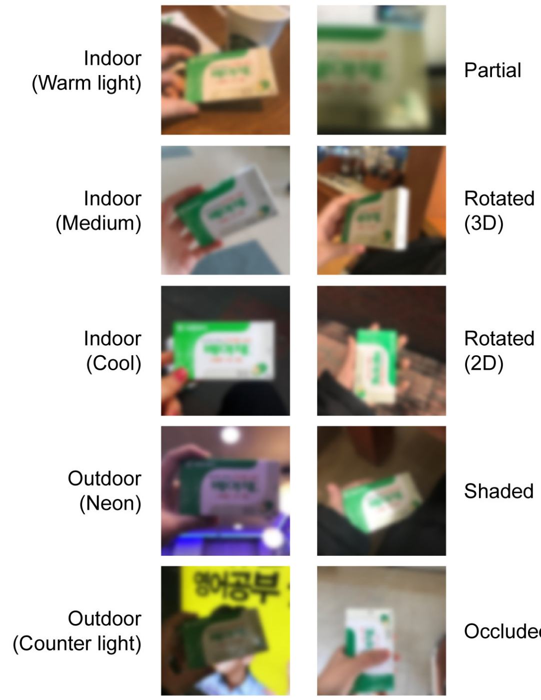

Fig. 3. Image samples with various light conditions (left) and compositions (right).

B. Training the Network

As the number of images in our dataset was not enough to train a complex CNN, we built a simple network with only four layers. We used our dataset for training and testing. Training and testing sets were randomly divided into 75% and 25% of the dataset, respectively. Each image was normalized into dimensions of 300 × 300 × 3 (width × height × color channels) using a Python image library. While this network showed accuracy of over 96% with the first three classes, it dropped to 91% after we added 11 types of drugs. As a result, we decided to transfer learning from the VGG-19 network [7], as shown in Fig. 4. The first four convolution layers in the VGG-19 network were trained with more than 1.3 million images and proven to be effective in finding features in an image. Thus, we froze the convolution layers and replaced them with two fully connected (FC) layers with 1,024 channels each. We used the ReLU activation function in the two layers. Between the two layers, we added a dropout layer with a 0.5 drop rate so as to prevent overfitting. The loss

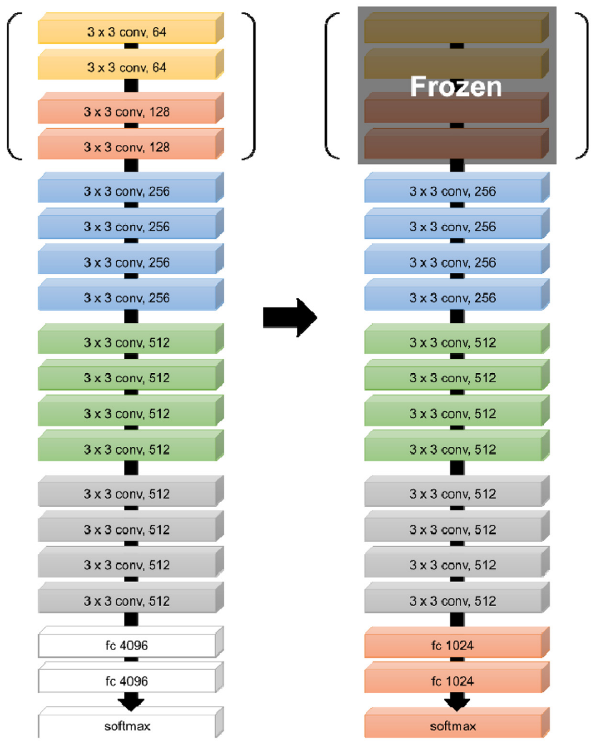

Fig. 4. Structure of our convolutional neural network for drug recognition (right). Convolution and max pooling layers of VGG-19 [7] network (left) were frozen and two fully connected layers were trained with our dataset.

function of the model was categorical cross entropy and optimized by applying a learning rate of 0.0001 and a momentum of 0.9 to stochastic gradient descent (SGD). The completed model has been converted to a TensorFlow model, which can be used directly on Android-based smartphones.

V. BRAILLE EMBOSSER

With the proposed model loaded on a smartphone application, one can immediately classify drugs by taking pictures. Still, this process has to be repeated each time one takes medicine. As a result, we adopted a braille embosser to avoid such inefficiency; one can print out a label for an identified medicine and place it on the package for future reference. However, commercial braille embossers were too expensive, as mentioned in the interviews. Moreover, only a few of them supported Bluetooth connection to a smartphone. Consequently, we designed and implemented a low-cost braille embosser that could directly print the classification result.

When designing the low-cost prototype, we aimed to minimize the total cost by reducing the number of parts. We started by designing the embossing mechanism. In order to achieve adequate pressure, we decided to use multiple solenoids instead of an off-the-shelf braille module with six integrated pins [17]; the modules were more suitable for display than embossing. However, since the dots are arranged in two columns of three dots, we only needed three pins when we used a stepper motor with two stride angles: one for advancing by column width and the other for progressing to the next alphabet character.

Then, we reviewed the Korean braille system in order to predict the output of our design. A Korean character consists of three parts: initial consonants, vowels, and final consonants, which are optional. This means at least two braille letters are needed to form a single Korean character, even when there is no final consonant; a character can be even longer when it has a heavy consonant. Since our solenoid module was 12 mm wide and 12 mm high, a single braille character occupied 24 mm by 36 mm. As a result, two Korean characters took at least 96 mm even

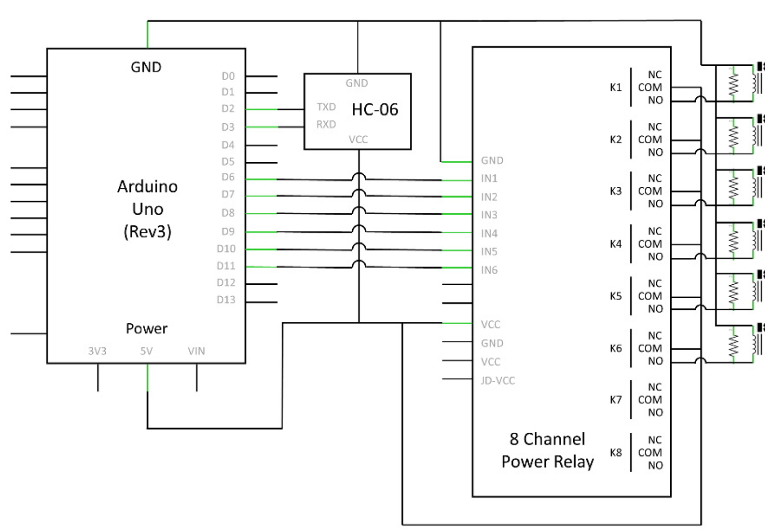

Fig. 5. Schematics of braille embosser. A Bluetooth module (HC-06) and 8-channel power relay is connected to an Arduino Uno board on the left. Six solenoids are wired to the power relay on the right.

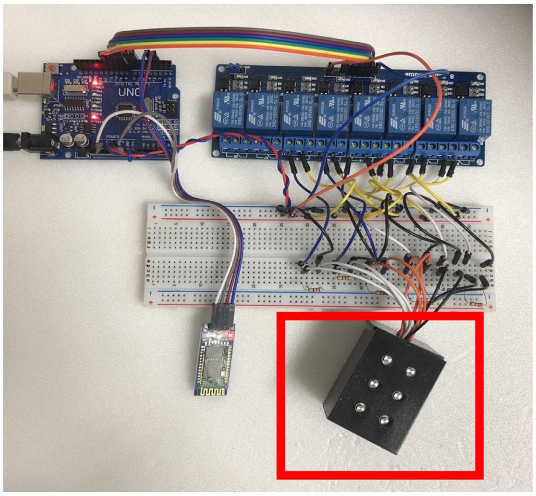

Fig. 6. Arduino-based braille embosser prototype with Bluetooth connectivity. Red box at the bottom right indicates a box with six solenoids.

Fig. 7. Screenshot of the mobile application. 'A' is a name of the recognized medicine, 'B' a print button for braille embosser and 'C' an efficacy and safety information of the recognized drug.

without any final consonants and spaces between them. Considering the size of a typical medicine package, this was too long for practical usage.

Thus, we decided to simplify the design by printing only a single initial vowel and removing the stepper motor. In our final prototype, we used the following parts, which costed approximately $80 in total: six push solenoids; an Arduino Uno board; a power adapter; a power relay module for solenoid control; a Bluetooth module (HC-06 in Fig. 5); cables; and resistors. We wired them as shown in Fig. 5, and tightly sealed six solenoids within a black box for stability, as shown in Fig. 6.

VI. THE MOBILE APPLICATION

We implemented a mobile application that could identify and print out the names of medicines ('A' in Fig. 7). There were two ways to integrate the recognition model, and we chose to embed it rather than to use a server-client approach with an external server. While the latter would be more efficient in the case of frequent model updates, it would also require a stable internet connection. Moreover, one must send pictures to the server for every recognition request, and this raised issues such as delayed response latency, data limits of the user's cellular service, and connection bandwidth of the server. As a result, we chose to load the trained model for offline usage.

Regarding the user interface of our application, we tried to minimize the number of components on the screen. However, since we decided to attach a braille embosser to our system, the application required extra components in addition to the name of the recognized drug, such as a print button ('B' in Fig. 7). At first, we used a TTS service to provide audible feedback to the user. However, we received feedback from the interviewees that they prefer to use accessibility services (e.g., TalkBack) officially provided by the Android operating system. As they were also using other applications in their daily lives, they hoped for an identical user experience from the official features. In accordance with this feedback, we revised the user interface by filling alternative texts with content descriptions and compressed the UI hierarchy so as to comply with the official accessibility guidelines.

Another comment from the interview was related to the difficulties in finding detailed descriptions of medications. Even when the respondent successfully identified the drug, they had to seek external help to determine dosage, efficacy, and safety information. We attempted to overcome this problem by culling the official information from the Ministry of Food and Drug Safety website. As a result, we were able to provide data for the recognized drug ('C' in Fig. 7) that could be browsed with audible feedback. In addition, we included official images of magnified pills to aid persons with low vision.

VII. DISCUSSION

A. Improving the Drug Recognition Model

In this research, we used an image dataset with 11 types of drugs, and we look forward to extending the database. According to the Ministry of Food and Drug Safety, there were over 15,000 approved and reported over-the-counter medications in 2016 [18]. However, as we were not able to find a consensus of household medicines, we had to consult a pharmacist for selection. Since it is not feasible to collect and handle all existing drugs, guidelines on household medicines by the ministry or demand survey results would be required to extend the classes for recognition. The number of classes used in ILSVRC [19] could be used as a reference for choosing a feasible number of classes.

As a step forward from taking pictures ourselves, we are working on a crowdsourcing approach to which users or volunteers can contribute by uploading pictures of additional drugs. With a larger dataset, we will be able to support a larger number of drugs. Meanwhile, as the number of drugs in the model grows, the classification accuracy could become too low for practical use. In such cases, we could adjust the network structure by adopting layers from other networks [6, 20] that show higher performance than VGGNet in terms of accuracy.

B. Overcoming Classification Errors

Our recognition model classified drugs with 99.6% accuracy. This could be satisfactory for other uses, but the identification of medicine for intake requires higher accuracy and greater confidence. Moreover, the accuracy may drop with a larger number of drugs, as mentioned in the previous paragraph. In order to remedy this problem, we are working on barcode or QR code recognition as an auxiliary method. Locating the side with the codes would be cumbersome and take additional time, as there are six such candidates for a box-shaped package. Moreover, in the case of a cylindrical package, one must rotate it to find the angle from which the codes are visible. Still, when the classification results are ambiguous, using the codes could provide a more reliable result.

While our model shows decent classification results for the images of 11 types of drugs, there is a limitation in terms of out-of-distribution images. Since we only use a simple softmax layer in the end of the network, it classifies every image as one of the trained classes. Thus, we tried to include out-of-distribution images in training and testing datasets, but the approach was not feasible for over 15,000 out-of-distribution classes, as reported in [21]. As a remedy to this problem, Liang et al. [21] proposed ODIN, which can detect images from untrained dataset. It showed a 4.3% false positive rate with a 95% true positive rate. We believe that adopting the method could enhance the robustness of our model in real world deployment.

C. Extending the Braille Embosser

We focused on providing an affordable braille embosser prototype and proving the feasibility of our approach. Thus, we adopted a simple design with multiple solenoids for embossing the braille, but these labels were too large to present the full names of drugs in Korean. We are hoping to extend and improve the embosser by using a module with densely arranged pins as well as by adopting a stepper motor for multiple characters. With these improvements, it could also be used to print sentences other than the names of registered drugs, as requested in the interview. For instance, one could print out labels for prescribed medicines in a customized package and attach them for later use.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we propose a drug recognition and braille embosser system for Android smartphones. For accurate medicine classification, we collected pictures of 11 domestic medicines in diverse conditions. In order to preserve the accuracy of the feature extraction layer, the first four convolution layers were frozen with the values from original VGGNet. We also implemented a braille embosser in order to overcome the limitation of having to rely on a smartphone every time. With the embosser, one can print out a recognized result as a braille label and attach it to the medicine package.

While this work was built on a close collaboration with supporting facilities, we were not able to proceed to a deployment study with the blind participants. Still, we look forward to conducting multi-dimensional in-depth long-term case studies (MILCs) [22, 23] with these facilities.

ACKNOWLEDGMENTS

This research was supported by Duksung Women's University Research Grants 2018.

REFERENCES

1. Korea Pharmaceutical Traders Association, "Notice of inquiry about braille on the medicine packages," 2017; http://www.kpta.or.kr/notice/notice02_01_view.asp?dnSeqNo=6262.
2. Aipoly vision, https://www.aipoly.com/.
3. ThirdEye, https://thirdeyeglass.com/.
4. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324, 1998.
5. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems*, vol. 25, pp. 1097-1105, 2012.
6. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Boston, MA, 2015, pp. 1-9.
7. K. Simonyan and A. Zisserman, "Very deep convolutional

networks for large-scale image recognition," in *Proceedings of International Conference on Learning Representations*, San Diego, CA, 2015.
8. Q. Xu and Q. Yang, "A survey of transfer and multitask learning in bioinformatics," *Journal of Computing Science and Engineering*, vol. 5, no. 3, pp. 257-268, 2011.
9. J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, and T. Darrell, "DeCAF: a deep convolutional activation feature for generic visual recognition," in *Proceedings of the 31th International Conference on Machine Learning*, Beijing, China, 2011, pp. 647-655.
10. ImageNet, http://image-net.org/.
11. K. M. Kramer, D. S. Hedin, and D. J. Rolkosky, "Smartphone based face recognition tool for the blind," in *Proceedings of 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, Buenos Aires, Argentina, 2010, pp. 4538-4541.
12. A. Rodrigues, K. Montague, H. Nicolau, and T. Guerreiro, "Getting smartphones to Talkback: understanding the smartphone adoption process of blind users," in *Proceedings of the 17th International ACM SIGACCESS Conference on Computers & Accessibility*, Lisbon, Portugal, 2015, pp. 23-32.
13. Be My Eyes, https://www.bemyeyes.com/.
14. D. Song, J. Lee and W. Choi, "Implementation of drug information search system using image recognition," in *Proceedings of Symposium of the Korean Institute of Communications and Information Sciences*, 2012, pp. 171-172.
15. Keras: The Python Deep Learning Library, https://keras.io/.
16. TensorFlow, https://www.tensorflow.org/.
17. Metec, "Braille cells," http://web.metec-ag.de/en/produkte-braille-module.php.
18. Korean Ministry of Food and Drug Safety, "Statistics on drugs," 2016; https://www.mfds.go.kr/wpge/m_314/de010603l0001.do.
19. O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, et al., "ImageNet large scale visual recognition challenge," *International Journal of Computer Vision*, vol. 115, no. 3, pp. 211-252, 2015.
20. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, NV, 2016, pp. 770-778.
21. S. Liang, Y. Li, and R. Srikant, "Enhancing the Reliability of Out-of-distribution Image Detection in Neural Networks," in *Proceedings of International Conference on Learning Representations*, Vancouver, Canada, 2018.
22. J. Seo and B. Shneiderman, "Knowledge discovery in high-dimensional data: Case studies and a user survey for the rank-by-feature framework," *IEEE Transactions on Visualization and Computer Graphics,* vol. 12, no. 3, pp. 311-322, 2006.
23. B. Shneiderman and C. Plaisant, "Strategies for evaluating information visualization tools: multi-dimensional in-depth long-term case studies," in *Proceedings of the 2006 AVI Workshop on Beyond Time and Errors: Novel Evaluation Methods for Information Visualization*, Venice, Italy, 2006, pp. 1-7.

Soyeong Lee

Soyong Lee is currently an undergraduate student in the Department of IT Media Engineering at Duksung Women's University. Her research interests include human-computer interaction, mobile applications, and deep learning.

Sunhae Jung

Sunhae Jung is currently an undergraduate student in the Department of IT Media Engineering at Duksung Women's University. Her research interests include human-computer interaction, mobile applications, and deep learning.

Hyunjoo Song

Hyunjoo Song received the B.S. degree in computer science and engineering, the M.S. degree in electrical engineering and computer science, and the Ph.D. degree in electrical engineering and computer science from Seoul National University, Seoul, Korea. He is currently an assistant professor in the Department of IT Media Engineering at Duksung Women's University. His research interests include human-computer interaction, information visualization, and gaze tracking.