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APPLIED RESEARCH

A Smart Leaf Blow Robot Based on Deep Learning Model

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ABSTRACT Although leaves are everywhere in the world, and they also play a vital role in our daily life, they tend to fall all over the ground in due course, thereby making it difficult for pedestrians and vehicles to move. In this paper, an automatic leaf blower was designed and based on the concept of convolutional neural network(CNN). This system can automatically collect leaves into a garbage bag. A four-wheel driving robot was implemented to drive a blow machine. The control sensors of this robot mainly include a camera, ultrasound, the electronic compass and acceleration. Besides, an ultra-wide band located module was used to obtain the position of the current robot during the working process. Also, the computer vision was employed to recognize whether the leaves are on the ground. For this, ResNet50 deep CNN was used as the training model to recognize the fallen leaves. Since there are many kinds of trees, their leaves are different shape. We collected the images of these leaves as dataset for training, and the recognition rate achieved 92.5%. The obtained result was sent to the controller to control the moving direction of the robot. For the real-time operation, the embedded system was used to sense the leaf data to decide the movement made by the machine based on a control algorithm. The CNN model was implemented with an accelerator on the embedded system for the real-time purpose, which the recognition speed can achieve 20 frames per second form the camera. The automatic leaf blow machine can be possibly used in an effective way instead of human power.

INDEX TERMS Leaf recognition, robot, blow machine, recognition, convolutional neural networks (CNNs).

I. INTRODUCTION

In recent years, the advancement of science and technology with artificial intelligence (AI) and automation technology have begun to develop rapidly. The intelligent robots are considered to be the most representative of the automation technology. In the past, most robots can only perform standard actions. AI with deep learning can replace the previous standard way because this can be smart control according to the electrical sensors. The technology of machine vision plays an important role in how a robot can work. There are a lot of leaves in schools or parks. The fallen leaves tend to cause the problem for pedestrians and vehicles when they are about to pass the road. Currently, workers most of the time use a leaf blower to clean the leaves. Science and technology always comes from human needs. For this reason, this study attempted to design an AI-based automatic leaf blower so as to help people to clear the road.

In order to realize this intelligence leaf blow robot, it is necessary to integrate robot navigation and positioning patrol, combined with the leaf recognition system. Robot navigation and positioning has been discussed in many papers in the past [1], [2], [3], [4]. The use of a laser locator to navigate robot can achieve high accuracy [1], but the cost is also high. The use of an ultrasonic sensor to detect distance entails low costs,

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but the sensing range is limited [2]. The wireless RSSI-based [3] for spatial positioning can estimate the current position of the robot in space, but the RSSI signal strength is not very stable, so the estimated position can contain a major error. A RSSI locator with laser auxiliary is proposed to navigate the robot realized in [4], which can find the best passing path for the robot going on. For leaf recognition, some scholars have provided discussions on the recognition of leaves [5], [6], [7], [8], [9]. Gargade and Khandekar [5] analyzed the current leaf recognition algorithms. These algorithms are mainly divided into the traditional image processing algorithms and learning methods. R.Hu et al. proposed to use image processing for leaf identification [6], including scaling, feature extraction, removing unimportant signals, and then classifying with the nearest neighbor distance method. Zhang et al. [7] proposed the method of image processing to find leaf Vein (leaf vein), which is considered as the basis for the identification of leaves. Besides, discussions on the deep learning method used to train leaves have been provided [8], [9]. Tomato leaves were detected to see whether the tomato tree was healthy [8] using the CNN model. The accuracy reached 96∼98%. Leaves and leaf veins are used as feature extraction [9] for deep training, which can effectively reduce the amount of data. Huixian [10] presented the leaf recognition using KNN-based neighborhood classification, Kohonen network, SVM-based support vector machine and neural network methods which can achieve the recognition rate with 86%, 87%, 86% and 92% respectively. The neural network method has the highest correct recognition rate and lowest computing time. DoubleGAN (double generative adversarial network) is used to generate images of unhealthy leaves, and then healthy leaves and unhealthy leaves input the WGAN (Wasserstein generative adversarial network) for training in [11]. Then, the generative adversarial network (SRGAN) was used to obtain the super resolution leaf images. The results show that the accuracy of plant species reached 99%.

At present, all leaf blower machines must be manually operated. To operate the leaf blow machine, a weight of 3∼10Kg must be carried by a worker. The loud noise from the leaf machine has a great impact on human hearing. Also, a cloud of dust tends to rise in the air while the blower machine is working. Meanwhile, this also further causes air pollution temporarily. In this study, what motivated us is to design the automatic robot navigation system through which, can detect the location of leaves using the method of computer vision. The robot carries on a blower machine, and the robot can be navigated, and so the moving direction and speed of the robot can be controlled moving according to the areas covered with distribution of fallen leaves. This machine can therefore blow the fallen leaves into the garbage bag automatically. The rest of this paper is organized as follows. The smart robot system for leaves correction is described in Section II. The use of a machine learning technology (deep learning) for leaves recognition is presented in Section III. Descriptions of the real-time implementation and experiments are provided in Section IV. The conclusions remarking are drawn in Section V.

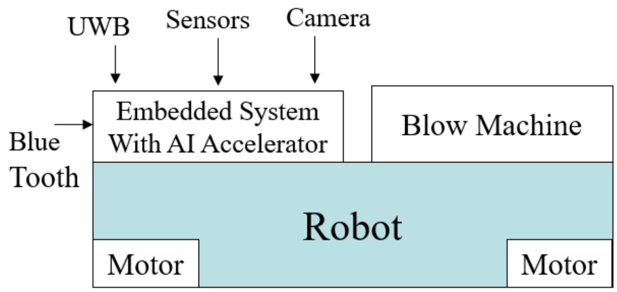


FIGURE 1. **The system architecure of blow robot.**

II. SMART LEAF COLLECTION SYSTEM DESIGN

To better realize this smart robot for a leaf blower system, the floorplan of system architecture is depicted in Fig. 1. Because this robot was designed with four wheels and its motors and drivers attached onto the bottom, the robot can carry an electrical blower machine [10] on the top. The controller employs an embedded system and AI accelerator built-in into the inside of robot. A camera is used for computer vision to detect the leaf based on CNN model. The sensors mainly include a 3D accelerator, a compass and an ultrasound module. The 3D accelerator was used to detect the x, y, z direction of the current robot. The compass is employed to decide the relative direction of the north earth. The ultrasound module is used to measure the distance between robot and obstacle. The ultra-wideband (UWB) locator is to localize the robot for navigation. The remote controller sends the command to the robot thorough the blue-tooth wireless system.

In order to save the battery power, the power switch of a blower machine was designed to be automaticelly controlled by the control system. Simply stated, if no leaves found, the power will be turned off. Once leaves are detected by our AI model, the power of the leaf blower machine will be turned on immediately to blow the leaves.

Figure 2 illustrates the processing flow associated with the control of this blower machine. First, the robot should be moved to a starting point, and the camera should be put on the front of the robot to sample the scene of ground. Then, the images can be recognized by a deep CNN model. If no leaves are found, the robot should continuously move until the leaves are detected. If so, the leaf blower machine is turned on to sweep and blow the leaves to the front until all leaves are cleaned and removed. Finally, the robot keeps moving forwards and follows the navigated path until its arrival at the destination.

For robot navigation, UWB modules are used as a locator. Its frequency operates on 3.5GHz ∼ 6.5GHz [11]. The maximum communication distance can be up to 50m. The three tags of UWB is used to detect the current position of the robot, as shown in Fig. 3 Each tag generates the RF

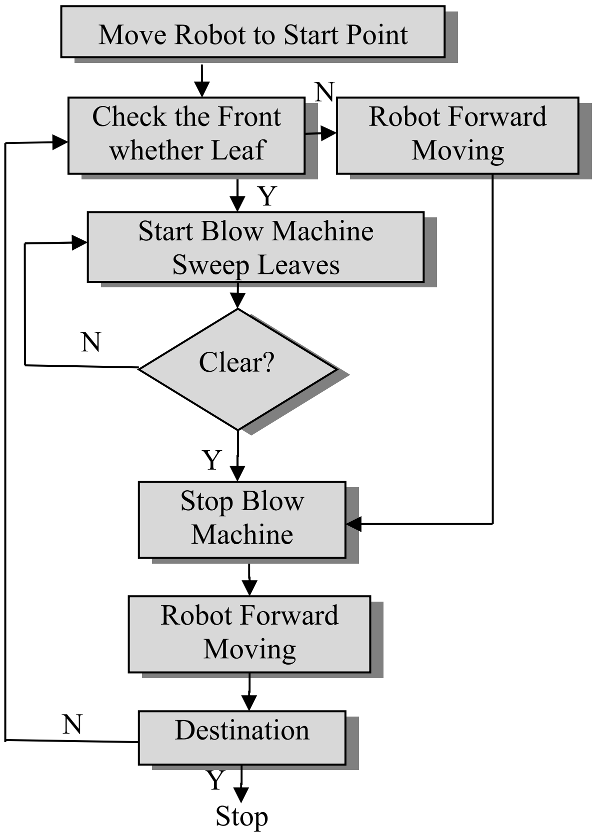


FIGURE 2. The algorithm of blow machine control.

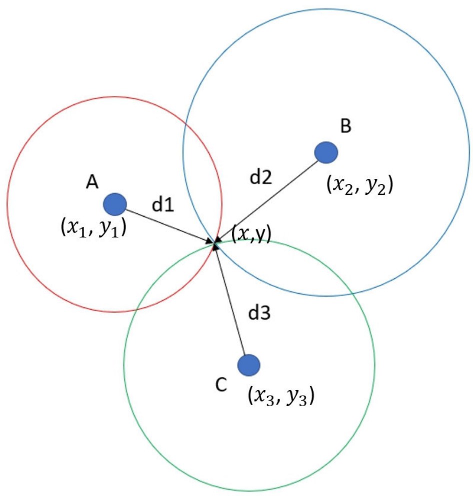


FIGURE 3. Three-point locator with UWB tags.

signal. The controller can calculate theses RF signal to decide the current coordinate of the robot (x,y). If the coordinates of three tag are (x1,y1), (x2.y2) and (x3,y3) respectively. One can calculate the distance between each tag and the robot with the following (1)-(3) equations,

$$\begin{cases} d_1^2 = (x^2 - x_1^2) + (y^2 - y_1^2) & (1) \\ d_2^2 = (x^2 - x_2^2) + (y^2 - y_2^2) & (2) \\ d_3^2 = (x^2 - x_3^2) + (y^2 - y_3^2) & (3) \end{cases}$$

Then the differential (1)-(2) can be obtained by

$$\begin{aligned} &(-2x_1 + 2x_2)x + (-2y_1 + 2y_2)y \\ &\quad = d_1^2 - d_2^2 - x_1^2 + x_2^2 - y_1^2 + y_2^2 \end{aligned} \tag{4}$$

Also, when (2)-(3), we have

$$\begin{aligned} &(-2x_2 + 2x_3)x + (-2y_2 + 2y_3)y \\ &\quad = d_2^2 - -d_3^2 - x_2^2 + x_3^2 - y_2^2 + y_3^2 \end{aligned} \tag{5}$$

Let $A = -2x_1 + 2x_2$, $B = -2y_1 + 2y_2$, and

$$C = d_1^2 - d_2^2 - x_1^2 + x_2^2 - y_1^2 + y_2^2,$$

The (4) can be simplified to

$$\mathrm{Ax} + \mathrm{By} = \mathrm{C} \tag{6}$$

Similarly, let $\mathrm{D} = -2\mathrm{x}_2+2\mathrm{x}_3$, $\mathrm{E} = -2\mathrm{y}_3 + 2\mathrm{y}_3$, and $\mathrm{F} = d_2^2 - d_3^2 - x_2^2 + x_3^2 - y_2^2 + y_3^2$, we have

$$\mathrm{Dx} + \mathrm{Ey} = \mathrm{F}. \tag{7}$$

From the equations (6) and (7), the coordinate of robot can be computed by

$$x = \frac{C * E - F * B}{E * A - B * D} \tag{8}$$

$$y = \frac{C * D - A * F}{B * D - A * E} \tag{9}$$

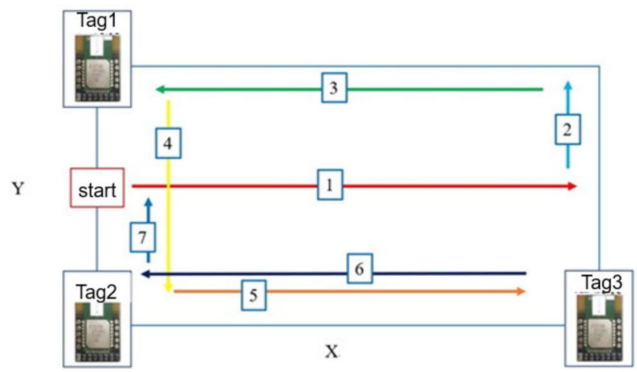


FIGURE 4. The robot moving control with WUB tags.

The robot is navigated with a particular loop to clear the leaves on the ground. Figure 4 illustrates the pre-scheduled path for robot navigation with three UWB tags on the road. The control flow is depicted in Fig. 5 First, the robot should move to a starting point with a manual remote control. Then, the auto- mode command should be sent to the robot. So, the robot can move forwards on the path 1 and then turn left along the paths 2 and 3. The garbage bag is put on the Tag1. Now the leaves on the paths 1,2,3 are all collected into this bag. Next, the robot turns left to the paths 4 and 5 until it arrives at the tag3. The another garbage bag is put on the position of tag3 to collect the leaves of the path 4 and 5. Finally, the robot returns to the starting point as the final destination along the path 6 and 7. At this time, the power of blow

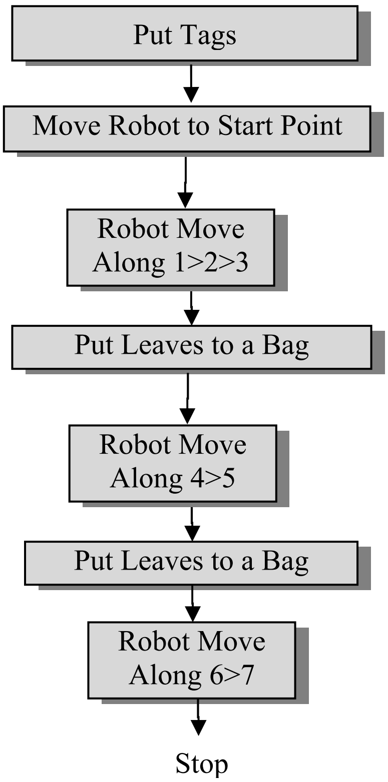


FIGURE 5. The robot control flow algorithm with UWB modules.

machine is turned off, and this AI leaf detector is idle. It is worthy notice that if the robot is not within the three reference points, its position detection would happen significant deviation

A leaf blower machine was attached onto the robot. Its power switch is controlled by a controller. The computer vision method was used to detect whether the leaves are on the ground. If the leaves are on the ground, the power is turned on to perform the leaf-blowing work. However, the power is turned off to save the battery energy instead if the leaves are not on the ground. The robot is navigated with three WUB tags, which follows the moving schedule. Once the leaves are detected, they would be cleared and removed by a leaf blower machine. Finally, the leaves would be collected by bags.

To drive the robot, two-power wheels controlled by two motor were put on the front. The Li-battery module is 14.8V, which was regulated by a power conversion to 12V. The DC 12V motor was used for our robot. In order to reduce the rotating angle, the robot with all-direction tires were designed to be driven with a DC motor controlled by pulse width modulation(PWM) method. The PWM duty can be used to control the moving speed and the moving direction. If there are no leaves found on the road, the robot moves forward quickly to save the clearing time. Once, the leaves are detected, the moving speed becomes very slow until the fallen leaves are cleared and removed from the ground.

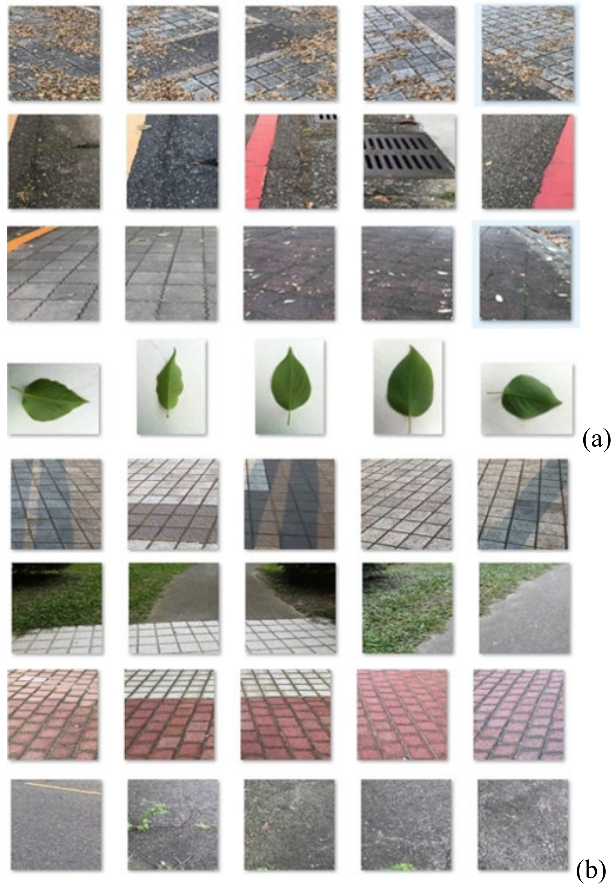


FIGURE 6. Dataset collection for training (a) leaf and leaves on the ground, (b) no leaves road including grasses. (c) training curve.

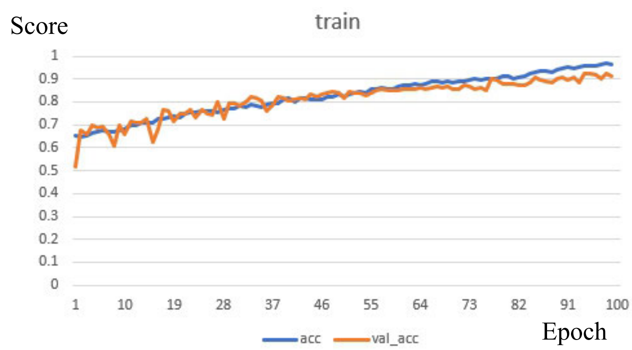
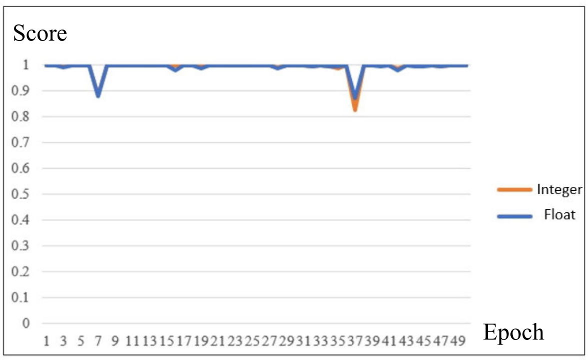


FIGURE 7. The training curve and its valid.

III. DEEP LEARNING FOR LEAF RECOGNITION

The CNN model with ResNet50 is employed to train the leaf [12] for computer vision. We collect the single leaf and leaves images about 2k, which is labeled as a "leaf. A partial collection of our dataset was composed of our samples, and a partial collection of our dataset was taken from the existing leaf dataset [13]. The partial leaves images are shown in Fig. 6(a). Also, the road without leaf is sampled with the similar quantity. The partial images are as shown in Fig. 6(b), which is labeled as "no leaf". These datasets are trained with CNN model to recognize the leaf or non-leaf. The training rate is 0.01 using a GPU card 2070, the time of Epoch/Batch is 66ms on Tensorflow training tool. In order to perform on an edge device with an embedded system, the training weights are quantized to full integer. The weight is scaled from -128 to127 with 8-bit resolution. The training curve is shown in Fig. 7. To verify this CNN model, the 1373 images are employed. The floating weight achieved an accuracy of 92.3%. After quantization, this also achieved a recognition rate of 92%. After training, the leaf and non-leaf images are employed to test the accuracy. The testing images all are non-trained. Figure 8 (a) shows the testing score of 50 leaf images, where the score is 0.85 to 1 when the weights used float number. As the weights are truncated to integer, the score is little reduced to 0.82 to 1. Figure 8(b) shows the real leaves images and its score. Similarly, the non-leaves images are tested, and the results are shown in Fig. 9(a) and (b) for the curve of score and the real non-leaf image respectively. Results show that their computing score of CNN can achieve 0.83 to 1 with float weights, and 0.81 to 1 with integer weights. These results have enough accuracy to detect the leaves on the ground. The AI-detected results demonstrate the successful implementation of the system to detect leaves and trigger the blow machine for automated leaf clearance. However, to further enhance the accuracy and robustness of the system, increasing the number of training data is suggested. By including more diverse and representative samples in the training dataset, the CNN model can learn more patterns and variations, leading to better generalization and performance in real-world scenarios.

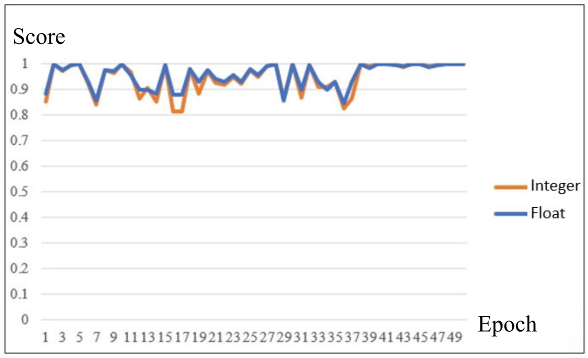


(a)

leaf	1.00	1.00	1.00	0.85	1.00
nonleaf	0.00	0.00	0.00	0.15	0.00
leaf	0.99	1.00	1.00	1.00	1.00
nonleaf	0.01	0.00	0.00	0.00	0.00

(b)

FIGURE 8. The test results with leaf images, (a) the score with 50 leaf images, (b)the partial images.



(a)

leaf	0.00	0.00	0.00	0.01	0.00
nonleaf	1.00	1.00	1.00	0.99	1.00
leaf	0.01	0.01	0.04	0.00	0.00
nonleaf	0.99	0.99	0.96	1.00	1.00

(b)

FIGURE 9. The test results with non-leaf images, (a) the score with 50 leaf images, (b)the partial images.

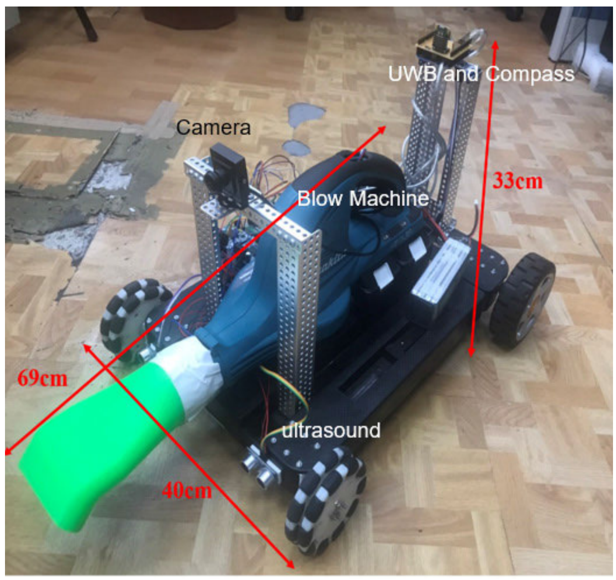


FIGURE 10. Implementation of a leaf blow robot.

IV. REAL-TIME EXPERIMENTS

In realize the automatic leaf-blow system, the mechanism of this robot is implemented, as demonstrated in Fig.10. The machine size is 69cmx40cmx33cm with four wheels driving. According to the blow machine structure, the mouth of the special blower was designed with a 3D printer to match a blow machine on the robot to clear the ground. The two sides of the front were built with two ultrasound modules. The purpose of doing so was to check whether the right or left was blocked by obstacles. Simply stated, if so, the robot can turn right or left or move back to better avoid the collision with the obstacles. The camera is located on the top of blow machine, which plays a computer vision with AI model. The UWB and compass modules are risen about 33cm, to increase the detection accuracy. The embedded system with Pi 4 version and 3D accelerator is built in inside of robot. The modules designed with a compass and a 3D accelerator [14], [15] can be effectively used to detect whether the mouth of the current blower is on the front. If no, the robot must turn 180^0 so as further, to make the robot moves for the forward direction.

The controller is realized with Pi embedded system running on a Linux operating system. The control software is implemented with C programming. In order to fasten the recognition speed. The USB-based AI accelerator with TPU is inserted to the embedded system. The controller determines the robot moving direction according to the results of sensors and AI leaf recognition. The processing frame rate for leaf recognition kernel can achieve 20 fps (frame per second), which can meet the real-time requirement.

Next, we tested the localized accuracy with WUB module according to the equations (1)-(9). The test plane used the rectangle region of 400∗800cm with three tags. Each step size is 48cm, to measure the coordinate of testing point. The measured results are shown in Fig.11. Most of the testing points can be located near to the (x,y) cross coordinate. The result show that the distance error is from 0 to 9.6 cm, which can be effectively employed for the robot navigation with this localized system.

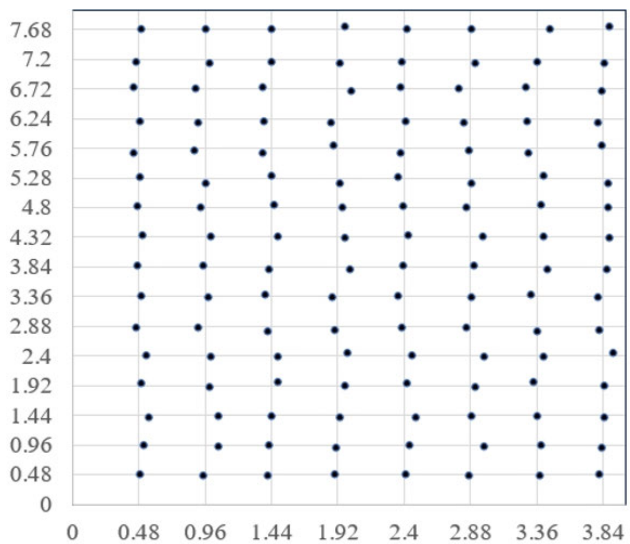


FIGURE 11. **The testing accuracy of locator with WUB module.**

To consider real-life situations, this machine was tested on the road practical. First, three tags were put on the rectangle size with about 10mx5m on the road. An APP program was developed with Java programming and installed onto the cell phone. This was to remote control the robot with a manual mode or an auto mode through the blue tooth network. First,

FIGURE 12. **The real test on the road (a) on the path 1, (b) on the path 5, (c) collect leaves into a bag.**

the robot should start to move from the starting point by the manual mode operation. Then, the user should send an automatic command to the robot. So, the robot can perform the leaf-blowing task following the pre-scheduled path as planned. This path is depicted g in Fig. 4, where the sweeping angle of this leaf blower machine is -45^0 to $+45^0$ to possibly clear leaves. Fig. 12 (a) shows the machine is tested on the path 1, which runs on the middle of road. Fig. 12 (b) shows the robot on the path 5 on the right side of road. Fig.12(c) shows the practical result of leaves collected by this machine. The real-time video is demonstrated on the Web. [16]. If there are paper and plastic rubbish on the road, the robot cannot recognize them without prior training on such data. Consequently, the robot refrains from activating the blow machine for rubbish since it cannot accurately identify the materials

The associative memory associated with the memristor-based neural network circuits have been developed in recent years [19], [20]. This kind of system can be possibly employed in robot platforms. This network can better realize human-like perceptions and associative cognitive functions so as further to control the robot moving by a remote device in the future.

V. CONCLUSION

In this article, the intelligent robot was designed and based on the AI-based computer vision to blow leaves automatically. The multi-sensors were embedded to this system to guide the robot to move to the correct position according to the path pre-scheduled. The UWB RF modules were used as the locator to navigate the robot with three tags. The leaf was recognized with ResNet model, which can achieve high accuracy to judge whether the leaves are on the road. The physical robot with a leaf blower machine carried was successfully implemented. The available experiments results indicate that this robot can perform successfully to clear fallen leaves, following the scheduled path, and the fallen leaves finally could be collected to the garbage bag automatically.

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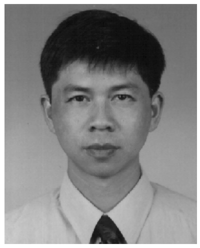

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