Sensors and Materials, Vol. 36, No. 12 (2024) 5283–5297
MYU Tokyo

S & M 3867

Smart-sensors-based Medicine Identification System

Ya-Hui Kuo,[1] Cheng-Yan Siao,[2*] Tzu-Ling Li,[2] Ching-Jen Wang,[2]
Hui-Chuan Lin,[3] Yi-An Chen,[2] Chia-Hui Liu,[1] and Rong-Guey Chang[2]

[1]Department of Nursing, Ditmanson Medical Foundation Chia-Yi Christian Hospital,
No. 539, Jhongsiao Rd., ChiaYi 621301, Taiwan
[2]Department of Computer Science and Information Engineering, National Chung Cheng University,
No. 168, Sec. 1, University Rd, Minhsiung, ChiaYi 621301, Taiwan
[3]Department of Pharmacy, Ditmanson Medical Foundation Chia-Yi Christian Hospital,
No. 539, Jhongsiao Rd., ChiaYi 621301, Taiwan

(Received July 17, 2024; accepted December 10, 2024)

Keywords: medicine identification, intersection over union, fast healthcare interoperability resources, object detection

Medication errors have long accounted for the majority of medical errors. The most significant cause of medication errors is human factors. Medical staff may give the wrong medicine during the medicine distribution process. In this paper, we discuss a medicine identification system to replace medical personnel dispensing medicine. In the medicine identification system, we classify and identify medicine on the basis of shape, color, and imprint data sets. In addition, we transplanted the medicine recognition hardware mechanism to the mobile nursing work vehicle so that medical staff can save time in distributing medicines at designated locations. The medicine identification results showed that the identification rate of various medicine types is markably high, and the probability of medicine identification errors is reduced to 34%.

1. Introduction

Medication errors are one of the leading causes of patient harm in healthcare systems worldwide.(1) The main reason is that medical treatment requires many steps between the doctor writing a prescription and the patient taking the medicine, such as the doctor writing the prescription, the pharmacist dispensing and giving the medicine to the patient, and the patient taking the medicine according to the instructions.(2)

Medical staff deliver medicine to patients in a hospital. According to the hospital's standard medicine delivery process, medical staff must first check the types and quantities of medicines before delivery. After confirming they are correct, the medical staff must deliver them to the patients and confirm in person that they are taking them. The process of medical staff counting medicine is very cumbersome and time-consuming. Although each medicine has already been confirmed after the pharmacist dispenses it, the

*Corresponding author: e-mail: hcyen103m@cs.ccu.edu.tw
https://doi.org/10.18494/SAM5244

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

medical staff still must recheck it. The inspection items include the color, appearance, and whether the front and back of the drug match the prescription. The characteristics of the medicines are recorded in the system, and finally, the medical staff distribute the drugs to the ward for the patients to take. If an error occurs in one of these steps, the patient may be seriously injured or even die. In addition, medical staff are required to identify the medicine under heavy workload and may give the wrong medicine owing to environmental and human factors. Therefore, it is essential to introduce an automatic medicine recognition mechanism, establish a safe medical environment, and reduce the error rate of medicine use.

The information system MedGuard is used to solve the problem of medication errors.(3) The system automatically summarizes erroneous data. MedGuard provides two modes. The first one is to detect a problem immediately when the doctor delivers the prescription. Once the prescription has a problem, it can immediately send back the most appropriate diagnosis and medication combination recommendations. The other is an offline regular medication safety analysis and tracking report, which provides a multi-dimensional analysis of major medicine safety events, most commonly prescribed wrong medicines, costs, and medication error analysis in each department. This application is aimed at doctors' preventive measures when writing prescriptions to prevent doctors from using the wrong medicines for treatment and to implement the method of prescribing the right medication. However, the previous precautionary steps are ineffective if the pharmacist dispenses the wrong medicine even though the correct medication has been prescribed.

The medicine dispensing system solves the problem of the human resources required for upstream drug procurement,(4) midstream medicine classification and storage, and downstream drug dispensing and delivery. This system stores one medication in a cabinet. If multiple medications are stored in one cabinet, it is easy to make a mistake when picking up the medication, so only one medication should be stored in each medicine cabinet. After the doctor writes the prescription, it is confirmed by the pharmacist's remote computer. The nurse only needs to scan the identification card and fingerprint, and the medicine cabinet can provide the medicines needed for the patient's treatment in order. The medicine cabinet will only open a medicine compartment to avoid getting the wrong medicine. However, pharmacists may make mistakes when preparing medications. This is because this application places one medicine in one medicine compartment, and medical staff skip dispensing and confirming the medications again.

Traditionally, pharmacists prescribe medications for patients according to the prescription, and then medical staff have to double-check the medications for errors before delivering them to the patients. This is time-consuming and error-prone. Moreover, most related artificial intelligence (AI) medication recognition system research nowadays uses a server as the model training environment, so the medical staff have to check whether the medications are correct before delivering them to the patients at the fixed point. Therefore, we use sensors such as Raspberry Pi 4 Model B, Jetson Nano, IMX219, and Raspberry Pi display to build the AI medication recognition mechanism. In addition, we have integrated the AI medication recognition mechanism into the mobile nursing work vehicle, so that medical staff do not have to confirm the medications at the fixed point. Instead, the mobile nursing work vehicle can identify the medication while it is moving, which reduces the time medical staff spend checking whether the medication is incorrect. In addition, our medicine data format adopts Fast Health Interoperability Resources (FHIR), which can significantly enhance the interoperability of medical data related to medical institutions, medical records, hospitalization, and referral records.

2. Related Work

Heo *et al.* proposed a set of novel coordinate encoding techniques in 2023.(5) They imported a language model to identify medicines through imprint detection, feature recognition, and imprint correction to identify the database's medicine features and similarity scores. The results showed that the accuracy of the identification of the medicine reached 85.6%.

In 2020, Ou *et al.* proposed an enhanced feature pyramid network for medicine positioning and identification among 612 drugs, and its recognition rate among the top 5 was as high as 94.7%.(6)

In addition, regarding medicine imprint recognition, Yu *et al.* increased the notch width and added loopy belief propagation to solve the problem of discontinuous notch strokes. Among the 2500 categories, the imprint recognition rate is as high as 97.1%.(7)

Chang *et al.* proposed the ST-Med-Box system,(8) which helps patients take multiple medications correctly and prevents patients from taking the wrong medications. The ST-Med-Box system can be executed on mobile devices with an Android system and is equipped with a back-end deep learning server. Currently, the ST-Med-Box system can identify eight types of medicine, with an identification accuracy of 96.6%.

In 2020, Ting *et al.* used the you only look once (YOLO) deep learning framework to identify blister-packaged medicine.(9) They used the F1 score as the model performance evaluation to detect and compare images of blister-packaged medicines' front and back sides. The results showed that the positive recognition rate of blister-packaged medicines is 93.7% and the reverse recognition rate of blister-packaged medicines is 95.7%.

The AI detection models commonly used in medicine identification are RetinaNet, single shot multi-box detector (SSD), and YOLOv3. Therefore, Tan *et al.* used these three models to analyze the same medicine. YOLOv3 is much faster at detecting medicines than RetinaNet and SSD, so it is very suitable for application in hospitals. The performance of YOLOv3 in mean Average Precision (mAP) is even better than RetinaNet and SSD.(10)

In addition, some studies focus on identifying the text on the outer packaging of a medicine to determine whether the medicine is legal to use. Drug label identification through the image and text embedding model combines the connectionist text proposal network and the tesseract optical character recognition engine to evaluate the text sentence level similarity recognition of the medicine outer packaging.(11) The recognition results are improved in terms of recall and precision. The 34% improvement effect further proves that the recognition rate of medicine can be considerably improved through text recognition on the medicine's outer packaging without opening the packaging.

Using smartphones for drug identification, Zeng *et al.* proposed the MobileDeepPill system in 2017 to identify medicines.(12) With the deep learning compression framework based on knowledge distillation, the size of the convolutional neural network model can be significantly reduced without reducing the recognition performance. Therefore, users only need to use their smartphone to take a photo of the medicine, and the medicine information will be displayed.

Chang *et al.* proposed the MedGlasses system.(13) This system combines smart glasses with an AI medicine recognition box to help the visually impaired improve the safety of the medication. When the visually impaired take medication, the medicine can be immediately recognized, and the sound of the medicine name and medication instructions will be played. The medicine identification rate of the MedGlasses system is as high as 95.1%.

Kwon *et al.* improved the accuracy of medicine identification with limited training set data.(14) They used various shapes and colors of drugs as training targets and added 3D amplification technology to give medicine photos a stereoscopic effect. The results were in 40 categories. The recognition rate among medicines is 94%.

3. Methods

3.1 Medicine identification system

The medicine identification system uses YOLOv8 as an object detection model for medicine identification.(15) The medicine identification model uses one-stage identification, so it has high identification accuracy and identification speed.

We conducted medicine data set preprocessing for 319 types of medicine. We took a total of 2896 photos. Each photo was marked with a feature value. The principle of feature value marking is that there is only one principal object in a picture, and the medicine area must exceed half of the overall image area.

After the labeling is completed, the photos are divided into training, verification, and test sets, totaling three medicine data sets. Since medicines with the same efficacies will differ in appearance depending on the age of the patient taking the medicine, medical staff will first identify the patient's age when dispensing the medicine and then classify the medicine after determining the patient's age. To reduce the time medical staff spend dispensing medicine, we classify the medicine data sets during medicine preprocessing. They are divided into shape, color, and imprint data sets. The number of photos in each data set is shown in Table 1.

Table 1
Category and quantity of data sets.

Data set	Category (types)	Training set (pictures)	Validation set (pictures)	Test set (pictures)
Total medicine data set	319	1600	806	484
Shape data set	6	171	65	49
Color data set	26	120	43	23
Imprint data set	6	458	134	58

We use different feature processing methods for medicine data sets. We use auto-orient technology to adjust the image direction automatically to avoid being unable to label features when medicine photos are reversed. Each medicine photo uses a resolution of 960 by 960. Each picture is cropped into 15–20% of the blank area, and Gaussian blur is used to give the feature values of each photo with different weights to each point.(16) The closer the pixels are to the center of the photo, the higher the weight. Finally, on the basis of the weights, the center point of the photo is calculated as a weighted average.

The shape data set also uses auto-orient technology to adjust the image direction automatically. Each photo is converted into a grayscale mode, processed in grayscale, and adjusted to a resolution of 560 by 560. It is divided into a capsule, an oval tablet, a polygon, a square tablet, a tablet, and a triangle.

The color data set has high requirements for ambient light in identifying medicines. Whether the light is sufficient will affect medicine color identification. When the light is insufficient, the color of the medicine will appear less clear. In addition, if the angle of the light illuminating the medicine is not adjusted correctly, it will cause the medicine to reflect light. When the medicine reflects light, the color of the medicine will turn white, which will affect the identification of the medicine. Therefore, we use an LED in the structural design of medicine identification to illuminate the medicine evenly while reducing the shadow area and avoiding reflections caused by specific angles. The color data set uses auto-orient technology to adjust the image orientation automatically, and each photo uses a resolution of 560 by 560.

The imprint data set is divided into graphics, line, nothing, word, word-graphics, and word-line. Since the medicine imprint is not noticeable, a resolution of 640 by 640 must be used. The scratch data set uses auto-orient technology to adjust the image direction automatically.

We adopt intersection over union (IOU) for the medicine identification method, as shown in Eq. (1). Since the IOU algorithm is intersection divided by the union and the result is greater than 0.5, it is judged that the object has been successfully identified. The probability of using IOU as an object identification algorithm in the worst case is 0.49. In other words, we assume that in 100 medicine identifications, 49 identification errors may occur.

$$IOU = (area\ of\ overlap)/(area\ of\ overlap) =$$

$$\frac{predicted\ bounding\ box \cap ground - truth\ bounding\ box}{\left(predicted\ bounding\ box + ground - truth\ bounding\ box\right) - \left(predicted\ bounding\ box \cap ground - truth\ bounding\ box\right)} \tag{1}$$

Therefore, we first assume that the ground-truth bounding box is $P(A)$ and the predicted bounding box is $P(B)$. We then assume the following:

- The coordinates of the upper left corner of the predicted bounding box are $(x1b, y1b)$ and those of the lower right corner are $(x2b, y2b)$.
- The coordinates of the upper left corner of the ground-truth bounding box are $(x1a, y1a)$ and those of the lower right corner are $(x2a, y2a)$.

To realize that the area of the predicted bounding box must be a subset of the ground-truth bounding box, the following conditions must be guaranteed: $x1a \leq x1b$, $y1a \leq y1b$, $x2a \geq x2b$, and $y2a \geq y2b$.

We find $P(A)$ = 1 (which indicates that the probability of event A occurring is 1, that is, rectangle A contains rectangle B) and $P(B) \leq 1$ (which indicates that the probability of event B occurring is less than or equal to 1, that is, rectangle B is contained by or equal to rectangle A). Therefore, we determined that under this formula, the area of the predicted bounding box must be within that of the ground-truth bounding box.

Since the medicine area is very small, the result of the IOU algorithm only needs to be greater than 0.5, meaning that the object identification judgment is correct. Therefore, to improve the worst case of the IOU algorithm, we set the following formula:

$$\textit{Area of predicted bounding box} > 2/3\ (\textit{Area of ground-truth bounding box}). \qquad (2)$$

In other words, $P(B) > 2/3\ P(A)$; therefore, $P(A \cup B) = P(A) = 1$, $P(A \cap B) = P(B)$. This algorithm allows us to determine that the area of intersection can be maximized, reducing the probability of the worst-case occurrence to 0.34.

3.2 Medicine data format design based on FHIR

To comply with health level 7 (HL7) regulations and ensure the interoperability of medicine data, the medicine database architecture of our medicine identification system is based on the FHIR medicine architecture, as shown in Fig. 1.[17]

We design the resource composition of the medicine. On the basis of the resource definition of FHIR, we customize the expanded version and expand the new fields, as shown in Fig. 2. The resource includes the prescription number, medicine order code, medicine file name, current product name, scientific name of medicine, application area, pharmaceutical dosage form, pregnancy grade, medicine manufacturers, medicine color, medicine shape, medicine characteristics, and medicine imprint.

Because FHIR uses RESTful API as a data indirection method, it can be used in more web applications. In addition, when users need to query medicine data, they can directly access medicine data through HTTP, and users do not need to learn database SQL syntax to operate.

After the medicine identification system completes the identification, it will connect the medicine data to the back-end medicine database. At this time, the medical staff can open the medicine database system. The system interface is shown in Fig. 3. The medical staff can query each medicine information. In addition, when the medical staff click on the description of each medicine (blue font), the system will display the detailed medicine information, as shown in Fig. 4.

3.3 Mechanism design of medicine identification system

The medicine identification mechanism is shown in Fig. 5. The length, width, and height of the mechanism are 30, 20, and 30 cm, respectively. The mechanism material is acrylic. The internal components of the mechanism include the CPU (Raspberry Pi4) and GPU (Jetson Nano) of the medicine identification system, coupled with the wide-angle camera (IMX219) for

```
<MedicationRequest xmlns="http://hl7.org/fhir"> doco
 <!-- from Resource: id, meta, implicitRules, and language -->
 <!-- from DomainResource: text, contained, extension, and
modifierExtension -->
 <identifier><!-- 0..* Identifier External ids for this request --></identifier>
 <basedOn><!-- 0..* Reference(CarePlan|ImmunizationRecommendation|
    MedicationRequest|RequestOrchestration|ServiceRequest) A plan or
request that is fulfilled in whole or in part by this medication request --
></basedOn>
 <priorPrescription><!-- 0..1 Reference(MedicationRequest) Reference to an
order/prescription that is being replaced by this MedicationRequest --
></priorPrescription>
 <groupIdentifier><!-- 0..1 Identifier Composite request this is part of --
></groupIdentifier>
 <status value="[code]"/><!-- 1..1 active | on-hold | ended | stopped |
completed | cancelled | entered-in-error | draft | unknown -->
 <statusReason><!-- 0..1 CodeableConcept Reason for current status --
></statusReason>
 <statusChanged value="[dateTime]"/><!-- 0..1 When the status was
changed -->
 <intent value="[code]"/><!-- 1..1 proposal | plan | order | original-order
| reflex-order | filler-order | instance-order | option -->
 <category><!-- 0..* CodeableConcept Grouping or category of medication
request --></category>
```

Fig. 1. (Color online) Medicine system format.

```
<Patient>
<id value=""/>
<identifier>
<value value=""/>
</identifier>
<name>
<text value=""/>
</name>
< Prescription number value=""/>
< Medicine order code value=""/>
< Medicine file name value=""/>
< Current product name value=""/>
< Scientific name of drug value=""/>
< Application area value=""/>
< Pharmaceutical dosage form value=""/>
< Pregnancy grade value=""/>
< Medicine manufacturers value=""/>
< Medicine color value=""/>
< Medicine shape value=""/>
< Medicine characteristics value=""/>
< Medicine imprint value=""/>
</Patient>
```

Fig. 2. (Color online) Format of medicine information field.

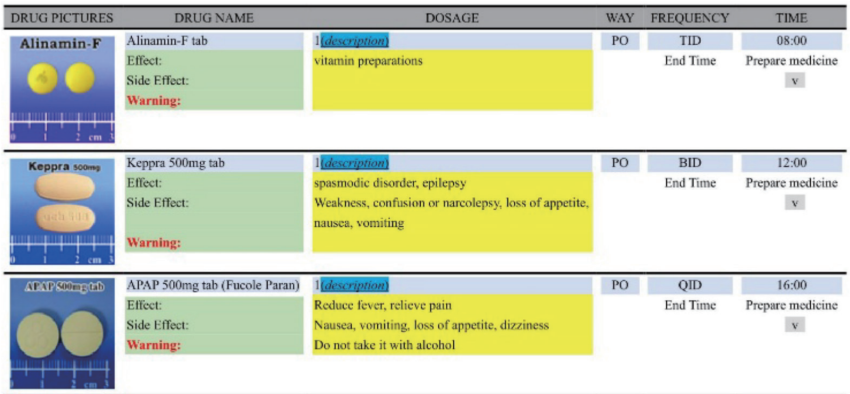

Fig. 3. (Color online) Medicine query system interface.

Prescription number	2912T
medicine order code	KEPPT
medicine file name	Keppra tablet
Current product name	Keppra tablet
Scientific name of medicine	Levetiracetam 500mg
Application area	Oral
Pharmaceutical dosage form	Film-coated tablets
Pregnancy grade	
medicine manufacturers	UCB S.A. Pharma sector
medicine color	Yellow
medicine shape	Oval
medicine characteristics	ucb500
medicine scratches	YES

Fig. 4. (Color online) Medicine details.

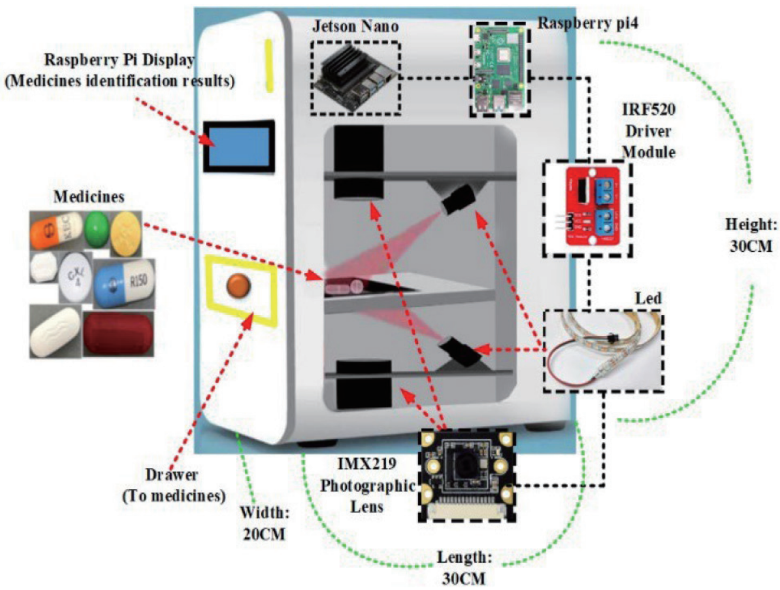

Fig. 5. (Color online) Medicine identification mechanism.

photographing drugs. To avoid insufficient lighting, we use LEDs to illuminate the medicine to prevent the system from being unable to identify the medicine. The communication between the CPU (Raspberry Pi4) and GPU (Jetson Nano) uses the driver module (IRF520). The detailed component specifications are shown in Table 2.

When a medical staff member needs to identify the medicine, after he/she puts the medicine into the drawer, the system automatically identifies it, and the identification result is shown on the display (Raspberry Pi display).

In addition, to reduce medical staff fatigue, we integrated the medicine identification system mechanism into the mobile nursing work vehicle. Figure 6 shows the work platform of the mobile nursing work vehicle. Its length is 59 cm and its width is 42 cm. The length and width of the medicine identification mechanism are 30 and 20 cm, respectively. Therefore, medical staff using a mobile nursing work vehicle can identify medicines at the same time. With this design, medical staff can save time distributing medicines at fixed points.

4. Medicine Identification Results

Each of the 319 types of medicine is different, as shown in Fig. 7. We use various colors as the basis of classifying the shapes of the medicines, and in the experimental data, we use the medicine color, shape, and imprint as the basis of identification.

Table 2
Component specifications.

Name	Specifications
Raspberry Pi 4 Model B	Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5 GHz, 8 GB LPDDR4-3200 SDRAM
Jetson Nano	Nvidia Maxwell with 128 Nvidia Cuda core, 4 GB 64-bit LPDDR4
IMX219	77-degree field of view, Supports Jetson Nano development kit
IRF520	Using original IRF520 power MOS tube, PWM adjustment output can be performed
LED	Light source: 120 pcs SMD3528, Lighting color temperature: white light 6500 K, warm light 4000 K
Raspberry Pi display	7 inch HDMI LCD (H), Resolution 1024 × 600, Supports all versions of Raspberry Pi, Supports Jetson Nano

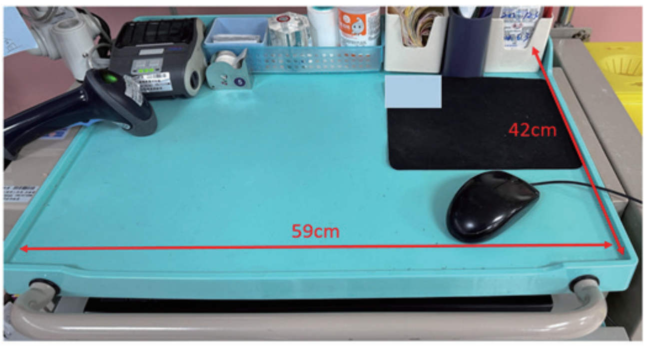

Fig. 6. (Color online) Work platform.

First, we analyze the medicine's color. Figure 8 shows the original image before the system identified the color of the medicine.

When the system performs medicine identification, the identification results are as shown in Fig. 9. The system indicates each medicine's accuracy and corresponding color.

Second, we analyze the medicine's shape. Figure 10 shows the original image before the system identified the shape of the medicine.

	tablet	oval tablet	square tablet	triangle	polygon
orange	Clonazepam	Betmiga 25 PR	Mirtapine OD	Salazine	Harvoni F.C
yellow	Aldomet tablets	Betmiga 50 PR	Nicorette	Bethanechol chlorode	Forxiga
green	Stogamet	Fucou	Haldol	Hodrin	Sinemet
blue	Ativan	Ditropan	Haldol	Viread	Viagra
pink	Bromazepam	Sedenton tablets	Chlorzoxazone tablets	Cofarin	Ventolin

Fig. 7. (Color online) Various medicines.

Fig. 8. (Color online) Colors of medicines.

Fig. 9. (Color online) Identification of medicine colors.

When the system performs medicine identification, the identification results are as shown in Fig. 11. The system indicates each medicine's accuracy and corresponding shape.

In addition, we analyze the medicine's imprint. Figure 12 shows the original image before the system identified the imprint of the medicine.

When the system performs medicine identification, the identification results are as shown in Fig. 13. The system indicates each medicine's accuracy and corresponding imprint.

We identify medicine color, shape, and imprint. The results of this color identification are shown in Table 3. We can see from Table 3 that the color recognition rate of various medicines is above 0.995, which indicates that our method of grayscale processing for each photo can produce remarkable results.

Table 4 shows the various shape recognition results of medicines. We can see that the shape recognition rate of different medicines is above 0.986. Our method of Gaussian blur processing for each photo can produce remarkable results.

The identification results of various imprints on medicines are shown in Table 5. We can see from Table 5 that the various imprint recognition rates of medicines are above 0.831.

Fig. 10. (Color online) Shapes of medicines.

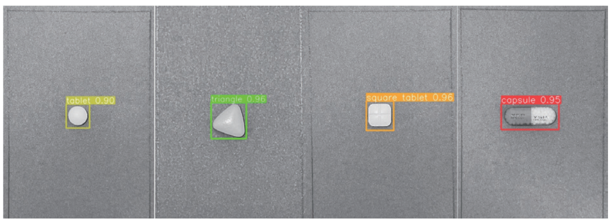

Fig. 11. (Color online) Identification of medicine shapes.

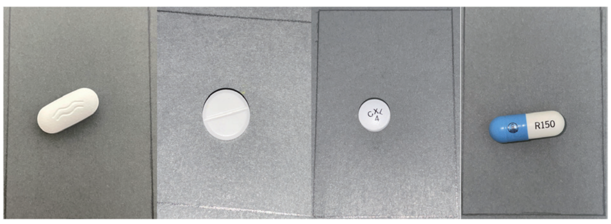

Fig. 12. (Color online) Medicine imprint.

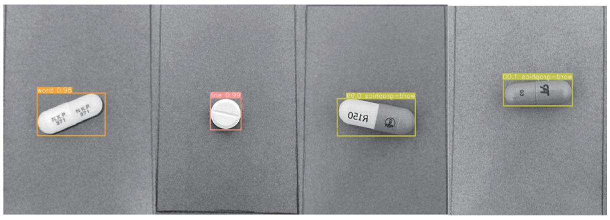

Fig. 13. (Color online) Identification of medicine imprint.

Table 3
Color recognition results of medicines.

	color	mAP50
1	black-red	0.995
2	blue	0.995
3	blue-green	0.995
4	blue-orange	0.995
5	blue-pink	0.995
6	brown	0.995
7	brown-orange	0.995
8	brown-pink	0.995
9	gray-green	0.995
10	green	0.995
11	green-pink	0.995
12	green-white	0.995
13	green-yellow	0.995
14	orange	0.995
15	orange-brown	0.995
16	orange-white	0.995
17	orange-yellow	0.995
18	pink	0.962
19	red	0.995
20	red-purple	0.995
21	red-white	0.995
22	red-yellow	0.995
23	white	0.995
24	white-yellow	0.995
25	yellow	0.995
26	yellow-white	0.995

Table 4
Shape recognition results of medicines.

	shape	mAP50
1	capsule	0.955
2	oval tablet	0.955
3	polygon	0.955
4	square tablet	0.955
5	tablet	0.986
6	triangle	0.955

Table 5
Imprint recognition results of medicines.

	imprint	mAP50
1	graphics	0.931
2	line	0.979
3	nothing	0.979
4	word	0.969
5	word-graphics	0.831
6	word-line	0.843

5. Conclusions

We introduce a medicine identification system through AI to reduce the burden of medical staff in distributing medicines and reduce the error rate of medical staff in dispensing medication. We classified the medicine by shape, color, and imprint among the 319 commonly used medicines. We conducted model training in the shape, color, and imprint data sets. The recognition accuracy of the shape data set was higher than 0.986 and that of the color data set was higher than 0.995. The recognition accuracy of the imprint data set is above 0.831. In addition, we designed the medicine identification mechanism to be directly integrated into the mobile nursing work vehicle to meet the needs of saving time and cost. Medical staff do not need to distribute medicines at fixed points. They can use the medicine identification system while operating the mobile nursing work vehicle. We modified the IOU formula to ensure that the system can mark the predicted bounding box within the ground-truth bounding box during medicine identification. In the worst-case scenario, we reduced the probability to 34%. Our medicine identification system uses the FHIR format as the design guideline to share all medicine information among different medical systems.

Acknowledgments

This work was supported by the Ditmanson Medical Foundation Chia-Yi Christian Hospital (Grant No. R111-058).

References

1 E. O'Shea: J. Clinin. Nurs. **8** (1999) 5. https://doi.org/10.1046/j.1365-2702.1999.00284.x
2 J. K. Aronson: QJM-An Int. J. Med. **102** (2009) 8. https://doi.org/10.1093/qjmed/hcp052
3 AESOP Technology: https://tw.aesoptek.com/index.html (accessed July 2024).
4 Taipei Medical University Hospital: https://www.tmuh.org.tw/ (accessed July 2024).
5 J. Heo, Y. Kang, S. Lee, D. H. Jeong, and K. M. Kim: J. Med. Internet Res. **25** (2023) 1. https://doi.org/10.2196/41043
6 Y. Y. Ou, A. C. Tsai, X. P. Zhou, and J. F. Wang: IET Comput. Vis. **14** (2020) 1. https://doi.org/10.1049/iet-cvi.2019.0171
7 J. Yu, Z. Chen, S. Kamata, and J. Yang: IET Image Process. **9** (2015) 12. https://doi.org/10.1049/iet-ipr.2014.1007
8 W. J. Chang, L. B. Chen, C. H. Hsu, C. P. Lin, and T. C. Yang: IEEE Access **7** (2019) 1. https://doi.org/10.1109/ACCESS.2019.2908843
9 H. W. Ting, S. L. Chung, C. F. Chen, H. Y. Chiu, and Y. W. Hsieh: BMC Health Serv. Res. **20** (2020) 312. https://doi.org/10.1186/s12913-020-05166-w
10 L. Tan, T. Huangfu, L. Wu and W. Chen: BMC Med. Inform. Decis. Mak. **21** (2021) 324. https://doi.org/10.1186/s12911-021-01691-8
11 X. Liu, J. Meehan, W. Tong, L. Wu, X. Xu, and J. Xu: BMC Med. Inform. Decis. Mak. **20** (2020) 68. https://doi.org/10.1186/s12911-020-1078-3
12 X. Zeng, K. Cao, and M. Zhang: Proc. 2017 15th Annual Int. Conf. Mobile Systems, Applications, and Services (ACM, 2017) 56–67.
13 W. J. Chang, L. B. Chen, C. H. Hsu, J. H. Chen, T. C. Yang, and C. P. Lin: IEEE Access **8** (2020) 1. https://doi.org/10.1109/ACCESS.2020.2967400
14 H. J. Kwon, H. G. Kim, S. W. Jung, and S. H. Lee: J. Sens. **2022** (2022) 1. https://doi.org/10.1155/2022/2339188
15 P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma: Procedia Comput. Sci. **199** (2022) 1. https://doi.org/10.1016/j.procs.2022.01.135
16 J. Flusser, S. Farokhi, C. Höschl, T. Suk, B. Zitová, and M. Pedone: IEEE Trans. Image Process. **25** (2015) 2. https://doi.org/10.1109/TIP.2015.2512108
17 M. Ayaz, M. F. Pasha, M. Y. Alzahrani, R. Budiarto, and D. Stiawan: JMIR Med. Inf. **9** (2021) 7. https://doi.org/10.2196/21929

About the Authors

Ya-Hui Kuo received her M.S. degree from the Department of Nursing at National Taipei University of Nursing and Health Sciences, Taiwan. She once served as a nurse at Chi Mei Medical Center. She currently serves as the deputy director of Ditmanson Medical Foundation Chia-Yi Christian Hospital, Taiwan. Her research interests include infection control, oncology, and nursing information human resource management. (02612@cych.org.tw)

Cheng-Yan Siao received his M.S. degree from National Chung Cheng University, Taiwan, in 2018. Since 2020, he has been a lecturer at Providence University. He is a fourth-year Ph.D. student in the Department of Computer Science and Information Engineering, National Chung Cheng University. His research interests are in robotic arms, blockchains, and artificial intelligence. (hcyen103m@cs.ccu.edu.tw)

Tzu-Ling Li received her B.S. degree from National Taichung University of Education, Taiwan, in 2022. She is a second-year M.S. student in the Department of Computer Science and Information Engineering, National Chung Cheng University. Her research interests are in artificial intelligence and telemedicine. (g11410073@ccu.edu.tw)

Ching-Jen Wang received his B.S. degree from National Chung Cheng University, Taiwan, in 2022. He is a second-year M.S. student in the Department of Computer Science and Information Engineering, National Chung Cheng University. His research interests are in embedded systems and object detection. (ryanwang407415024@alum.ccu.edu.tw)

Hui-Chuan Lin received her Ph.D. degree from the Department of Information Management and M.S. degree in health information management from National Chung Cheng University, Taiwan. She once served as the quality management commissioner of Chiayi Hospital of the Ministry of Health and Welfare. She currently serves as the acting head nurse at Ditmanson Medical Foundation Chia-Yi Christian Hospital, Taiwan. Her research interests include big data, text mining, and clinical pharmacy. (02398@cych.org.tw)

Yi-An Chen received his B.S. degree from National Taipei University of Education, Taiwan, in 2022. He is a second-year M.S. student in the Department of Computer Science and Information Engineering, National Chung Cheng University. His research interest is in fast healthcare interoperability resources. (chenyian@alum.ccu.edu.tw)

Chia-Hui Liu received her M.S. degree from the Department of Pharmacy at Kaohsiung Medical University, Taiwan. She once lectured in the Department of Pharmacy at Chia Nan University of Pharmacy and Science and Tajen University. She currently serves as the pharmacy department director at Ditmanson Medical Foundation Chia-Yi Christian Hospital, Taiwan. (02217@cych.org.tw)

Rong-Guey Chang received his B.S. and M.S. degrees from National Chung Hsing University, Taiwan, in 1991 and 1993, respectively, and his Ph.D. degree from National Tsing Hua University, Taiwan, in 2000. He was an assistant professor from 2002 to 2009 and an associate professor from 2009 to 2014 at National Chung Cheng University, Taiwan. Since 2014, he has been a professor at National Chung Cheng University. His research interests are in robots, compilers, and embedded systems. (rgchang@cs.ccu.edu.tw)