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Recognition of Medicine Using CNN for Visually Impaired

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ABSTRACT:
The capacity to carry out routine activities, such as taking medication, is impaired by low vision. While those with normal vision may simply use their eyes, the blind need supplementary aid in order to find and recognize medications. Therefore, it is vital to get timely assistance in order to prevent drug abuse. Thirty people who are either legally blind or legally deaf were interviewed about the medications they use at one of three support centers. The participants' present techniques for locating their medicine have limitations, which has led to their taking inadvertent irregular amounts. We built an Android-based drug detection model and braille embosser system in response to the information gleaned from the interview. The CNN-based recognition model achieves 99.6% accuracy when presented with an image of a medication obtained using the device's built-in camera. Additionally, the categorization findings may be printed as a braille label for future identification without a smartphone using a low-cost braille embosser that connects to a smartphone through Bluetooth.

I. INTRODUCTION

One of the most difficult activities for the visually impaired is taking medication, since finding the right medication without sight is a significant obstacle. Those who have trouble seeing may get by with the use of magnifying glasses or other aids. On the other hand, those who are blind or visually impaired must depend on the braille labels printed on pharmaceutical packaging. However, a 2017 study [1] found that just 0.2% of currently available medications had braille printing. This forces the visually impaired to depend on the sighted for help when procuring necessary medications, which may not always be readily accessible.

Several smartphone apps [2, 3] use object identification and OCR (optical character recognition) methods to aid the blind in this regard. Additionally, improvements in object identification accuracy and integration with other methods, such as text-to-speech (TTS), have resulted from advancements in deep learning approaches. For instance, a smartphone's camera may be used to provide real-time narration of detected outcomes. However, it is possible that over-the-counter and prescription medications seem same to general-purpose commercial object identification systems like Aipoly [2]. In addition, the smartphone app should be used each time a patient needs to administer medication.

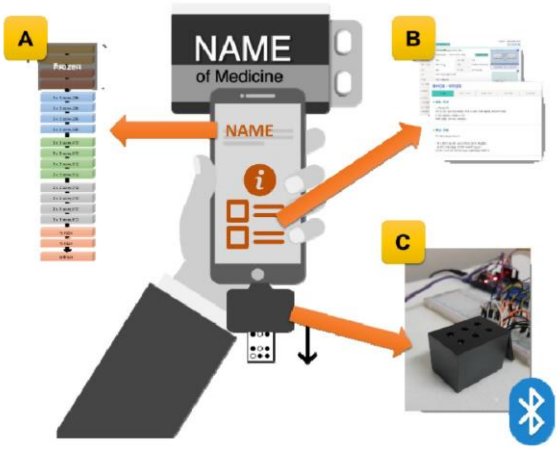

Fig. 1. Overview of proposed system. (A) Convolutional neuralnetwork for drug recognition. (B) Efficacy and safety information of the drug. (C) Braille embosser.

Braille legislation would thus be the most efficient means of assisting the blind in taking medication. medication labeling. Braille printing is now optional in Korea due to Article 69 of the legislation on the safety of medicine and pharmaceuticals, while efforts are ongoing to change this. The effectiveness of modification may still be restricted to over-the-counter meds, since prescription medications are now packed in powder paper or bottles in pharmacies. Printing out braille labels for one's medications is one solution to this issue, but a commercial braille labeler is too expensive for individual usage.

To help the visually impaired take their medications, we present a system that combines a drug identification model with a braille embosser (Fig. 1). The deep learning-based recognition algorithm was integrated into a mobile app for use by users. We then connected an inexpensive braille label embosser based on the Arduino platform to the software. Previous research on this topic is summarized in Section II, and interview data from people with visual impairments are presented in Section III. Our drug identification model using a convolutional neural network (CNN) and a braille embosser built using the interview data are discussed in Sections IV and V. Discussion, a conclusion, and suggestions for future study follow a description of the smartphone application presented in Section VI.

II. RELATED WORK

A. CNN-Based Object Recognition

Classification of objects is one use of CNN-based models. Character recognition has been greatly advanced by the introduction of a CNN-like framework by LeNet [4], which has influenced other earlier efforts. Since 2010, several different classification algorithms have competed in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) to see which could attain the highest level of accuracy. In 2012, AlexNet [5] demonstrated significant progress with a deep CNN, reaching an error rate of 16% (down from the about 25% reported in 2011). Since then, CNN has been seen as a feasible option for categorizing images. In 2014, the ILSVRC was won by GoogLeNet [6] and placed second by VGGNet [7]. VGGNet's performance was comparable to that of GoogLeNet's, despite the latter's more complex architecture. We have developed a convolutional neural network-based system to detect narcotics from their pictures.

However, there is a drawback to CNN-based design: it is difficult to train the network if there are not enough pictures. VGGNet, with its 138 million parameters, for example, not only needs a massive dataset, but also takes hours to tune the parameters. Transfer learning [9] was utilized to address similar constraints in the bioinformatics sector [8]. The approach has also shown promising results in studies of picture categorization. Parameters optimized in earlier work were used, and only newly trained layers were employed to address target issues. Because ImageNet [10] supplied a big enough picture collection to train the feature extraction layers, subsequent research could reuse the learned models from the earlier work. We used transfer learning here as well, since drug identification is essentially a classification issue with a limited dataset.

B. Applications to Aid the Blind

With the development and widespread use of smartphones, a new tool to help the visually impaired has been available. Kramer et al. [11] presented a face recognition app for smartphones to help with criminal investigations. The user, however, was required to have an active wifi connection to the server that handled the face recognition. Our technology, too, relied on a recognition model, but we built it into a mobile app so that it could be used even when there was no network connectivity. Rodrigues et al. [12] conducted an 8-week research on the smartphone use of the blind. Users of TalkBack (the screen reading accessibility capabilities in the Android operating system) were surveyed for this study, and they indicated that the provided instruction was insufficient to help them get familiar with the tool. For this reason, we launched our TTS service to the public. However, our respondents indicated a preference for TalkBack's default accessibility function (Section VI) due to familiarity and the reliability it offers. ThirdEye [3] offered audible feedback for object identification and OCR, two important application areas. It was able to identify commonplace items and even the packaging of certain well-known drugs like ibuprofen. The program 'Be My Eyes' [13] offers an alternative method of object recognition. It uses a matching algorithm to set up video calls between blind people and sighted people. These individuals assist the visually handicapped with more complex tasks, such ensuring that perishable food is not spoiled. The interviews in Part III suggest that both apps are popular among smartphone users. However, the former program was unable to accurately identify Korean domestic

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narcotics, while the latter requires the disclosure of sensitive information about willing participants. Song et al. [14] classified seven commonly used drugs in the home market, however their method was not made with the visually handicapped in mind. It used information gleaned from a pill's color, shape, and font. The Korean blind are aiming to become more independent by learning how to take their medications without assistance.

III. INTERVIEWS WITH THE BLIND

We interviewed 30 persons with visual impairments (4 partly blind and 26 fully blind) to learn about their experiences with medication challenges. They had all signed up at one of three separate centers that help the visually handicapped. We contacted a professional at one of the locations to provide the most conducive interview setting possible. Therefore, we had facility instructors, who already had frequent contact with the participants, take the lead in conducting interviews. As a result, we developed and refined the questions for the proxy interview. We compiled 15 questions (Table 1) on medication use (Q1-Q5), smartphone app use (Q6-8), braille embossing (Q9-11), utilizing a smartphone camera and a braille embosser to identify drugs (Q12-14), and other feedback (Q15). About ten dollars were given to each person who took part.

Twenty-three people out of thirty reported having trouble with medication compliance. Fifteen of the twenty-one totally blind participants reported having trouble with medication identification, while the rest complained about the difficulty of finding data on medicines' effectiveness and safety. Two of the study's blind participants had trouble making out the fine print on the packaging. Sixteen people relied on their own recollection to determine which substances they were using, either by storing them in easily identifiable locations or by placing them in clearly labeled containers. Eight people sought the help of friends and relatives in order to determine the nature of the substances. They said that when their plan fell through, they had to find someone to assist them. Given the responses to question 5, this was to be expected. Twenty participants said they had never seen a medication box with braille writing on it, and three of those who had seen such medicine still complained that the lettering was unintelligible.

Then, we looked at people's actual-world encounters with smartphone software. Both an OCR-capable object identification software [3] and a crowd-sourced app [13] received positive feedback from participants. One member, though, remained worried about OCR software's lackluster accuracy. Some applications omitted alternate text, and some of the text was inaccessible when using a screen reader (such VoiceOver or TalkBack).

About two-thirds of the participants were familiar with the operation of a braille embosser. Nine people said it was helpful but they couldn't justify spending the money on the commercial product. Twenty-five people were polled, and all of them said they would spend less than $100 for a handheld braille embosser. Twenty-four people gave us good responses when we asked for their thoughts on connecting the recognition app with the embosser. And moreover

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

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pay for it?	
Q12	Are you willing to use a smartphone application that uses a camera for drug I dentification?
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

Fig. 2. Image samples of domestic drugs for drug recognitionmodel.

Participants want the embosser to be a versatile device capable of printing a variety of texts, not only drug names. We developed a braille embosser and drug detection system based on information gleaned from these interviews.

IV. DRUG RECOGNITION MODEL

There are many successful approaches for categorizing objects. To the best of our knowledge, however, these models were not developed to recognize differences between Korean home-grown pharmaceuticals. For instance, pill, pill container, and multivitamin are among the few generic phrases included in ImageNet [10]. Participants in the interviews who had to use an OCR program to identify medications voiced concerns about its accuracy and said it was difficult to determine which side of the pill had the drug's label.

To address this issue, we created a collection of images of commonly used drugs in the United States and used those images to train a classification algorithm. The first model for recognizing drugs was developed in Keras [15], and then it was exported to TensorFlow [16] for use in an Android app. Our system's CPU was an AMD Ryzen5 2400G, and our GPU was an NVIDIA GTX1080 with 8GB of memory.

A. Drug Image Dataset

Early on in our study, we worked on a method for automatically trawling the Internet for photos of common home drugs. However, there were very few photos for each medication, and those numbers dropped significantly once duplicates were eliminated. Therefore, we manually photographed 11 commonly used local pharmaceuticals (4 antipyretics, 2 digestives, 2 cold remedies, 1 stomach remedy, 1 anti-diarrhea, and 1 contraceptive; see Fig. 2). For reasons of safety, we didn't include prescription medications.

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

as the pharmacist has prescribed. The results of our efforts are shown in Fig. 3; we collected a total of 7,040 photographs over a wide range of lighting situations and compositions, with an average of 640 images per medication. Since our system is designed for the blind, we included rotated and partly visible images on purpose in the dataset to simulate real-world conditions.

B. Training the Network

Because there weren't enough photos in our dataset to train a deep CNN, we resorted to a simpler network consisting of only four layers. We did both training and testing on our own dataset. The dataset was randomly split into a 75% training set and a 25% testing set. With the help of a Python image library, we resized all of the images to 3003003 (widthheightcolor channels). Accuracy was above 96% for the first three classes, but decreased to 91% when we added 11 more medication kinds to the mix. As may be seen in Fig. 4, we therefore settled on transferring knowledge from the VGG-19 network [7]. More than 1.3 million photos were used to train the first four convolution layers of the VGG-19 network, demonstrating its efficacy in identifying visual attributes. Therefore, we paused the convolution layers and added two 1,024-channel fully connected (FC) layers. In both of the layers, we used the ReLU activation function. Overfitting was prevented by inserting a dropout layer with a drop rate of 0.5 between the two input layers.

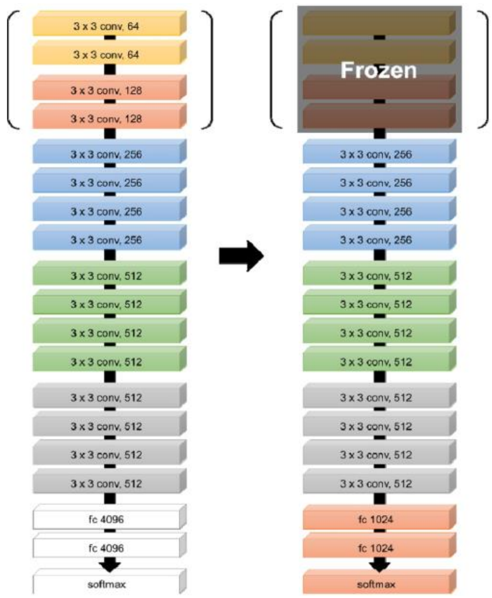

Fig. 4. Structure of our convolutional neural network for drug recognition (right). Convolution and max pooling layers of VGG-19 [7] network (left) were frozen and two fully connected layers were trained with our dataset.

The model's objective function was the categorical cross entropy, and it was optimized using stochastic gradient descent (SGD) with a learning rate of 0.0001 and a momentum of 0.9. After being transformed to a TensorFlow model, the finished model may be utilized on Android-based devices immediately.

V. BRAILLE EMBOSSER

The suggested model may be put into a smartphone app, allowing for instantaneous drug classification through photo. However, this step is necessary for every dose of medication. To prevent this waste, we've started using a braille embosser, which allows us to create a label for a specific medication and attach it to the packaging. Interviewees remarked that commercial braille embossers were too costly for their budgets. Furthermore, only a few of them allowed for Bluetooth pairing with a mobile device. We solved this problem by developing a cheap braille embosser that could immediately print the outcome of the categorization.
We tried to keep the low-cost prototype's price down by using as few components as possible in its design. The

embossing mechanism was the first thing we designed. Instead of using a commercially available braille module with six integrated pins [17], which would have been better suited for display than embossing, we opted to employ a series of solenoids to provide the necessary pressure. Since the dots are placed in two columns of three, we were able to utilize a stepper motor with two stride angles (one for moving across the column, and another for moving on to the next letter of the alphabet) and just three pins.

Then, to foretell the results of our design, we studied the Korean braille system. Initial consonants, vowels, and final consonants (which are sometimes omitted) are the three components of a Korean character. significantly when there is no final consonant, a single Korean character requires at least two braille letters; a character may be significantly longer if it contains a heavy consonant. Our solenoid module measured 12 mm on the side and 12 mm in height, therefore one braille dot required 24 mm by 36 mm of space. Therefore, it required at least 96 mm to even begin writing two Korean characters.

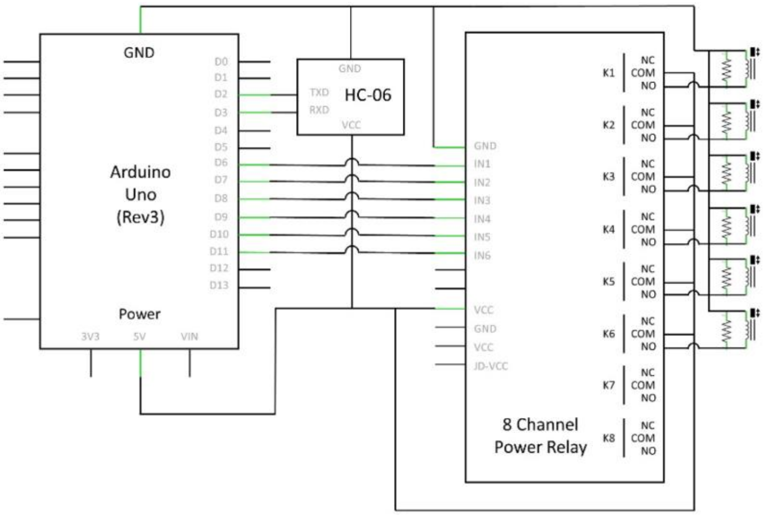

Fig. 5. Schematics of braille embosser. A Bluetooth module (HC-06) and 8-channel power relay is connected to an Arduino Uno board on the left. Six solenoids are wired to the power relay on the right.

without a final consonant and with no pauses in between. This was impractically lengthy when compared to the size of a standard medication bottle.

Therefore, we eliminated the stepper motor and chose to merely print the first vowel. The following items, totaling about $80, were utilized in our final prototype: Figure 5 shows the components you'll need, including six push solenoids, an Arduino Uno board, a power adapter, a power relay module for solenoid control, a Bluetooth module (HC-06), connections, and resistors. To ensure their stability, we enclosed six solenoids within a black box and linked them as shown in Fig. 5.

VI. THE MOBILE APPLICATION

As shown in Fig. 7, we developed a smartphone app that could read barcodes and print out the names of medications. We could have implemented the recognition model using a server-client architecture with an external server, but we opted instead to incorporate it. The second option would be preferable when dealing with regular model changes, but it would need a constant data connection. On top of that, sending images to the server for every recognition request has its own set of problems, such as increased response latency, cellular data constraints, and server connection capacity. Therefore, we decided to save the learned model locally for use later.

We made an effort to reduce the amount of interface elements included in our program. To add a braille embosser to our system, however, the software needed features beyond only the identified drug's name, such as a print button ('B'). Initially, we employed a text-to-speech service to provide the user aural input. However,

Our respondents told us that the official Android accessibility services (such TalkBack) are the ones they utilize most often. They expected the official features to provide the same level of comfort and familiarity as the apps they already used in their everyday lives. In response to this, we changed the UI to conform to official accessibility rules by adding content descriptions to alternative texts and streamlining the UI hierarchy.

One of the interviewees also mentioned how hard it is to get comprehensive explanations of various medications. When a responder did succeed in identifying the medicine, they still needed assistance from others to learn about dosing, effectiveness, and safety. To address this issue, we combed through the Ministry of Food and Drug Safety's website for authoritative information. As a consequence, we were able to provide audio feedback when browsing data for the identified medicine ('C'). To further assist the visually impaired, we have also included official photos of enlarged tablets.

VII. DISCUSSION

A. Improving the Drug Recognition Model

We utilized an image dataset including 11 different medications for this study and plan to add to it in the future. Over 15,000 OTC drugs were authorized and reported in 2016, [18] according to the Ministry of Food and Drug Safety. Since we couldn't agree on a standard list of over-the-counter medications, we sought advice from a pharmacist. Recognizability might be expanded by adding new classes, but this would need either ministry instructions on over-the-counter medications or demand survey findings due to the impossibility of collecting and managing all currently existent substances. An appropriate number of classes might be based on the number of classes utilized in ILSVRC [19].

Instead of shooting photographs ourselves, we're developing a crowdsourcing strategy in which users and volunteers input images of medications not yet included in the database. More medications can be supported if we have access to a bigger dataset. However, the classification accuracy may drop too low for practical usage as the number of medications in the model increases. In such a scenario, we might make adjustments to the network topology by including layers from other networks [6, 20] that achieve better accuracy than VGGNet.

B. Overcoming Classification Errors

Our drug classification system has a 99.6 percent success rate. While this may be enough in certain contexts, identifying medicines for ingestion calls for more precision and certainty. Furthermore, as was noted in the preceding paragraph, the accuracy may decrease with a greater number of medications. To address this issue, we're developing supplementary methods like barcode and QR code recognition. There are six potential faces of a box-shaped item from which to read the codes, making the process laborious and time-consuming. In addition, if the package is cylindrical, you'll have to spin it around to get the optimal viewing angle for the codes. Nonetheless, the codes may offer a more trustworthy conclusion when the categorization findings are unclear.

While our algorithm performs well on 11 different drug image classifications, it falls short when it comes to out-of-distribution pictures. Every input picture is correctly assigned to one of the predefined classes since we simply utilize a single softmax layer as the last stage of the network's processing. For this reason, we attempted to include out-of-distribution photos into both the training and testing datasets; however, as stated in [21], this strategy was not practical for more than 15,000 out-of-distribution classes. Liang et al. [21] presented ODIN, an untrained dataset image detector, as a solution to this issue. It had a true positive rate of 95% and a false positive rate of 4.3%. We think this approach has the potential to make our model more resilient in production.

C. Extending the Braille Embosser

Our primary goals were to demonstrate the viability of our technique and provide a low-cost prototype of a braille embosser. Therefore, we decided on a straightforward layout with many solenoids for embossing the braille; nevertheless, the resulting labels were too large to display the whole Korean medicine names. By employing a module with closely spaced pins and switching to a stepper motor for numerous characters, we hope to increase the embosser's functionality and enhance its efficiency. Once these changes are implemented, it will be possible to publish phrases in addition to registered medication names, as asked in the interview. You may, for instance, print up labels for your medication and affix them to a personalized container for later usage.

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VIII. CONCLUSION AND FUTURE WORK

In this research, we present a system that can identify medications and emboss them in braille on Android devices. We gathered images of 11 common home remedies in a range of preparations to more precisely categorize the medications. The first four convolution layers were frozen with their values from the original VGGNet to maintain the accuracy of the feature extraction layer. In addition, we installed a braille embosser so that users wouldn't always need to depend on their smartphones. The embosser allows a verified result to be printed as a braille label, which may then be affixed to the container of medication.

Although this effort relied heavily on partnerships with enabling infrastructure, a deployment study with blind volunteers was ultimately not feasible. Still, we anticipate using these infrastructures to carry out MILCs [22, 23] that include several dimensions and extend over an extended period of time.

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