A DEEP LEARNING-BASED ACCURATE DRUG DETECTION, IDENTIFICATION AND CONFIRMATION MECHANISM FOR MEDICATION DISPENSING PACKAGE OF INPATIENTS

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ABSTRACT

In this study, a deep learning based accurate drug detection, identification and confirmation mechanism (DLADDICM) for medication dispensing package is proposed for inpatients. In this proposed DLADDICM, a medication dispensing package with a printed QR code is photo taken and drugs in the image are detected and identified using a deep learning object detection algorithm, namely You Only Look Once (YOLO). The QR code information is deciphered and compared with the detected drugs to confirm the correctness of the medication dispensing. If there are mismatch situation(s), the computer with the proposed DLADDICM will generate different warning sound in responding to different incorrect situations. A data set with 30 drugs form the National Library of Medicine of NIH, USA is used for testing the DLADDICM using the object tracking and detection deep learning algorithm YOLOv3. Experimental results shown that the DLADDICM can detect and identify the incorrect drugs and generate the appropriate warning sound for the incorrect drug in pharma package for further human inspection. The experimental results also exhibits that by using the AI-enabled mechanism an accurate, safer, healthier with precision medication environment for the medical industries could also be achieved.

KEYWORDS

Deep Learning, machine vision, YOLOv3, Drug detection, identification and Confirmation.

1. INTRODUCTION

Correct prescription of medication is an important factor for a patient's health, however medication errors are one of the most important issues affecting medical safety. Fatigue and fast vision of pharmacists are the most common medication errors caused by human factors. One of the most common mistakes made by pharmacists or doctors is "look-alike and sound-alike" (LASA) [1]. A good strategy to prevent LASA is to change drug names and their packaging [2], while some researchers have used chart comments and mathematical methods to identify problematic drug name pairings and built automated detection systems to detect and prevent LASA errors [3]. However, there are still many problems in drug identification, such as many drugs look alike, drugs are generally relatively small in size for vision identification, and large numbers of drugs need to be identified from time to time. At present, there are some auxiliary tools for drug identification, such as automatic dispensing cabinet (ADC) [4][5], which can

automatically dispense drugs with identification purpose. The use of ADCs is the development of software to accurately identify drugs without pre-processing the drugs, and the main problem is that the dispensing department needs a large space to use ADCs, and that it also needs to ensure that the addition of these systems does not increase pharmacist's workload in the prescription process. Some studies have used barcode system to identify and prevent medication errors, RFID and Bluetooth in identifying the location of drugs have also been designed, and even some large hospitals use robots for precision identification of drugs. For drug identification, solutions based on machine vision and image processing have already been developed. Traditional image recognition algorithms identify drug images by finding image features and designing appropriate image classifiers [6] [7]. The method proposed by Lee et. al [8] encodes colour and shape into 3D histograms and geometric matrices, and encodes the engraved symbols of drugs through SIFT descriptor and Multiscale Local Binary Pattern (MLBP) as feature vector. Taran et al. [9] proposed to use a variety of traditional feature integration methods to extract high-dimensional drug features from images to realize the identification of pharma packaging.

Developing a variety of intelligent services in providing solution to the needs of various industries has become the trend in the artificial intelligence (AI) era, and the medical industry is obviously one of the key development areas. In the medical field, various medical imaging data have begun to accumulate into huge amounts of data, i.e., big data. If medical imaging big data can be further combined with AI technique to drive medical big data analysis and applications, more breakthrough progress can thus be made to achieve smart, intelligent and precise medical treatments. Current general AI development is based on machine learning, starting various algorithmic training to establish different recognition models for the target tasks. Wong et al. [10] developed a groundwork using deep convolutional network and pill images captured with mobile phones under unconstraint environments for automatic pill identification and verification. In this study, a deep learning-based accurate drug detection, identification, and confirmation mechanism (DLADDICM) for dispensing of medication is proposed for the inpatients. YOLO. In this proposed DLADDICM, a pharma package with a printed QR code is photo taken and drugs in the image are detected and identified using a deep learning object detection algorithm, namely You Only Look Once (YOLO). The drugs information of the QR code is deciphered to be used to compare the detected and identified drugs such that the correctness of the medication dispensing can be confirmed. If there are mismatch situation(s), the computer with the proposed DLADDICM will generate different warning sound(s) in responding to different incorrect situations. The major contributions of this paper are:

- An deep learning based accurate drug detection, identification and confirmation mechanism is proposed in this study, which is novel in the area of pill detection and recognition for pharma package.
- The YOLOv3 of the deep learning is utilized to detect and identify each drug inside the pharma package utilizing the QR code printed in the pharma package such that the correctness of the pharma package can be confirmed.
- The proposed DLADDICM not only can detect and identify each drug inside the pharma package, but the matching accuracy rate of the drug with that particular drug in the medication dataset can also be computed and shown.
- Experimental results exhibit the potential and advantage of the DLADDICM as an AI-enabled solution to the LASA errors.
- The rest of this paper is organized as follows. Section 2 presents the proposed DLADDICM for the pharma package for inpatients. Section 3 provides dataset and experimental configuration. Experimental results and discussions are shown in Section 4. Finally, Section 5 concludes this paper.

2. METHODOLOGY AND SYSTEM REQUIREMENT

Human error in distinguishing the same drug name but different dosage forms is the most commonly mistaken situation, with which an accurate detection, identification and confirmation mechanism might be required to assist the pharmacists in solving such kind of problems. For example, it should be an injection drug such as a dry powder or liquid in a glass bottle, but an oral drug, lozenge or capsule is mistakenly taken by the pharmacist. If a machine vision based system can be used to scan the barcode, which was printed on the surface of the dispensing package, such that the computer with AI software can be employed to identify the inpatient medication prescribed by the doctor, and the machine vision can quickly identify the difference in the dosage form and give a false alarm to reduce the mistakes. In this study, a deep learning-based accurate drug detection, identification, and confirmation mechanism (DLADDICM) for medication dispensing package of inpatients is proposed. The methodology used in the study is YOLO [11] algorithm and is described in the following.

2.1. You Only Look Once (YOLO)

The YOLO [11] algorithm was proposed by Joseph Redmon et al. in 2015. The concept of its artificial neural network is to use a single convolutional network, as shown in Figure 1, to simultaneously predict these bounding boxes, as shown in Figure 2, and to calculate the probability of an object for each bounding box. During training, the entire image is directly provided as the input data to the convolutional network, and when the entire image is trained, the model of the training images can thus be obtained and the performance of object detection is directly optimized.

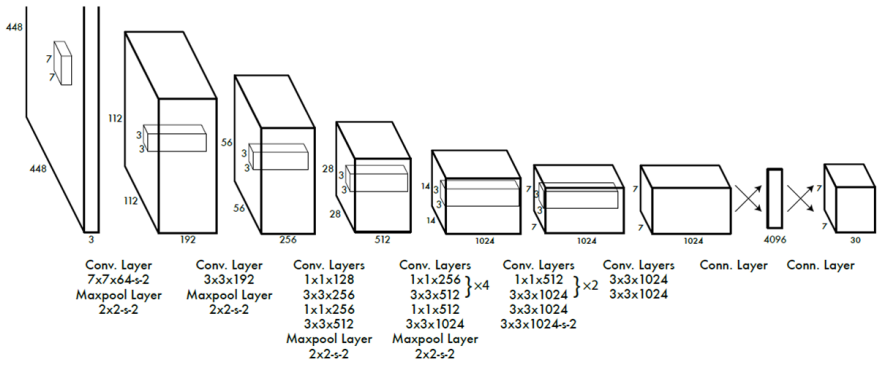


Figure 1. Structure diagram of YOLO [11]

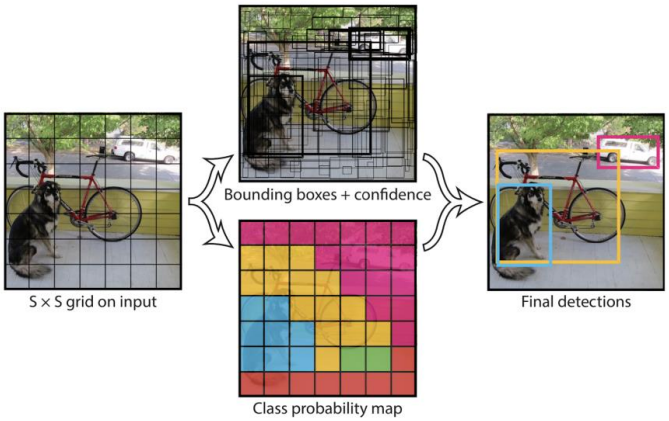


Figure 2. The recognition stage of YOLO [11]

The original YOLO has a total of 24 convolution layers and 2 fully connected layers, and the final output obtained is a 7x7x30 tensor. The purpose of the "convolution layer" is to perform a convolution operation between the original input image and a specific feature detector in extracting important features from the image. The " fully connected layer" is the most basic neural network after receiving the previous results and in calculation to obtain the final outputs. In object detection process, YOLO detects objects from the entire image, and each image is cut into SxS grids. If an object is in the middle of the grid, the grid will be responsible for detecting the object, which is the class probability map as shown in Figure 2. B bounding boxes and their confidence scores of each grid will be predicted, as shown in Bounding boxes + confidence in Figure 2, where bounding boxes are the boxes that can be framed by each grid and confidence scores represent the confidence levels of the corresponding bounding box containing the objects. The accuracy of the objects in the bounding box, are finally merge to obtain the final result of the object detection. The most widely used algorithm in the YOLO series for object detection is YOLOv3 [12]. There are two main changes in YOLOv3. One is to use ResNet (Residual Network), because YOLOv3 use Darknet-53 as the new backbone network, Darknet-53 has 53 convolution layers. As the number of network layers deepens, there will be a problem of gradient disappearance, so the YOLOv3 employed ResNet structure to solve this problem. The other one is to use feature pyramid networks (FPN) to change the feature layer from a single layer of 13x13 to a multi-layer 13x13, 26x26 and 52x52, and predict 5 kinds of bounding boxes in a single layer into 3 kinds of bounding boxes per layer. Through the FPN multi-level prediction architecture, the lower-level better target location and higher-level semantic features are fused, and the predictions are performed independently in different feature layers, which improves the effect of small object detection significantly. Therefore, in this study, YOLOv3 is used for the proposed DLADDICM.

2.2. System Requirement

The system requirement of the proposed DLADDICM is shown in Table 1, where the required software tools and function libraries for developing the systems are listed. The software tools/ programs and function libraries used include software tools for image processing, development platform, data processing, mathematical operations, Keras, Tensorflow for machine learning, and function libraries for operating QR codes and making sounds, to name a few.

Table 1. Required software tools and function libraries for the DLADDICM

Software Tool/Programs	Usage	Function Description
Spyder	Data processing and generation	Open the LebelImg tool, Create QR code image file
Pycharm	Modify parameters, train model	Quick modification for the training parameters and training model
LebelImg	Annotation tool	Drugs be labeled in the training set
Python 3.6.13	Development Platform	Program Development
Yolov3	Train the model	For object detection and obtain detected object information
Library	**Usage**	**Function description**
OpenCV-contrib-python 4.5.1.48	image processing	Read/Write image files and perform image processing
Keras 2.1.5	Implementing Deep Learning Networks	Open source neural network library, Yolov3 is implemented under this architecture
Tensorflow 1.15.0	Machine Learning Training Platform	Realize the function and enable the machine to perform object detection
Tensorflow-gpu 2.1.0	Machine Learning Training Platform	Tensorflow GPU version
Matplotlib 2.2.2	Drawing library	Visualization of numerical data
Numpy 1.19.5	Handling array operations	Handling array operations
Pillow 5.1.0	Process images	Read image file and display the detection result image
Zxing 0.12	Read and decode QR codes	Can decode QR code content
Qrcode 6.1	Make QR code	Can make the required QR code
Beepy 1.0.7	sound a warning tone	Let users be alerted

3. DATA SET AND EXPERIMENTAL CONFIGURATION

In this section, the data set, the image pre-processing, and the image data annotation will also be discussed. The experimental configuration for the proposed DLADDICM for inpatients will be described using flowcharts.

3.1. Data Set

Figure 3 shows the drug database from the National Library of Medicine of the National Institutes of Health of the United States [13]. Through the URL provided by [13], pill images can be searched and downloaded from the website, and drug-related information can also be obtained. The drugs provided by this database include pictures of the same drug in different resolutions,

and various information (shape, colour, lettering...) of the drug, which is quite suitable for this study. Therefore, 30 kinds of medicines were first selected for training, including medicines in three shapes, namely: oval, round and capsule.

Figure 3. The 30 medicine used for this study.

The detailed information of medicines is shown in Table 2. These 30 kinds of medicines are divided into two sides. Each medicine has a different lettering printed on the surface, and the shape and lettering on the medicine are used as the type, which can be compared with the content of the QR code to achieve the purpose of drug identification. Table 2 provides the lettering, shape and colour of the selected drug, yet the drug names are not listed. Drug lettering is represented by adding a semicolon to separate after each paragraph of text on the pill, and then writing another paragraph of text. For example, the No. 20 pill in Table 2 is engraved with N; 4, and the words N and 4 will be engraved on the pill in the fourth column and fifth row of Figure 3.

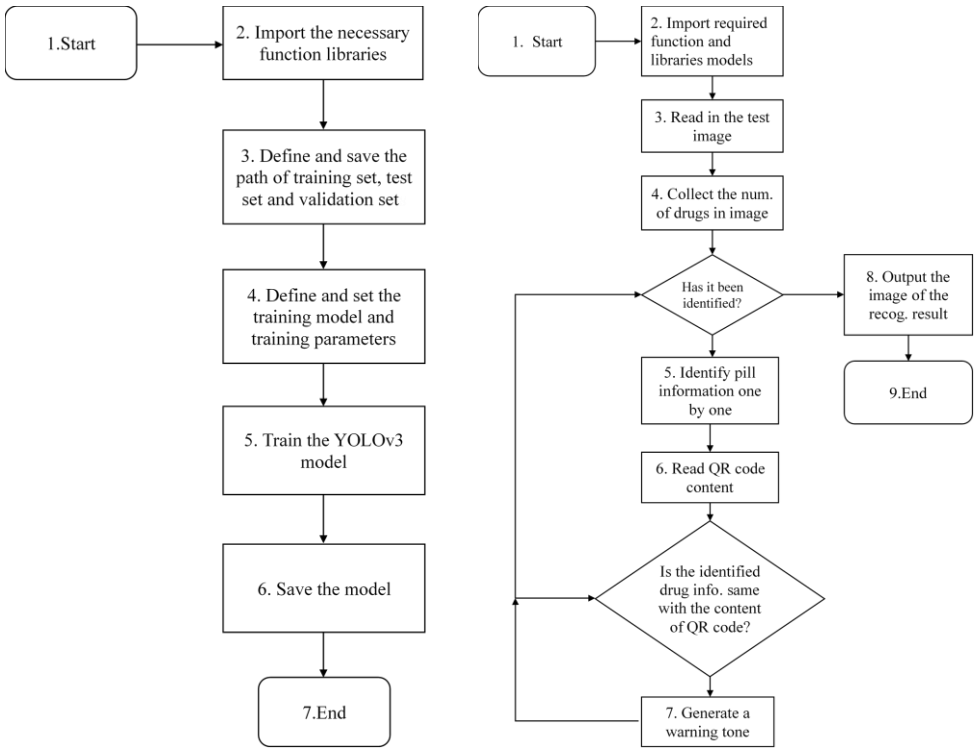
Table 2. List of drug data for training.

Medicine lettering	shape	color
1. 2.5;1000;4222	oval	yellow
2. 80	oval	green
3. 39;SB	oval	White
4. 4141;SB	oval	White
5. GS;3V2	oval	Pink
6. PROTONIX	oval	yellow
7. XANAX;0.5	oval	orange
8. ZYVOX;600;mg	oval	White
9. Y;Y	oval	White
10. ALDACTAZIDE;50;SEA;RLE;10;21	oval	Brown
11. SOMA;250	round	White
12. 54;760	round	White
13. 54;346	round	White
14. 54;327	round	White
15. 54;857	round	Red
16. 54;741	round	Pink
17. 54;943	round	Pink
18. 1;COUMADIN	round	Pink
19. A	round	White

20. N;4	round	White
21. Lilly;3228;25;mg	capsule	White、blue
22. Lilly;3235;20;mg	capsule	green
23. Lilly;3239;60;mg	capsule	blue、yellow
24. Lilly;3250;80;mg	capsule	White、Brown
25. Lilly;3251;100;mg	capsule	Brown
26. CellCept;250;Roche	capsule	blue、orange
27. ROCHE;45;mg	capsule	grey
28. 464;40;mg	capsule	White、yellow
29. GSK;Coreg;CR;10;mg	capsule	White、green
30. HYCAMTIN;0.25;mg	capsule	White

3.2. Experimental Configuration

Figure 4(a) and 4(b), respectively, shows the flowchart for the training and the testing of the proposed DLADDICM for dispensing package of medication. In the data set, letters are printed on the surface of the drugs. The proposed DLADDICM takes the whole pharma transparent pack as input image and each drug and the QR code, printed on the transparent pack, are identified and the matching probability of the drug are calculated. That is, the proposed DLADDICM does not identify the letters printed on the drugs but it identifies the whole drug instead.



(a) Flowchart for training the proposed DLADDICM using the training set

(b) Flowchart for testing the proposed DLADDICM using the testing dataset.

Figure 4. The flowchart for training (a) and testing (b) the proposed DLADDICM using the training set and the testing dataset, respectively.

3.3. Image pre-processing and data annotation

Figure 5 shows the flowchart of creating training images. The pre-processing of the image and it's annotations in the training set are described in the following.

1. Start the processing
2. Remove the background and retain the drug body only, as the step 2 in Figure. 5.
3. Place and synthesize the processed drugs randomly, as shown in Figure 6 (a).
4. Label the drug using LabelImg software, as shown in Figure 6(b). The format of the label is: *drug shape_drug lettering*, such as OVAL_2.5/1000;4222. The 30 drugs in Figure 3 are labelled, that is, a total of 30 classes will be trained for obtaining the model.
5. Save the picture as the xml file that will be used for training the Yolov3 model in the future to complete the labelling. After processing a training set photo, the remaining pictures can be continued to process.
6. Finish.

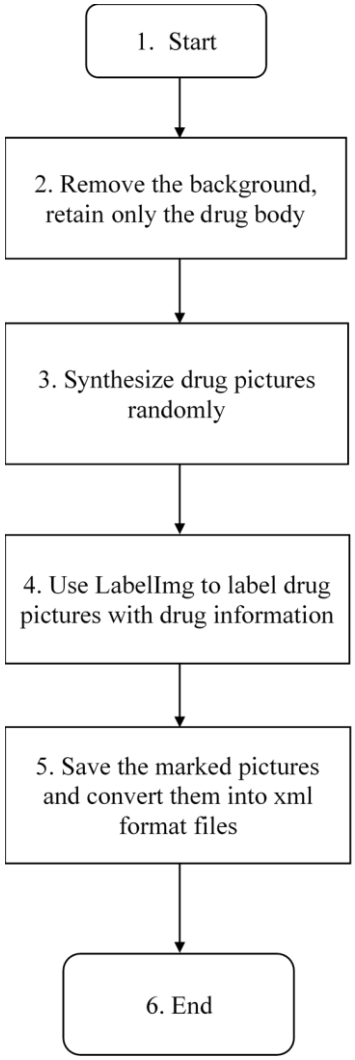


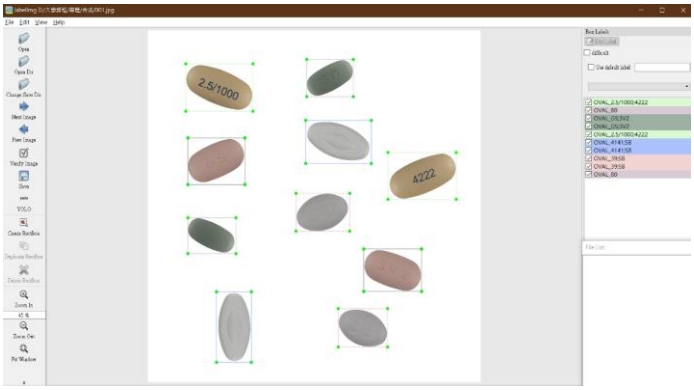
Figure 5. Drug image pre-processing and it's data annotations in the training set.

(a) Original medicine

(b) The drug image after removing the background

Figure 6. Removing the background and retaining the medicine body only.

(a) Place and synthesize the processed drugs randomly

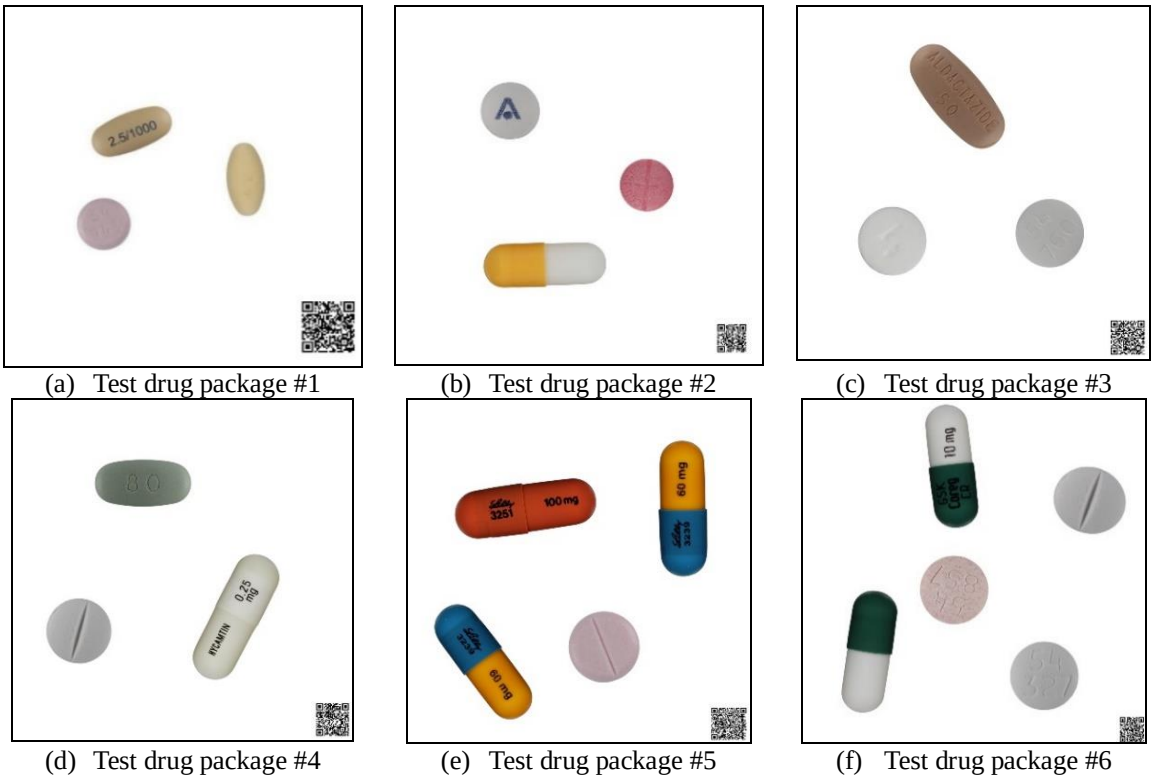


(b) Use LabelImg software to label drugs.

Figure 7. (a) Synthesize the drug randomly and 7(b) use LabelImg software to label drugs.

3.4. Test Data Set

After the drugs are randomly synthesized, the QR code of this drug is created and placed onto the transparent package picture to obtain the test images of dispensing medicine package. Hence, the test image is a simulated picture of the drugs inside the transparent pack with the QR code of the drug information printed on the surface of the transparent pack. Figures 12 to 17, respectively, are the simulated images of the transparent medicine packages used for testing the proposed DLADDICM as shown in Figure 8(a) to 8(f). Figure 8(a) to 8(c), and Figure 8(e) are the test images without the wrong drug, while Figure 8(d) and 8(f) are the test transparent pharma packages with the wrong drug(s) within the transparent package.



(a) Test drug package #1 (b) Test drug package #2 (c) Test drug package #3

(d) Test drug package #4 (e) Test drug package #5 (f) Test drug package #6

Figure 8. Figure 8(a) to 8(c) and 8(e) are the cases without wrong drug. Figure 8(d) and 8(f) are the cases with the wrong drug.

In Figure 8, Figure 8(d) package contains drug of CAPSULE_HYCAMTIN;0.25;mg, ROUND_54;327, OVAL_80, while the QR code information contains CAPSULE_HYCAMTIN;0.25;mg, ROUND_54;327, OVAL_Y;Y, the drugs in the package are not consistent with the content of QR code. The OVAL_80 is the wrong drug, and this case is the dispensing medicine package with one wrong drug. Figure 6(f) package contains drug of 2 CAPSULE_GSK;Coreg;CR;10;mg, ROUND_54;327, ROUND_54;857, the QR code content is CAPSULE_CellCept;250;Roche, ROUND_54;327, ROUND_54;857, the drugs inside the transparent pharma package are not consistent with the QR code information and this is the case of two wrong drugs inside.

4. EXPERIMENTAL RESULTS

4.1. Test case #1: The drugs in the dispensing package are consistent with the content of the QR code

Figure 8(a) to 8(c) and Figure 8(e) are the cases of the drugs in the dispensing package are consistent with the content of the QR code. And for demonstration purpose, only the case of Figure 6(a) is used as the test case #1. The test procedures and the experimental results are described steps by step as below.

1. Enter the test image path: the following image shows the file path.

```
Input imagename:D:\testimg\001.jpg
```

2. Output the prediction result: From the process 8 in the Figure 4(b), after the program is executed, the detected drug type and accuracy rate will be printed, as shown in the fourth to sixth columns in the image below. The detected drugs are consistent with the QR code content to realize correct drug identification with the results as described below.

```
Input imagename:D:\testimg\001.jpg
(416, 416, 3)
Found 3 boxes for img
ROUND_54;943 0.9997326
OVAL_PROTONIX 0.90907943
OVAL_2.5/1000;4222 0.9793583
2.4300601000000057
OVAL_2.5/1000;4222 ROUND_54;943 OVAL_PROTONIX
```

a. Detected drug types: ROUND_54;943, OVAL_PROTONIX and OVAL_2.5/1000;4222
b. The accuracy rates are 0.999, 0.909 and 0.979, respectively for the above three drugs
c. The total time taken from reading the image to the end of the detection is 2.43 seconds
d. The bottom line shows the decoded QR code content. After visual inspection, it can be seen that it is consistent with the detected drug type. Next, if required, whether the result predicted by the proposed DLADDICM is the same as the result or not can be judged again by visual inspection.

3. Generate a picture of the prediction result: Figure 9 below is the picture of the prediction result of the proposed DLADDICM, which can be checked whether the type of drug predicted by the proposed DLADDICM is correct or not.

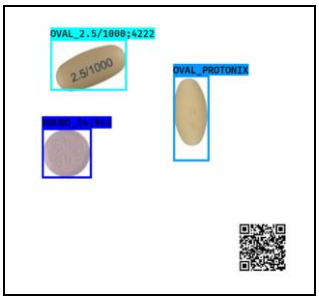


Figure 9. The detection, identification and confirmation results as shown in the computer screen for the test case #1.

4. Discussion: This test case #1 is an error-free condition, and the expectation is that no warning sound will be issued. In this identification, after comparing the detected drug type with the drug information decoded by the QR code, it is found that they are the same, so there is no warning sound. The identification results are correct, consistent with expectations, and the confirmation is successful. Test video is in the URL: https://youtu.be/3hbJHobjn6A

4.2. Test case #2: The drugs in the dispensing package are not consistent with the content of the QR code with one incorrect drug.

This test case is the case in Figure 6(d), that is, the drugs in the dispensing package are not consistent with the content of QR code with one incorrect drug. The test procedures and the experimental results are described step by step as below.

1. Enter the test image path: the following image shows the file path for Figure 6(d)

```
Input imagename:D:\testimg\004.jpg
```

2. Output the prediction result: From the process 8 in the Figure 4(b), after the program is executed, the detected drug type and accuracy rate will be printed, as shown in the 4th to 6th columns of the following figure. The results are described as below.

```
Input imagename:D:\testimg\004.jpg
(416, 416, 3)
Found 3 boxes for img
CAPSULE_HYCAMTIN;0.25;mg 0.814407
ROUND_54;327 0.96289814
OVAL_80 0.91772205
5.65098660000001
CAPSULE_HYCAMTIN;0.25;mg ROUND_54;327 OVAL_Y;Y
```

a. Drugs CAPSULE_HYCAMTIN;0.25;mg, ROUND_54;327, OVAL_80 are detected
b. The accuracy rates are 0.814, 0.963 and 0.918, respectively for the 3 drugs
c. The total time from reading the image to the end of the identification is 5.65 seconds
d. The bottom line is the decoded QR code content. It can be seen that the dispensing drug package should contain OVAL_Y;Y, but the drug type OVAL_80 is detected. After visual inspection, the two drugs do not match, and a warning sound should be issued. Next, it is necessary to judge whether the result predicted by the proposed DLADDICM is the same as the result of the visual inspection.

3. Generate a picture of the prediction result: Figure 10 shown below is the picture of the prediction result of the proposed DLADDICM, which can be checked by visual inspection to see whether the drug predicted by the proposed DLADDICM is correct or not.

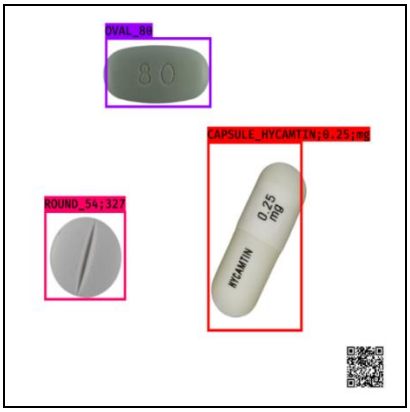


Figure 10. The detection, identification and confirmation results as shown in the computer screen for the test case #2 with one incorrect drug.

4. Discussion: This test is for the condition of a incorrect drug, and a warning sound was issued. In this identification, the drug type OVAL_80 was detected. After the string comparison, it was not included in the drug information coded in the QR code, so a warning sound was issued. The identification results are correct, agree with expectations, and the confirmation is successful. Test video is in URL: https://youtu.be/vWbwYCzTZig

4.3. Test case #3: The drugs in the dispensing package are not consistent with the content of the QR code with one incorrect drug.

This test case is the case in Figure 8(f), that is, the drugs in the dispensing package are not consistent with the content of QR code with 2 incorrect drugs. The test procedures and the experimental results are described step by step as below.

1. Enter the test image path: the following image is the file path of Figure 8(f).

```
Input imagename:D:\testimg\006.jpg
```

2. Output prediction results: From the process 8 in the Figure 4(b), the detected drug type and accuracy rate will be printed after the program is executed, as shown in the 4th to 8th columns in the following figure

```
Input imagename:D:\testimg\006.jpg
(416, 416, 3)
Found 5 boxes for img
CAPSULE_GSK;Coreg;CR;10;mg 0.32928818
CAPSULE_GSK;Coreg;CR;10;mg 0.91828036
ROUND_54;857 0.48079464
ROUND_54;327 0.7416136
ROUND_54;327 0.7732106
5.718367400000034
CAPSULE_CellCept;250;Roche ROUND_54;327 ROUND_54;857
```

a. Detected drugs CAPSULE_GSK;Coreg;CR;10;mg (x2), ROUND_54;857 and ROUND_54;327 (x2)
b. The accuracy rates are 0.329, 0.918, 0.481, 0.742 and 0.773 respectively
c. The total time taken from reading the image to the end of the detection is 5.72 seconds
d. The bottom row is the decoded QR code content. It can be seen that the drug should contain two CAPSULE_CellCept;250;Roche, but two drugs CAPSULE_GSK;Coreg;CR;10;mg are detected, and two warning sounds are issued. The two drugs do not match the content of the QR code and it is necessary to judge whether the result predicted by the proposed DLADDICM is the same as the result by visual inspection.

3. Generate a picture of the prediction result: Figure 11 shown below is the picture of the prediction result of the proposed DLADDICM, which can be checked by visual inspection whether the type of drug predicted by the proposed DLADDICM is correct or not.

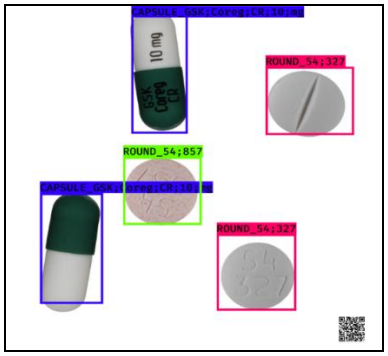


Figure 11. The detection, identification and confirmation results as shown in the computer screen for the test case #3 with two incorrect drugs.

4. Discussion: This test is the case of two wrongly dispensed medicines of the same type, and the expectation is that two warning sounds will be issued. In this test, the drug type CAPSULE_CellCept;250;Roche was predicted. After the string comparison, it was not included in the drug information read by the QR code, so two warning sounds were issued. The identification results are correct, agree with expectations, and the confirmation is successful. Test video of this case is in URL: https://youtu.be/t6W5jFnkNtw

5. CONCLUSION AND FUTURE WORK

In this study, a deep learning based accurate drug detection, identification and confirmation mechanism for medication dispensing package is proposed for inpatients. In this proposed DLADDICM, a medication dispensing package with a printed QR code is photo taken and drugs in the image are detected and identified using a deep learning object detection algorithm, namely YOLO. The QR code information is deciphered and compared with the detected drugs to confirm the correctness of the medication dispensing. If there are mismatch situation(s), the computer with the proposed DLADDICM will generate different warning sound in responding to different incorrect situations. A data set with 30 drugs form the National Library of Medicine of NIH, USA is used for testing the DLADDICM using the most commonly used object detection deep learning algorithm YOLOv3. Experimental results shown that the DLADDICM can detect and identify the incorrect drugs and generate the arranged warning sound for the incorrect dispensing package for further human inspection. Experimental results exhibit the potential and advantage of the DLADDICM as an AI-enabled solution to the LASA errors. Currently, the proposed DLADDICM is implemented on a computer with simulated medication dispensing package, it can further be modified to a deep learning embedded system, named Jetson Nano [14], with a SONY small camera for testing real medication dispensing package. Development of a full robotic drug detection, identification and confirmation mechanism for medication dispensing package could be possibly feasible by using jetamax[15] robotic arm. By utilizing the AI-enabled mechanism an accurate, safer, healthier with precision medication environment for the medical industries could also be realized in the near future.

REFERENCES

[1] Rash-Foanio, C., Galanter, W., Bryson, M., Falck, S., Liu, K. L., Schiff, G. D., ... & Lambert, B. L. (2017). Automated detection of look-alike/sound-alike medication errors. *American Journal of Health-System Pharmacy*, 74(7), 521-527.

[2] Tseng, H. Y., Wen, C. F., Lee, Y. L., Jeng, K. C., & Chen, P. L. (2018). Dispensing errors from look-alike drug trade names. *European Journal of Hospital Pharmacy*, 25(2), 96-99.

[3] Aldhwaihi, K., Schifano, F., Pezzolesi, C., & Umaru, N. (2016). A systematic review of the nature of dispensing errors in hospital pharmacies. *Integrated pharmacy research & practice*, 5, 1.

[4] Grissinger, M. (2012). Safeguards for Using and designing automated dispensing cabinets. *Pharmacy and Therapeutics*, 37(9), 490.

[5] Lichtner, V., Prgomet, M., Gates, P., & Franklin, B. D. (2021). Automatic dispensing cabinets and governance of controlled drugs: an exploratory study in an intensive care unit. *European Journal of Hospital Pharmacy*. http://dx.doi.org/10.1136/ejhpharm-2020-002552

[6] Wang, Y., Ribera, J., Liu, C., Yarlagadda, S., & Zhu, F. (2017, April). Pill recognition using minimal labeled data. In *2017 IEEE Third International Conference on Multimedia Big Data* (BigMM) (pp. 346-353).

[7] Chen, R. C., Chan, Y. K., Chen, Y. H., & Bau, C. T. (2012). An automatic drug image identification system based on multiple image features and dynamic weights. *International Journal of Innovative Computing, Information and Control*, 8(5), 2995-3013.

[8] Lee, Y. B., Park, U., Jain, A. K., & Lee, S. W. (2012). Pill-ID: Matching and retrieval of drug pill images. *Pattern Recognition Letters*, 33(7), 904-910.

[9] Taran, O., Rezaeifar, S., Dabrowski, O., Schlechten, J., Holotyak, T., & Voloshynovskiy, S. (2017, August). PharmaPack: mobile fine-grained recognition of pharma packages. In *2017 25th European Signal Processing Conference* (EUSIPCO) (pp. 1917-1921).

[10] Wong, Y. F., Ng, H. T., Leung, K. Y., Chan, K. Y., Chan, S. Y., & Loy, C. C. (2017). Development of fine-grained pill identification algorithm using deep convolutional network. *Journal of biomedical informatics*, 74, 130-136.

[11] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 779-788).

[12] Redmon, J., & Farhadi, A. (2018). Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767.

[13] RxImage U.S. NIH. [online]. Available: https://www.nlm.nih.gov/databases/download/pill_image.html

[14] nVidia Jetson Nano, [online]. Available: https://www.nvidia.com/zh-tw/autonomous-machines/embedded-systems/jetson-nano/.

[15] Jetmax, [online]. Available: https://forums.developer.nvidia.com/t/jetmax-ai-vision-robotic-arm-powered-by-jetson-nano/193058

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