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MedGlasses: A Wearable Smart-Glasses-Based Drug Pill Recognition System Using Deep Learning for Visually Impaired Chronic Patients

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ABSTRACT Today, with the arrival of an aging society, the average age of the population is rising. It is known that the physiology of a person degrades with age. There are approximately 285 million visually impaired people in the world, of whom 140 million are elderly people over the age of 50, and 110 million of these visually impaired elderly people suffer from multiple chronic diseases. In the case of multiple medication usage, these 110 million vulnerable people will be more likely to take the wrong medicines or forget to take their medication. To solve this problem, this paper proposes a wearable smart-glasses-based drug pill recognition system using deep learning, named MedGlasses, for visually impaired people to improve their medication-use safety. The proposed MedGlasses system consists of a pair of wearable smart glasses, an artificial intelligence (AI)-based intelligent drug pill recognition box, a mobile device app, and a cloud-based information management platform. Experimental results show that a recognition accuracy of up to 95.1% can be achieved. Therefore, the proposed MedGlasses system can effectively mitigate the problem of drug interactions caused by taking incorrect drugs, thereby reducing the cost of medical treatment and providing visually impaired chronic patients with a safe medication environment.

INDEX TERMS Artificial intelligence over the Internet of Things (AIoT), deep learning, drug pill recognition, image sensor, image processing, medication-use safety, visually impaired, wearable devices.

I. INTRODUCTION

Currently, with the arrival of an aging society, the average age of the population is rising, human body functions are declining, and average visual acuity is also worsening year by year. According to a statistical report released by the World Health Organization (WHO) [1] in October 2017, there are approximately 285 million visually impaired people in the world, of whom 140 million are elderly people over the age of 50; moreover, 110 million of these visually impaired elderly people suffer from multiple chronic diseases.

It is known that the physiology of a person degrades with age. In the case of multiple medication usage, these 110 million vulnerable visually impaired elderly people will be more likely to take the wrong medicines or forget to take their medication.

To address this problem, several recent works [3]–[11] have investigated the medicine-use safety issues faced by visually impaired people. Bashyal *et al.* [3] studied the issues and challenges arising during medication use among visually impaired patients in Nepal. In particular, they found that 65.8% of these patients did not understand their medication information.

Kentab *et al.* [4] explored statements regarding medication use by blind patients in Saudi Arabia. They reported that the most common challenges encountered by visually impaired patients were linked to dose recognition (for approximately 82% of patients) and medicine recognition (for approximately 75% of patients); moreover, the medication information and related services provided were also inadequate.

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Ling *et al.* [5] noted the challenges of medication handling among the visually impaired population. Killick *et al.* [6] reviewed the scope of the pharmaceutical care needs of sensory-impaired people. Alhusein *et al.* [7] performed a multiple-method study on the medical care requirements of sensory-impaired elderly people in the polypharmacy context. This study reported that the subjects feared they would take too much by accident by taking the same medicine twice.

The same authors also applied their proposed multiple-method approach to study the medical care requirements of sensory-impaired elderly people in the polypharmacy context in Scotland [8]. Furthermore, a qualitative exploration of the perspectives of community pharmacy personnel was also conducted [9] regarding the pharmaceutical care of sensory-impaired elderly people. Lee and Lee [10] also evaluated the medication-use and pharmacy services available to visually impaired people.

Meanwhile, the number of deaths related to improper drug use throughout the world already accounts for one-third of deaths related to disease [12]. Accordingly, errors in drug use affecting visually impaired patients are expected to cause high medical losses, and such patients may not have access to sufficient support in this regard.

To overcome this problem, we consider the need for a means of drug pill recognition for visually impaired chronic patients. To address this need, in this paper, we propose a wearable smart-glasses-based drug pill recognition system using deep learning, called MedGlasses. The proposed MedGlasses system can support the medication-use safety of visually impaired chronic patients.

The remainder of this paper is organized as follows. Section II reviews related works. The proposed MedGlasses system is introduced in Section III. The related analysis and selection of deep learning modules are discussed in Section IV. Experimental results obtained using the proposed MedGlasses system are presented and explained in Section V. Finally, Section VI concludes this work and discusses future research directions.

II. RELATED WORKS

To provide related functionalities (such as drug pill recognition and medication reminders) to facilitate safe medication use, many related tools [13]–[22] have been developed and assessed.

Xie [13] developed a drug recognition system that uses image processing techniques. A LabView-based program was adopted as the development environment. This drug recognition system can measure the length, shape, weight, color, *etc.*, of a drug.

Yu *et al.* [14] developed a highly accurate automatic drug pill recognition system that uses pill imprint information. In this system, both imprint extraction and description partitions are applied to obtain the pill imprint information. Vieira Neto *et al.* [15] presented a pill feature extractor *named* CoforDes, which enables classification based on shape and color parameters.

Ushizima *et al.* [16] investigated drug pill recognition methodologies for automatically segmenting drug pill images from the National Library of Medicine (NLM), USA. Based on the segmentation results, certain features were extracted to associate the drug pill group with the USA Food and Drug Administration (FDA) recommendations for the physical attributes of each type of pill.

Yaniv *et al.* [17] reported the results of a 2016 challenge competition concerning drug pill image recognition, which was held by the NLM, USA, to encourage the development of related software systems. In this report, many drug recognition methodologies submitted to the competition were introduced.

Calix *et al.* [18] proposed a deep-learning-based medication-use safety scheme called the Deep Gramulator, which tracks and monitors the use of medication by medical personnel to facilitate medication-use safety. The Deep Gramulator can automatically extract tweets to obtain relevant personal health experiences from social media.

Chang *et al.* [19] developed a deep-learning-based intelligent medicine recognition system for chronic patients called ST-Med-Box, which consists of a mobile device app, an intelligent medicine recognition device, a deep learning training server, and a cloud-based management platform. ST-Med-Box can recognize eight types of drug pills, with a recognition rate of up to 96.6%. However, the needs of visually impaired people were not considered in the development of the above mentioned medicine recognition systems.

Regarding dedicated schemes for visually impaired patients, Almuzaini and Abdullah-Al-Wadud [20] reviewed the available medication recognition techniques of this kind. This review discussed the corresponding advantages and disadvantages of each technique.

Ervasti *et al.* [21] presented a touch/audio-based medication management mechanism, which was implemented by a near field communication (NFC)-enabled personal digital assistant (PDA). The presented mechanism provided a basic function of reading the drug name and dosage information aloud by touching the drug package. Almuzaini and Abdullah-Al-Wadud [22] also developed a smartphone-based medication recognition aid, which was designed as a mobile device app to recognize drug packages.

Benjamim *et al.* [23] proposed a computer-vision-based medicine box recognition system based on feature matching. Riheiro *et al.* [24] developed a three-stage medicine box recognition system that combines barcode recognition, text processing, and feature matching.

However, these related schemes merely enable the recognition of the appearance of medicine boxes. They do not provide useful related functionalities, such as drug pill recognition and medication reminders for visually impaired chronic patients. Hence, these related schemes cannot meet the requirements of such patients.

To address this problem, we consider the need for drug pill recognition to ensure safe medication use by visually impaired people. On the other hand, some recent previous

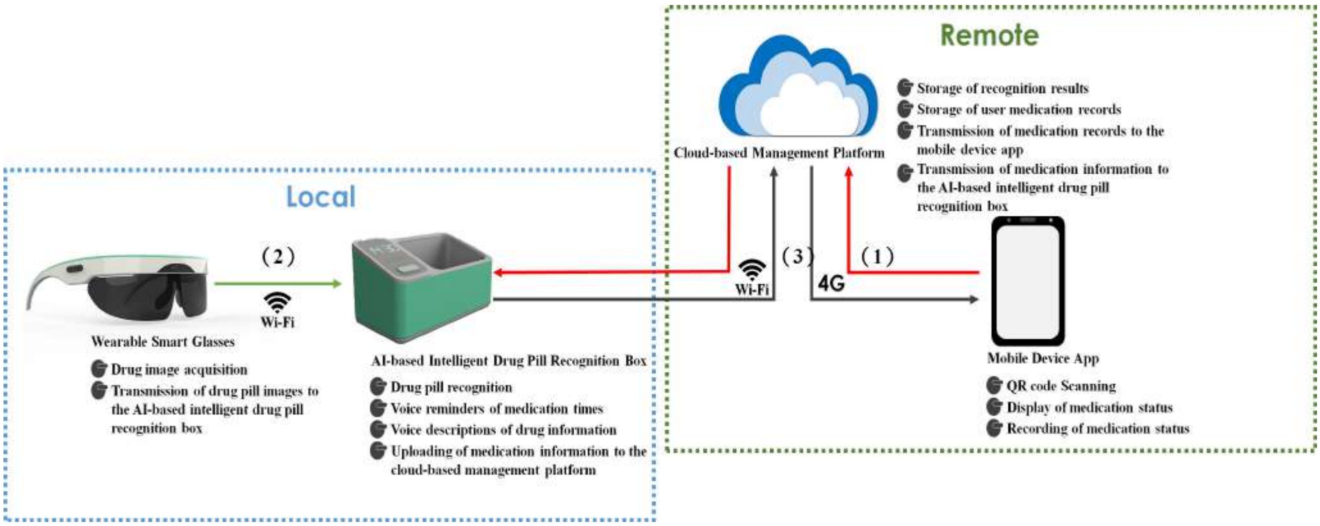


FIGURE 1. System architecture of the proposed MedGlasses system.

works [26]–[32] based on wearable smart glasses were developed for assisting visually impaired people. For example, the designs in the literature [26]–[31] were developed for walking navigation. Furthermore, the literature [31], [32] discusses designs and implementations for walking safety such as aerial obstacle avoidance and fall detection, and zebra-crossing walking.

It is known that visually impaired people cannot clearly see any objects. Generally, visually impaired people always wear sunglasses in their daily lives. Hence, for them, the wearable glasses are the most convenient assistive device because they do not need to hold anything.

Based on the above-mentioned concerns, in this paper, we propose a wearable smart-glasses-based drug pill recognition system using deep learning that provides a convenient drug pill recognition functionality and medication time reminders for visually impaired chronic patients.

III. THE PROPOSED MEDGLASSES SYSTEM

A. DESIGN CONCEPT

This paper presents a wearable smart-glasses-based drug pill recognition system to help ensure the medication-use safety of visually impaired chronic patients by reducing their risk of taking the wrong medicine or forgetting to take their medicine, thereby reducing the harm caused by such medication-use errors.

The proposed MedGlasses system uses deep learning technology for drug pill image recognition, combined with Internet of Things (IoT) and cloud technology. Moreover, the proposed MedGlasses system can be divided into two parts: local and remote.

- Local: drug image acquisition is achieved by the proposed wearable smart glasses, and its image recognition processing is obtained by the proposed AI-based intelligent drug pill recognition box (RBox).
- Remote: Storage of user settings and data and medicines is accomplished remotely, allowing family members' or caregivers' access to the data.

Fig. 1 shows the system architecture of the proposed MedGlasses system, which consists of a pair of wearable smart glasses, an artificial intelligence (AI)-based intelligent drug pill recognition box, a mobile device app, and a cloud-based information management platform. Steps of operation of in a typical scenario are also shown in Fig. 2.

The proposed MedGlasses system can instantly recognize drug pills and broadcast related sound instructions or reminders to ensure the medication-use safety of visually impaired chronic patients, especially in the polypharmacy context. At the same time, it transmits the medication of patient records to the cloud-based management platform and then pushes corresponding notifications to the app to keep family members or caregivers apprised of the medication-use status of patient. The steps of the application flow of the proposed MedGlasses system are as follows.

Step (1): First, the QR code on a drug package is scanned using the mobile device app to obtain the associated medication information for a visually impaired chronic patient. This information is then uploaded to the cloud-based management platform via a 4G wireless network.

Step (2): The proposed AI-based intelligent drug pill recognition box receives the medication information of the visually impaired chronic patient. When the medication time arrives, the patient will be reminded to take his or her medicine by a voice prompt from the proposed drug pill recognition box.

At this time, the patient will place the selected drug pills in his or her hand and press the image sensor (camera) button on the proposed smart glasses to take a drug pill image, which is then transmitted to the drug pill recognition box via a Wi-Fi wireless network.

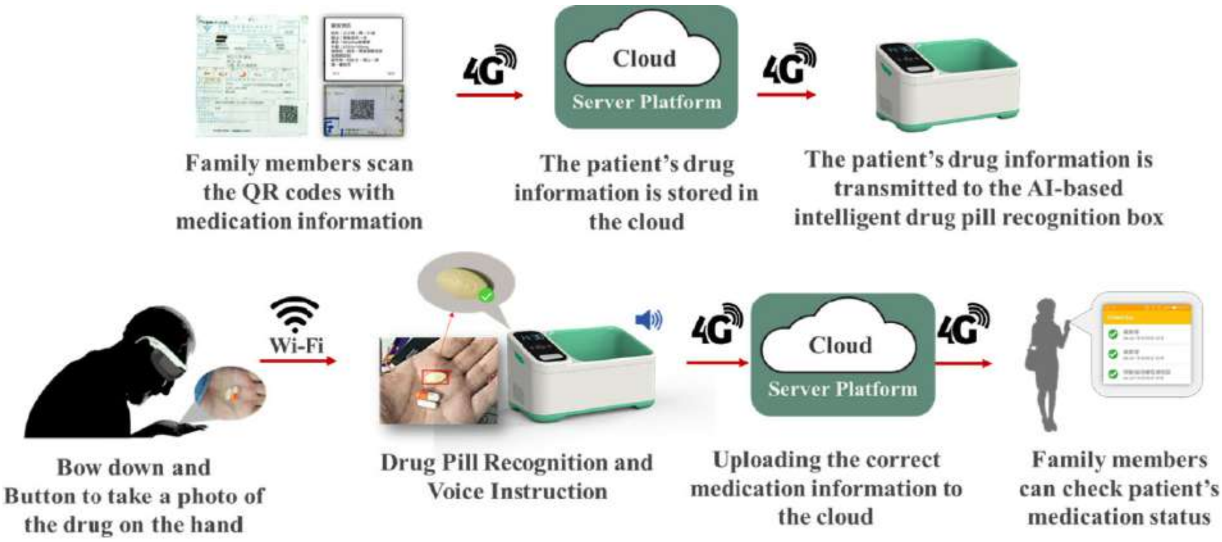


FIGURE 2. Steps of operation of in a typical scenario.

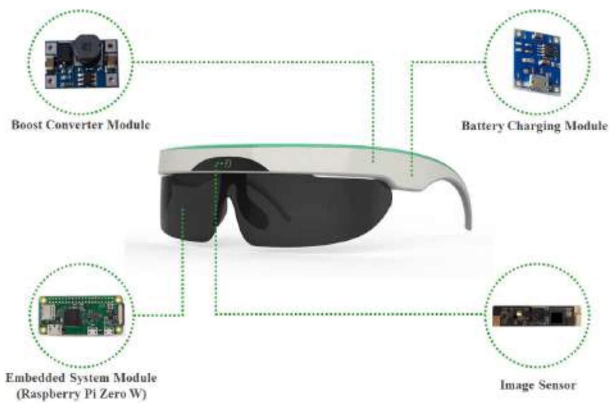


FIGURE 3. Structure of the proposed wearable smart glasses.

FIGURE 4. Structure of the proposed AI-based intelligent drug pill recognition box.

The proposed drug pill recognition box recognizes the drug pills in the hand of the patient, and a voice prompt will tell the patient whether the selected pills are correct to ensure medication-use safety.

Step (3): Then, the proposed AI-based intelligent drug pill recognition box transmits the medication-use records of the visually impaired chronic patient to the cloud-based management platform via Wi-Fi. Thus, the patient's family members or caregivers can check his or her medication status at any time by means of the mobile device app.

B. WEARABLE SMART GLASSES

We consider that the proposed wearable smart glasses should not be too heavy or uncomfortable to wear. Therefore, all the electronic components used are small and light in weight. Fig. 3 shows the structure of the proposed wearable smart glasses, which consist of an embedded system module, an image sensor (camera), a battery charging module, and a boost converter module.

In addition, the proposed wearable smart glasses should be capable of image acquisition and wireless transmission to allow the captured drug pill images to be transmitted to the proposed AI-based intelligent drug pill recognition box via a Wi-Fi wireless network. The adopted image sensor lens contains eight million pixels, sufficient for the requirements of drug pill image recognition.

For the power supply of the proposed wearable smart glasses, we initially tested the use of only a 3.7 V/1,200 mA lithium battery. However, we found that the voltage was too low to drive the embedded system module. We therefore incorporated a voltage boost converter module, which boosts the original 3.7 V from the battery to 5 V before use.

C. AI-BASED INTELLIGENT DRUG PILL RECOGNITION BOX

As shown in Fig. 4, the proposed AI-based intelligent drug pill recognition box consists of an AI-based embedded edge computing module and a power amplifier with a micros-peaker. A commercial AI-based embedded edge computing module is adopted. When the next medication time is approaching, the AI-based embedded edge computing module will control the microspeaker to issue a sound-based notification to remind the patient to take his or her medication. At this time, the patient will use the proposed wearable smart glasses to acquire an image of the selected drug pills and transmit it to the proposed AI-based intelligent drug pill recognition box. The AI-based embedded edge computing module of the drug pill recognition box will then immediately recognize the pills, and a voice prompt will indicate whether the selected medication is correct. If it is correct, then the pills can be taken safely; otherwise, an error will be indicated.

In such a situation, a visually impaired chronic patient must subject the selected drug pills to the recognition process one by one to avoid taking the wrong medication. Finally, the results for the correct medication will be stored in the cloud-based management platform.

D. MOBILE DEVICE APP

The proposed mobile device app can communicate with the proposed AI-based intelligent drug pill recognition box.

The user interface design of the app adopts simple color tones and easy-to-understand graphics. Hence, the user can easily understand the medication status of a visually impaired chronic patient. The options provided in the app include access to account information, quick response (QR) code scanning, drug package information, medication reminders, and medication records. The related functions of the proposed mobile device app are explained as follows.

1) QR CODE SCANNING

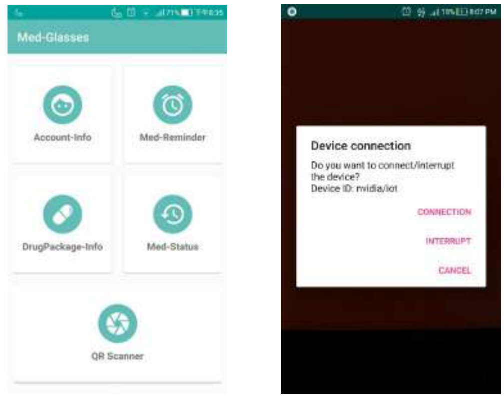
The menu screen of the proposed mobile device app is shown in Fig. 5(a). The QR code scanning option must be selected to connect to the proposed AI-based intelligent drug pill recognition box and obtain medication information by scanning the QR code on a drug package. When this option is selected, the app will connect to the drug pill recognition box, as shown in Fig. 5(b). Once the connection is successful, the medication information is transmitted and saved to the cloud-based management platform.

Once the drug information has been successfully stored, the user can access the information obtained from the drug packages of a visually impaired chronic patient via the app as shown in Fig. 6 (a).

As shown in Fig. 6(b), when the proposed AI-based intelligent drug pill recognition box completes the recognition process, the correct recognition results are transmitted to the cloud-based management platform. The user can the click on the medication status option in the mobile device app to see whether a patient is taking his or her medication correctly.

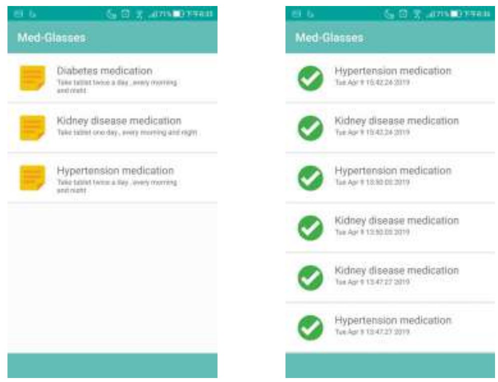
2) MEDICATION REMINDERS

For the medication reminder function, a medication time of the visually impaired chronic patient can be quickly and easily set; there is no need to be afraid to forget to take the medicine at the correct time or to set the alarm reminder in the app. The user can simply go to the medication reminder setting screen (see Fig. 7(a)) to enter the next time the visually impaired chronic patient will need to take his or her medicine, and the app will start counting down until the set reminder time has arrived (see Fig. 7(b)).



(a) (b)

FIGURE 5. (a) Menu screen of the proposed mobile device app. (b) The mobile device app is connected to the proposed AI-based intelligent drug pill recognition box.



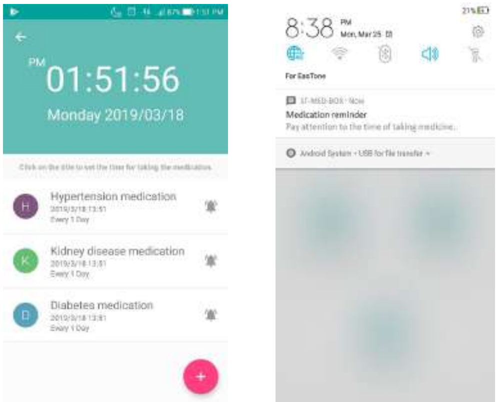
(a) (b)

FIGURE 6. (a) Medication information obtained from drug packages. (b) Correct drug pill recognition results.

E. CLOUD-BASED MANAGEMENT PLATFORM

The operation screen of the proposed cloud-based management platform is shown in Fig. 8. This platform is an important bridge connecting all elements of the proposed MedGlasses system. Because the AI-based intelligent drug pill recognition box must transmit the drug pill recognition information to the proposed mobile device app and the app must also transmit medication information to the drug pill recognition box, there is a need for an intermediate platform where these data can be stored. For this purpose, we use the free open-source management tool phpMyAdmin for database administration over the Web and use MySQL to manage the related data.

Notably, we hope that in addition to using the mobile device app, the family members and caregivers of a visually impaired chronic patient will also wish to view the patient's multiple medications directly. Therefore, they can also use the proposed cloud-based management platform to view this information at home to ensure a safe medication-use environment for the patient.



(a) (b)

FIGURE 7. (a) Medication reminder setting. (b) The proposed mobile device app will start counting down until the set time has arrived to remind the visually impaired chronic patient to take his or her medication.

FIGURE 8. Operation screen of the proposed cloud-based management platform.

IV. ANALYSIS AND SELECTION OF DEEP LEARNING MODULES

Two types of deep learning modules are usually used for object detection. The first module is an object position detection module, such as an R-CNN module (based on region proposals) [33], the module you only look once (YOLO) (based on regression) [34], or a single shot detector (SSD) module (based on regression) [35]. The second is an image classification module, such as an Inception series module [36], a residual network (ResNet) module [37], or a mobilenetv1 module [38].

The purpose of the former is to determine the position of each object of interest and extract a corresponding range for classification, allowing multiple objects to be detected. For the proposed system, we chose to adopt an SSD module [35] and a ResNet module [37] for object detection based on the speed and accuracy requirements of the application. These two deep learning modules are introduced as follows.

A. SINGLE SHOT DETECTOR [35]

Among object position detection modules, although Faster R-CNN [39] offers high accuracy, its computational burden is too large, and it also uses high-level hardware, causing the recognition time to be very long. To adjust such a module to increase its identification speed, its accuracy must be sacrificed. In contrast, SSD is faster and more accurate than YOLO, and it achieves a multiobject average accuracy (mAP) comparable to that of the region-proposal-based Faster R-CNN technique while maintaining an acceptable speed [35]. To meet the requirements of our drug pill recognition system, the chosen object position detection module must be both accurate and not too time consuming; therefore, we chose an SSD module for this purpose. Several key features of the SSD module are explained follows.

1) The basic infrastructure of the feature extraction network is VGG-16 [40]; however, the fully connected (FC) layer FC8 of VGG-16 is removed, and FC6 and FC7 are replaced with convolutional layers. Pool5 does not reduce the resolution and uses reduced convolution to compensate for the receptive field in FC6. Several convolutional layers with decreasing resolution are also added. The architecture of the adopted SSD module is shown in Fig. 9.

2) The SSD module does not perform a region proposal generation phase. Instead, the anchor mechanism is used. An anchor is a box with a fixed position and size. It can be understood as a predefined region proposal.

3) The SSD module uses convolutional layers at different depths to predict targets of different sizes. For small targets, it uses lower resolution layers to place smaller anchors in lower-layer feature maps. Larger anchors are set in higher-level feature maps, as shown in Fig. 10.

4) The prediction module uses 3×3 convolution to directly regress the category position of each anchor.

5) The data augmentation applied in the SSD module has a significant impact on performance.

TABLE 1. ResNet architecture comparison [37].

Layer Name	Output Size	34-Layer	50-Layer
conv1	112×112	7×7,64, stride 2	
conv2_x	56×56	3×3 max pool, stride 2	
		$\begin{bmatrix}3\times3, & 64\\3\times3, & 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, & 64\\3\times3, & 64\\1\times1, & 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, & 128\\3\times3, & 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, & 128\\3\times3, & 128\\1\times1, & 512\end{bmatrix}\times4$
conv4_x	14×14	$\begin{bmatrix}3\times3, & 256\\3\times3, & 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, & 256\\3\times3, & 256\\1\times1, & 1024\end{bmatrix}\times6$
conv5_x	7×7	$\begin{bmatrix}3\times3, & 512\\3\times3, & 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, & 512\\3\times3, & 512\\1\times1, & 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax	
FLOPs		3.6×10^9	3.8×10^9

B. RESIDUAL NETWORK (ResNet) [37]

Compared with a traditional neural network, the ResNet architecture includes an additional "$y = x$" layer (identity mapping layer), whose main function is to ensure that the network does not degenerate with increasing depth. The convergence effect is shown in Table 1. ResNet's neural networks (NNs) can be divided into 5 parts, *namely*, conv1, conv2_x, conv3_x, conv4_x, and conv5_x. The [ ] on the right is the

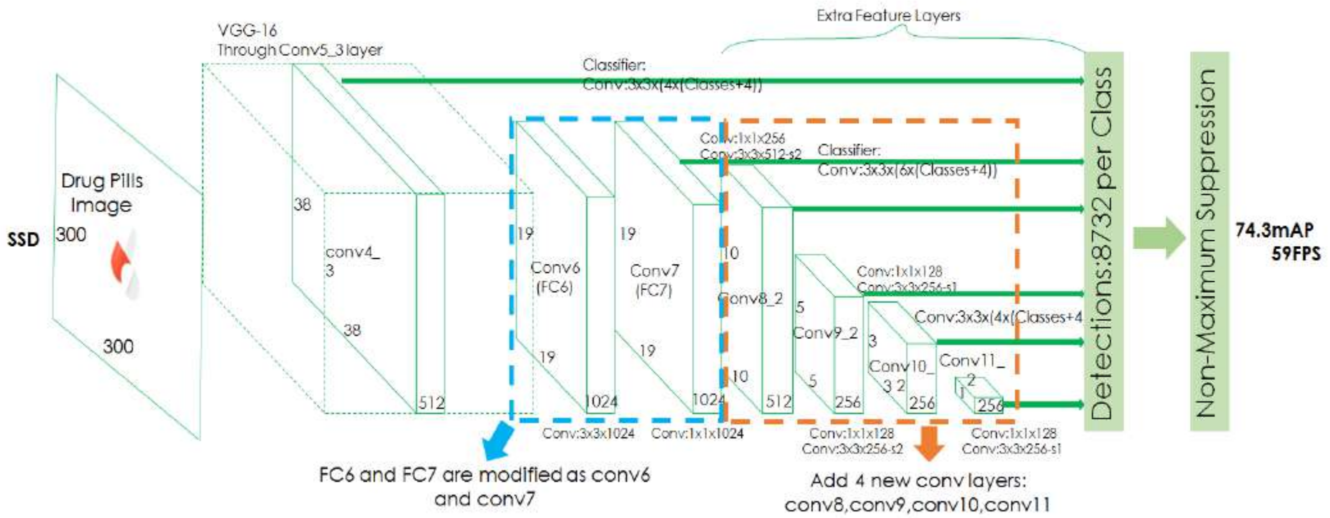


FIGURE 9. The architecture of the adopted SSD module.

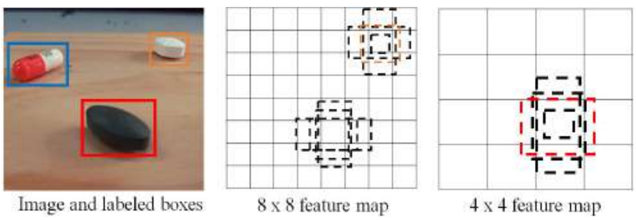


FIGURE 10. Anchor settings of the feature layers.

ResNet block, and the [ ] is the convolution layer in the block. "×3" means there are 3 blocks. Moreover, floating-point operations per second (FLOP) is a measure typically used to estimate the performance of a computer. Here, it is used to determine the amount of computation of a neural network.

Based on the data in this table, we chose ResNet50 as the basis of the deep learning module for drug pill image classification.

As shown in Fig. 11, each ResNet block consists of a series of layers and a shortcut connection. The shortcut connection connects the input and output of the module and executes an add operation at the element level. If the input and output are different in size, zero padding or projection (1×1 convolution) is used to match their sizes. Note that the rectified linear unit (ReLU) is a linear activation function, which is a commonly used activation function in artificial neural networks (ANN). It is now widely used in image recognition.

To reduce the amount of calculation, ResNet50 first uses 1×1 for dimension reduction in its block, and then uses 1×1 for recovery to reduce the number of parameters. For example, the number of 2-layer block parameters is $3 \times 3 \times 256 \times 256 \times 2 = 1,179,648$ when inputting the same 256-dimensional channel, and $1 \times 1 \times 256 \times 64 + 3 \times 3 \times 64 \times 64 + 1 \times 1 \times 64 \times 256 = 69,632$ when inputting 3-layer blocks. Therefore, the number of parameters for 2 layers is 16.941 times that of 3 layers. The 3 layers are used to reduce the amount of calculation and parameters.

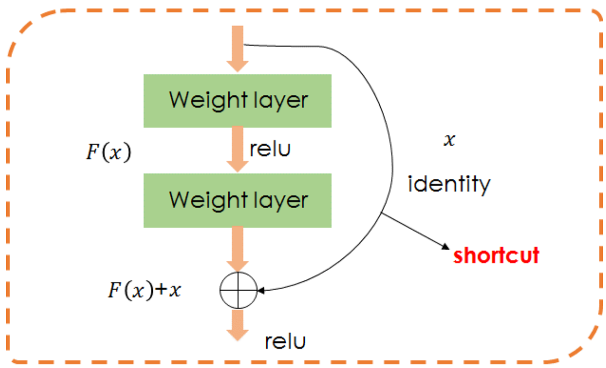


FIGURE 11. Structure of a ResNet block.

The ResNet50 architecture adopted here is actually a modified version of the ResNet34 architecture, as shown in Fig. 12. The 2-layer blocks used in ResNet34 are changed to 3-layer blocks in ResNet50, as shown in Fig. 13.

Most object detection algorithms use only high-level features for prediction because lower-level features carry relatively little semantic information, although the information they provide on the target position is accurate. In contrast, high-level features carry richer semantic information, but their position information is coarser. In other words, the image pyramid network used different levels of features to predict objects of different sizes. Most of these NNs use high-order features to predict large-sized objects in pictures. For small-sized objects in low-level feature prediction pictures, the prediction of small-sized objects is difficult due to insufficient learning of low-level features, which points out the problems encountered when using a general SSD-based neural network module. In addition, some algorithms make use of multiscale feature fusion; such algorithms generally calculate predictions based on the fused features, whereas the most distinctive characteristic of a feature pyramid network (FPN) [41] is its ability to generate independent predictions based on different feature layers. Four general feature-based prediction methods are adopted, as follows.

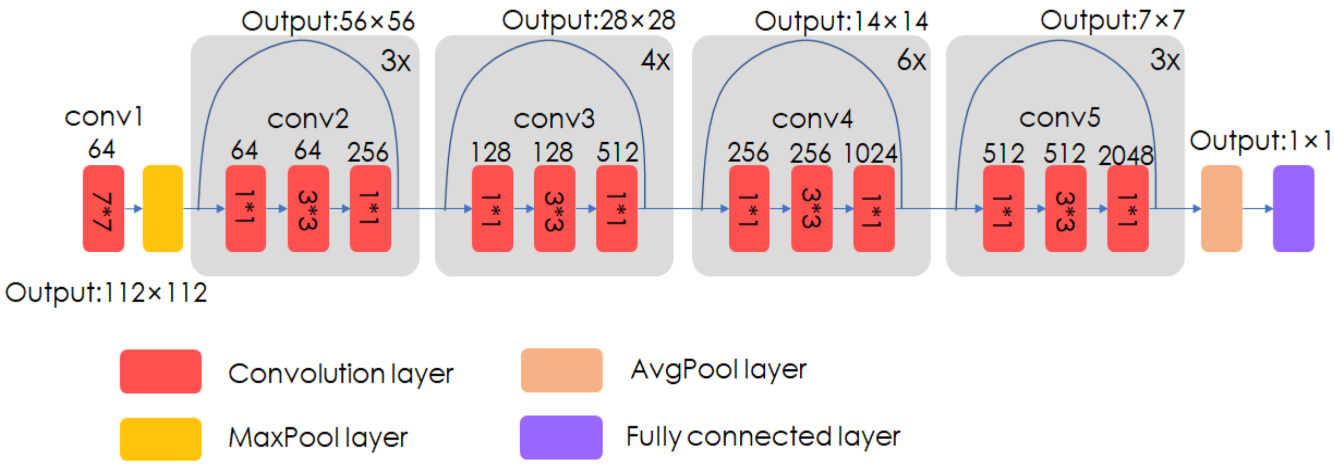


FIGURE 12. Architecture of ResNet50.

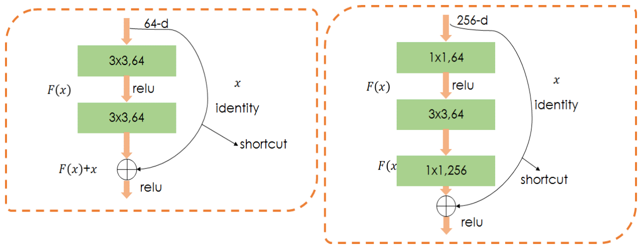


FIGURE 13. Change in block structure from ResNet34 (left) to ResNet50 (right).

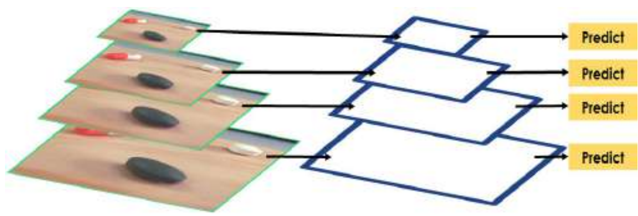


FIGURE 14. Prediction based on an image pyramid.

1) The first method is to use an image pyramid, which consists of images at different scales and generates features corresponding to each scale. The disadvantage of this method is its high time cost. Fig. 14 illustrates the use of image pyramids for prediction.

2) The second method is to use only the top-level features for prediction, as is done in Faster R-CNN, as shown in Fig. 15.

3) The third method is to use multiscale feature fusion. The different layers of the network extract features at different scales for prediction, without upsampling. This method does not incur additional calculations, but it has the disadvantage that it does not use sufficient low-level features. The SSD method, which we use, is a method of this type. The advantage of the SSD module is that it is fast, but its disadvantage is that the detection accuracy for small objects is not ideal. The lowest layer is characterized by VGG-16. The conv4_3 layer extracts sufficiently low-level features to be helpful for detecting small objects, as shown in Fig. 16.

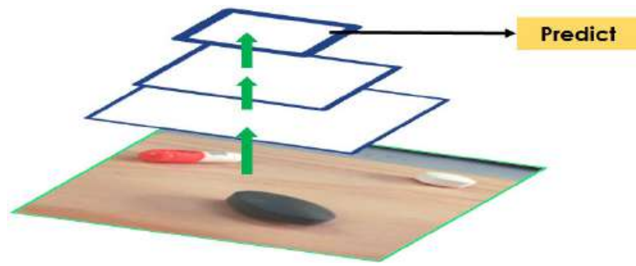


FIGURE 15. Prediction based on a single feature map.

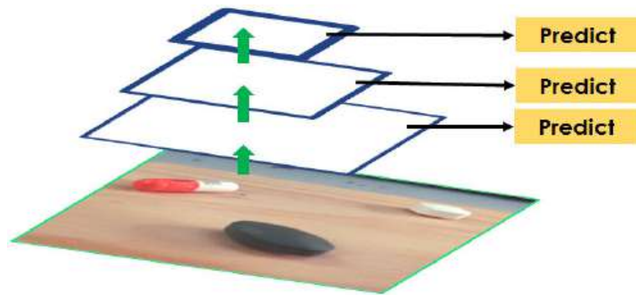


FIGURE 16. Prediction based on multiscale feature fusion.

4) The fourth method is to use an FPN. In such a network, the top-layer features are merged with the lower-layer features, but independent predictions are also generated based on each layer.

Although this approach increases the computational load and thus reduces the speed of processing, it is used in the proposed system. The SSD_ResNet50_FPN module plays an important role in helping solve the problem of the traditional SSD module's low accuracy in detecting small objects, as shown in Fig. 17.

Fig. 18 illustrates the implementation of the feature pyramid used in this work, which is explained in detail below.

First, we send the acquired image to the ResNet module to build the bottom-up network. Next, we construct the corresponding top-down network by upsampling from the fourth layer. First, we use a 1×1 convolutional layer to reduce the

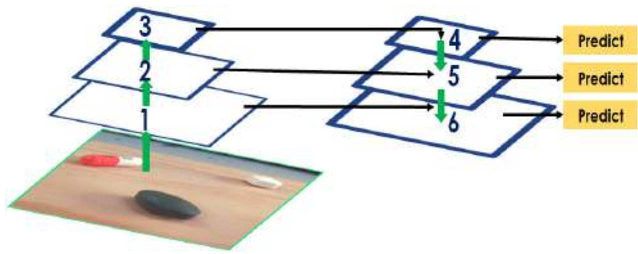


FIGURE 17. Prediction based on a feature pyramid.

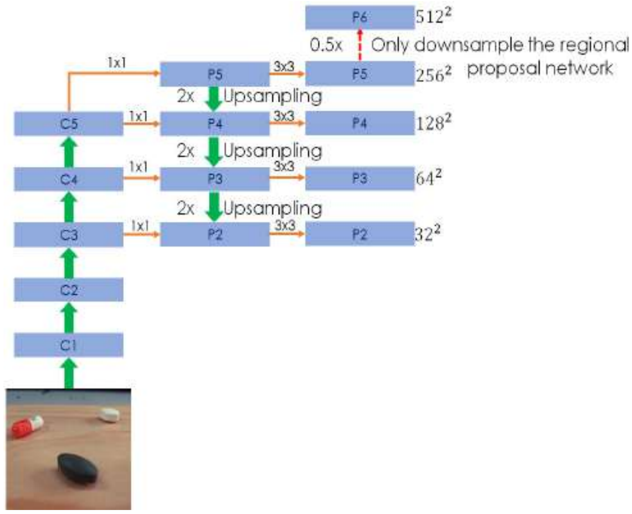


FIGURE 18. Feature pyramid implementation.

dimensions of the second layer, and then, we add the corresponding elements from both layers. Finally, we apply a 3×3 convolutional layer. Please note that C means convolution and P means prediction in Fig. 18.

The bottom layer is actually obtained by removing the first layer of the ResNet module, because the shallow feature map does not carry sufficient semantic information and consumes too much memory. Then, the other layers of the ResNet module are reduced in size by a factor of 2 by convolution with stride=2. The top-down network is built by upsampling the high-level, low-resolution semantic information by a factor of 2.

A horizontal connection is used to adjust the channels for top-down fusion, and the above operation is iterated to generate the features of the best resolution, as shown in Fig. 19.

Then, in the 4th to 6th layers, regional proposal network (RPN) operations are performed separately; that is, after the 3×3 convolution, a 1×1 convolution is performed for classification and regression.

Each obtained candidate region of interest (ROI) is input into the 4th to 6th layers individually, and ROI pooling is performed to fix the feature dimensions to 7×7.

Finally, two 1024 FC layers are added and divided into two separate links to the corresponding classification layer and regression layer.

Ultimately, the execution time of the ResNet50 module is 76 milliseconds, which is slower than that of a Faster

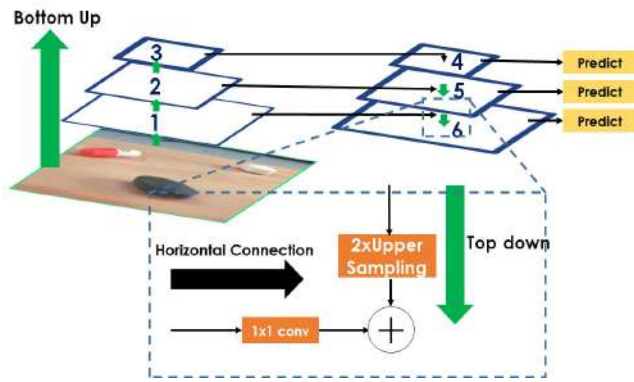


FIGURE 19. Consolidation of channels through a horizontal connection for top-down fusion.

TABLE 2. Comparison of object detection modules on the coco data set based on speed and accuracy [43].

Module Name	Execution Time (ms)	COCO Data Set mAP
ssd_mobilenet_v1_coco	30	21
ssd_inception_v2_coco	42	24
ssd_resnet50_fpn_coco	76	35
faster_RCNN_inception_v2_coco	58	28
faster_RCNN_resnet50_coco	89	30

FIGURE 20. Drug codes and corresponding images.

R-CNN Inception V2 module, but a markedly higher mAP of 35 is achieved, as shown in Table 2. These experiments were executed and processed by an NVIDIA GeForce GTX TITAN X graphics card [42]. The ssd_mobilenet_v1_coco is a module that is used for mobile devices. The computation speed is very fast, but its mAP is only 21. The two modules (ssd_mobilenet_v1_coco and ssd_inception_v2_coco) still use image pyramids to predict objects of different sizes, resulting in unsatisfactory small object recognition accuracy. Finally, we select the ssd_resnet50_fpn_coco module as our recognition module. This module replaces the image pyramid network in the SSD with an FPN. It has the feature of generating the final feature combination based on each layer of features, which can solve the problem of the small object recognition accuracy of the SSD.

V. EXPERIMENTAL RESULTS

Before training the deep learning modules, we needed to prepare drug pill image data. The total image size for the drug pill images was 640×480; 4,000 images of single drug pills and 4,000 images of multiple drug pills were acquired. In this work, we trained the deep learning modules on four types of drug pills. The drug names were anonymized using codes, as shown in Fig. 20.

TABLE 3. Specifications of the deep learning training server.

CPU	Intel i7 7800X
GPU	NVIDIA GTX 1080
RAM	Kingston 16 GB x 4
SSD	512 M.2 PCIE
HHD	Seagate 1 TB, 7,200 RPM Enterprise Disk

TABLE 4. Resource used analysis.

	RAM	CPU	GPU	GPU Occupation Time
ssd_mobilenet_v1	1,716 MB	16.43 %	99%	0.3 s
ssd_inception_v2	2,847 MB	18.16 %	99%	0.6 s
ssd_resnet50_fpn	3,672 MB	29.16 %	99%	2.1 s
faster_RCNN_inception_v2	4,096 MB	19.16 %	99%	1.8 s
faster_RCNN_resnet50	4,802 MB	20.8 %	99%	2.6 s

TABLE 5. Experimental results for object detection accuracy based on 1,000 drug pill images.

Tested Module	Image with Correct Object Detection (#)	Multiobject Average Accuracy (mAP)	Average Detection Time (s)
ssd_mobilenet_v1	683	19	3.6
ssd_inception_v2	726	22	4.88
ssd_resnet50_fpn	951	33	18.75
faster_RCNN_inception_v2	874	25	16.63
faster_RCNN_resnet50	922	27	22.66

It was necessary to convert the images and JSON files for the various drug types into TFRecord files and use the packaged binary files to accelerate the training speed of the deep learning modules.

The TFRecord [45] file is a binary format for efficiently encoding long sequences of the photos. Hence, we used the Google TensorFlow official API [46] to adjust the parameters of the SSD ResNet50 FPN module. To accomplish this with the object detection API, we need to modify one line in the model Config file [47], where the TensorFlow models repository is cloned.

Then, we further adjusted the Config file and then carried out 148,576 steps of training on a deep learning training server. The training time was approximately 46 hours. The specifications of the deep learning training server are shown in Table 3.

Next, we implemented the trained modules in a commercial high-performance AI-based embedded edge computing development platform (NVIDIA Jetson TX2 [48]) for drug pill image recognition and compared their performance on the same number of patterns.

As shown in Table 4, the ssd_resnet50_fpn deep learning module was found to be faster than the faster_RCNN_resnet50 module. Moreover, we tested the multiobject average accuracy (mAP) of the modules on 1,000 single-drug-pill images and 1,000 multiple-drug-pill images.

As shown in Table 5, the speed and mAP results obtained in this experiment show that the ssd_resnet50_fpn module is the most suitable for detecting drug pill objects.

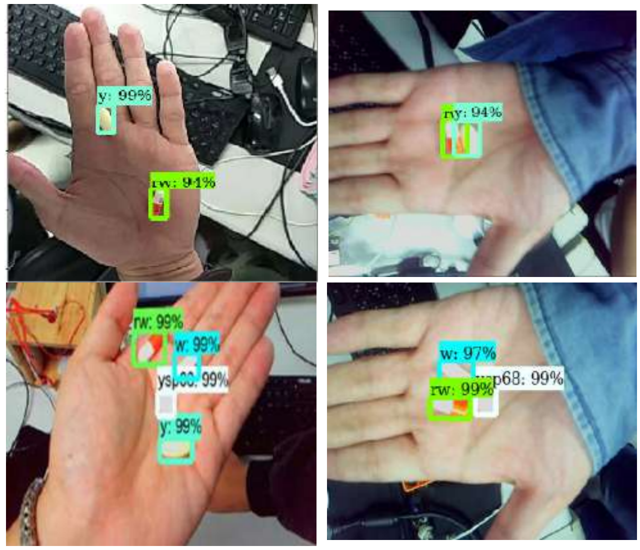


FIGURE 21. Actual drug pill recognition results obtained on images of pills in the hand.

Fig. 21 presents actual drug pill recognition results obtained on images of pills in the hand. The results show that a recognition rate of up to 95.1% can be achieved.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we have proposed a wearable smart-glasses-based drug pill recognition system using deep learning, named MedGlasses, for visually impaired chronic patients. The proposed MedGlasses system consists of a pair of wearable smart glasses, an artificial intelligence (AI)-based intelligent drug pill recognition box, a mobile device app, and a cloud-based information management platform and is designed to support safe medication use.

The proposed MedGlasses system uploads medication information to the cloud-based management platform to build medication-use records, allowing family members or caregivers to monitor the medication status of visually impaired chronic patients by using the mobile device app. The proposed MedGlasses system achieves a recognition rate of up to 95.1%. Hence, the proposed MedGlasses system can effectively mitigate the problem of drug interactions caused by taking incorrect medications, thereby reducing the cost of medical treatment and providing visually impaired chronic patients with a safe medication environment.

In the future, we will continue to improve the appearance and reduce the circuit complexity of this product, thus improving its durability and wearing comfort. The accuracies of different types of drugs and their related factors (such as the environment light and captured image angles) will be analyzed in detail. In addition, we will also cooperate with the hospital pharmacy to recognize more medications for chronic diseases and establish a complete medication-use safety process for visually impaired people. Moreover, we can also incorporate the functions of GPS positioning, voice navigation, and health status detection provided by various auxiliary wearable devices to provide complete and comprehensive healthcare support for visually impaired chronic patients.

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附件二：專利

中華民國專利證書

發明第 I704914 號

發 明 名 稱：智慧藥物辨識系統

專 利 權 人：南臺學校財團法人南臺科技大學

發　明　人：張萬榮、陳良築、許家豪、顏宜德、邱致誠、楊子進、
林晁暘、林承沛

專利權期間： 自2020年 9 月21日至2038年12月10日止

上開發明業經專利權人依專利法之規定取得專利權

經濟部智慧財產局 局長　洪淑敏

中華民國 109 年 9 月 21 日

注意：專利權人未依法繳納年費者，其專利權自原繳費期限屆滿後消滅。

附件三：競賽獲獎資料

『2020 第二屆智慧聯網專題實作競賽』智慧工業聯網應用組 - 榮獲金獎

臺教資(二)字第1090117822號

教育部

教育部獎狀

南臺科技大學 電子工程系 張萬榮教師
指導學生榮獲第二屆智慧聯網專題實作競賽
智慧工業聯網應用 金牌
特頒此狀 以資鼓勵

部長 潘文忠

中華民國 109 年 8 月 25 日

中央社訊息平台

舒適閱覽 : 小 中 大

南臺科大電子系榮獲「智慧聯網專題實作競賽」智慧工廠聯網應用組金獎

「MedEye」團隊榮獲「第二屆智慧聯網專題實作競賽」智慧工廠聯網應用組金獎團隊。

「MedEye」團隊與張萬榮指導教授合影。團隊(由左至右) 徐吏憲、吳培義、張萬榮教授、鄭慎弘、王家宏

南臺科大電子系榮獲「智慧聯網專題實作競賽」智慧工廠聯網應用組金獎

(中央社訊息服務20200826 16:49:30)由教育部指導，雲林科技大學主辦之「第二屆智慧聯網專題實作競賽」頒獎典禮日前於台中長榮桂冠酒店舉辦，南臺科技大學電子工程系張萬榮副教授與機械工程系沈毓泰教授所指導的參賽團隊，分別取得金獎與佳作之成績，表現亮眼。

舉辦「智慧聯網專題實作競賽」主要是為鼓勵大專學生，從事智慧聯網系統相關之核心技術研究，並且發揮設計技巧及創新應用，希望藉由此項競賽，深化智慧聯網技術並增加智慧聯網系統之附加價值。此次競賽區分四個應用主題，有來自48校、218支隊伍參加，參賽學生計有1013名，競爭相當激烈。為配合新冠肺炎防疫工作，決賽審查以線上視訊評審方式進行，主辦單位並提供線上交流平台，使參賽學生能互相觀摩與學習。

由南臺科大電子系張萬榮副教授所指導的學生鄭慎弘、王家宏、徐吏憲及吳培義同學，以作品「MedEye」榮獲智慧工廠聯網應用組金獎。該專題為一套應用於醫院調劑室之智慧藥品辨識系統。當調劑師進行藥物調劑時，可將藥袋放置於藥物辨識儀器進行AI邊緣運算辨識，判斷該藥袋資訊與內部放置之藥品與數量是否相符,如果調劑不相符則會透過藥物辨識儀器螢幕以及語音提醒調劑師重新調劑，降低調劑錯誤率。此外。該校機械系沈毓泰老師所指導的團隊，亦以作品「軸承損壞雲端大數據分析與診斷系統」取得佳作，可謂雙喜臨門。

南臺科大電子工程系張萬榮副教授表示，教育部於去年起開始舉辦「智慧聯網專題實作競賽」至今邁入第二屆，其目的為鼓勵校園學子持續勇於投入科技創意發想及創新創業。電子工程系繼去年勇奪一金一銀一佳作後，今年的表現持續活耀，勇奪智慧工廠聯網應用組金獎，創造優秀成績。未來該系也將持續培養學生實作能力，並鼓勵參與更多全國競賽，除了能為校爭光外，也能讓學生於競賽的過程中不斷學習與自我成長。

南臺科大校長盧燈茂表示，該校非常重視學生專題製作，理論的講解只是架構及概念，重點是如何讓學生將所學概念有效運用於解決問題，才能發揮學以致用的效益。因此南臺科大非常鼓勵教師指導學生參與校外各類競賽，希望透過競賽的方式，讓學生在作品開發過程中，習得各項專業知識與產業應用技術，藉由這些知識與技術的學習，讓學生畢業後可直接投入職場與產業界無縫接軌，或促成學生創業的發展機會。

資料來源：Southern Taiwan University of Science and Technology
https://www.stust.edu.tw/

訊息來源：南臺科技大學

本文含多媒體檔 (Multimedia files included)：
http://www.cna.com.tw/postwrite/Detail/278023.aspx

附件下載

- 「MedEye」團隊榮獲「第二屆智慧聯網專題實作競賽」智慧工廠聯網應用組金獎團隊。 (jpg檔)
- 「MedEye」團隊與張萬榮指導教授合影。團隊(由左至右) 徐吏憲、吳培義、張萬榮教授、鄭慎弘、王家宏 (jpg檔)

『2020 經濟部技術處搶鮮大賽』創新實作類 - 榮獲冠軍

南台科大師生包辦經濟部「搶鮮大賽」冠亞季軍獎金30萬

2020-12-18 09:34 聯合報 / 記者周宗禎／台南即時報導

南台科大電子、產設系師生包辦經濟部「搶鮮大賽」冠亞季軍獎金30萬。圖／校方提供

南台科大今天表揚電子工程系副教授張萬榮及創新產品設計系副教授歐陽昆為校爭光，指導學生團隊15日參加經濟部技術處主辦的「2020搶鮮大賽-創新實作類」勇奪冠亞季軍「大滿貫」佳績與30萬元獎金。

今年大賽參選件數超過300件，35件進總決賽，南台作品「MedHelper」研發可應用於醫院藥物調劑室的人工智慧藥物辨識系統與取樣系統獲得評審委員青睞得到全國冠軍、獎金15萬；作品「Bed Vision」聚焦預防醫院長期臥床病患離臥床跌倒事件並與醫學中心完成臨床實驗獲得亞軍、獎金10萬；作品「基於深度學習應用於視障者引導輔助系統」則以智慧墨鏡為主體提供視障者戶外行走安全保障而榮獲季軍(獎金5萬)；而作品「PCB銲點瑕疵智慧視覺檢測系統」克服現今AOI光學檢測的限制，針對自動焊接機與手焊等PCB電路研發人工智慧視覺檢測以取代現有人力視檢而榮獲優選獎。

這4項參賽作品整合電子系邊緣運算人工智慧技術與產設系產品設計。張萬榮、歐陽昆表示，為鼓勵學子投入科技創意發想及創新創業，經濟部技術處每年舉辦「搶鮮大賽」，高額獎金及高競爭吸引各大專校院師生，是每年不會錯過的競賽。

校長盧燈茂表示，兩系為校爭光，一舉奪下冠、亞、季軍及優選，這是對學校教學成果與學生跨領域學習最大的肯定。南台教育目標就是培育務實致用的科技人才，資源積極投入實務能力訓練，鼓勵參加國內外各項競賽並給經費補助，提升就業競爭力與國際視野，達到畢業即就業，上工即上手的教育目標。

南台科大電子、產設系師生包辦經濟部「搶鮮大賽」冠亞季軍獎金30萬。圖／校方提供

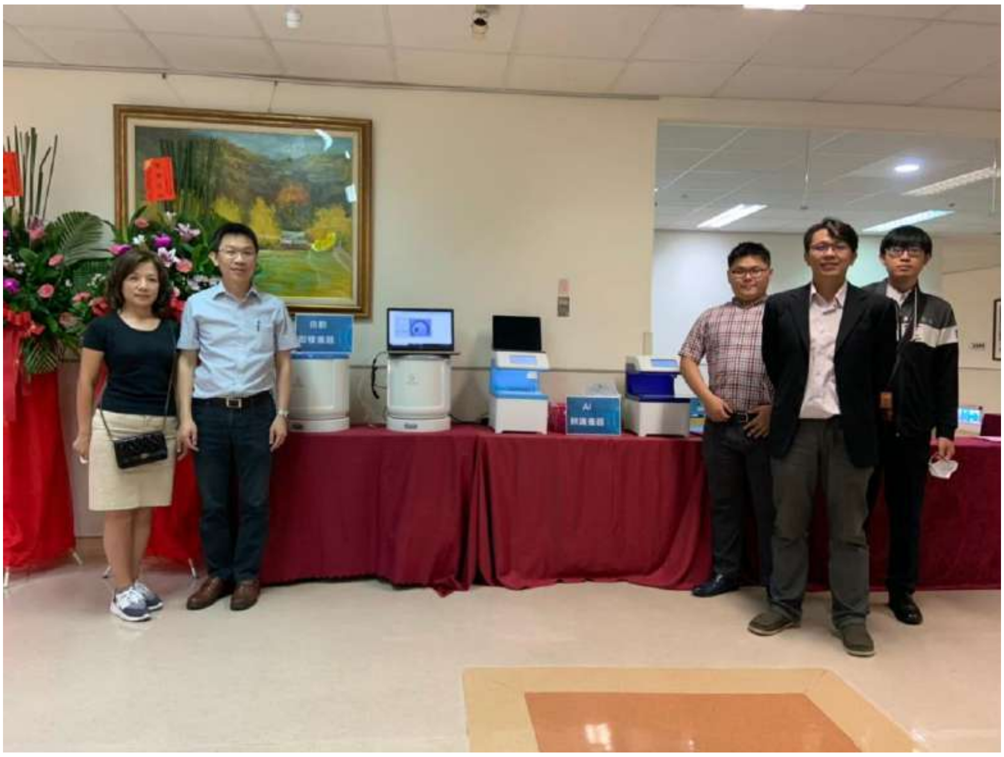
【推薦閱讀】

- 【圖卡】全民停課要瘋了！家變孩子的神人實境秀
- 教育部宣布全台各級學校停課 五大配套一次看
- 高中職以下停課 家長的防疫照顧假QA速讀

視障

附件四：醫學中心合作佐證

高雄醫學大學



圖：研發團隊受邀參加高雄醫學大學院慶，展出「適用於醫院藥品調劑室之人工智慧藥品辨識與覆核系統」。

圖：研發團隊向參觀醫師展示「適用於醫院藥品調劑室之人工智慧藥品辨識與覆核系統」

奇美醫院

圖：研發團隊親訪奇美醫院藥劑部，並實際導入「適用於醫院藥品調劑室之人工智慧藥品辨識與覆核系統」進行系統驗證。

圖：研發團隊向藥劑師展示「適用於醫院藥品調劑室之人工智慧藥品辨識與覆核系統」操作流程

附件五：技轉合約

學校合約編號：12001080032-TT

□政府補助研究計畫成果

南臺學校財團法人南臺科技大學

技術移轉授權合約書

計畫名稱「人工智慧藥物辨識方法及其自動辨識系統技術移轉暨專利授權計畫」

簽約單位:

南臺學校財團法人南臺科技大學

計畫主持人：電子系　張萬榮 副教授

百國科技股份有限公司

附件六：參加醫療科技展

2019 台灣醫療科技展參展

圖：由百國科技股份有限公司、國軍花蓮總醫院於 2019 臺灣醫療科技展聯合展出「適用於醫院藥品調劑室之人工智慧藥品辨識與覆核系統」，並由臨床藥劑科主任郭進忠上校介紹研發成果。

圖：研發團隊張萬榮教授(右)、陳銘哲助理教授(左)於 2019 醫療科技展合影

2020 台灣醫療科技展參展

圖：研發團隊與百國科技股份有限公司聯合於 2020 台灣醫療科技展展出「適用於醫院藥品調劑室之人工智慧藥品辨識與覆核系統」合影

圖：臨床藥劑科主任郭進忠上校介紹「適用於醫院藥品調劑室之人工智慧藥品辨識與覆核系統」研發成果