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Identification of Fruit Tree Pests With Deep Learning on Embedded Drone to Achieve Accurate Pesticide Spraying

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ABSTRACT *Tessaratoma papillosa* (Drury) first invaded Taiwan in 2009. Every year, *T. papillosa* causes severe damage to the longan crops. Novel applications for edge intelligence are applied in this study to establish an intelligent pest recognition system to manage this pest problem. We used a detecting drone to photograph the pest and employed a Tiny-YOLOv3 neural network model built on an embedded system NVIDIA Jetson TX2 to recognize *T. papillosa* in the orchard to determine the position of the pests in real-time. The pests' positions are then used to plan the optimal pesticide spraying route for the agricultural drone. Apart from planning the optimized spraying of pesticide for the spraying drone, the TX2 embedded platform also transmits the position and generation of pests to the cloud to record and analyze the growth of longan with a computer or mobile device. This study enables farmers to understand the pest distribution and take appropriate precautions in real-time. The agricultural drone sprays pesticides only where needed, which reduces pesticide use, decreases damage to the environment, and increases crop yield.

INDEX TERMS Edge intelligence, unmanned aerial vehicles (UAV), real-time embedded systems, slope land orchard, object detection, agricultural pests damage, precision agriculture, intelligent pest recognition.

I. INTRODUCTION

Since *T. papillosa* invaded Kaohsiung, Taiwan in 2009, it has spread quickly throughout Taiwan and severely endangered the crops of the Sapindus family, such as *Dimocarpus longan*, *Litchi chinensis*, *Sapindus saponaria*, and *Koelreuteria elegans*. *T. papillosa* feeds on litchi and longan with piercing-sucking mouthparts, which suck the buds, shoots, flower spikes and young fruits of these crops, resulting in blossom drop, fruit drop, twigs, young fruit withering, skin blackening, and other injuries. Consequently, the damage from *T. papillosa* seriously affects the yield and quality of litchi and longan.

Taiwan is in a subtropical region with a mostly warm climate suitable for crop cultivation throughout the entire year. Many agricultural products are exported worldwide annually. However, rapidly spreading diseases and pests cause crop damage and affect farmers' incomes. During the crop growth period, to prevent pest infestations, farmers apply large dosages of chemical pesticides to reduce crop damage from diseases and pests, even though the excessive pesticide use harms the environment. It is usually all-consuming for the workforce to kill insects and spray pesticides on the entire field. If pests and diseases can be detected quickly and early before they spread, UAVs can apply pesticides only where needed to reduce crop damage and minimize harm to the overall environment. Therefore, we hope that this research can help farmers reduce the cost of pesticides and increase human resource efficiency.

The UAVs have high maneuverability and are often equipped with the Global Positioning System (GPS), automatic flight control, real-time image transmission, wireless communication systems, multiple sensors, and other functional components. They can obtain extremely

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high-resolution surficial information, making it easier to collect and investigate spatial data, while greatly accelerating the acquisition of spatial information. They can also conduct routine patrols and keep track of abnormal conditions.

In recent years, the development of drones in smart agriculture has become increasingly prevalent. In spring 2019, the onset of the rainy season caused severe flooding in many places in Taiwan. Drones capable of aerial photography were used to document damage to rice paddies. Through analysis of the aerial images, the lodging degree, the distribution and the area of rice were effectively determined, thus significantly improving the efficiency of disaster investigations.

In recent years, the development of drones in smart agriculture has become increasingly prevalent and very suitable for applying edge intelligence to agriculture. In spring 2019, the onset of the rainy season caused severe flooding in many places in Taiwan. Drones capable of aerial photography were used to document damage to rice paddies. Through analysis of the aerial images, the lodging degree, the distribution and the area of rice were effectively determined, thus significantly improving the efficiency of disaster investigations.

Around the world, German drone companies have used insecticidal drones to drop *Trichogramma*, a natural enemy of the European Corn Borer, into cornfields to control these pests. The industrial drones are equipped with high-resolution sensor arrays that perform a variety of applications and they are robust enough for outdoor operations around the clock.

In this study, we used two types of drones: a small reconnaissance drone and a large pesticide-spraying drone. The small size of the reconnaissance drone helps to avoid leaf disturbance. It is used for treetop inspections to take images of *T. papillosa*, which are then transmitted to the edge server to determine the pest's life stage and location. The edge computing server is used to plan the optimal pesticide application route. The pesticide-spraying drone then sprays the precise pesticide application based on the route.

The remaining sections of this article are arranged as follows. Section 2 introduces relevant references and inspiring applications that are used in this work. Section 3 presents the data set, the hardware environment and the implementation methods. Section 4 describes the architectural framework of the study and illustrates the customizations performed for small object detection. Section 5 describes and discusses the experimental results before providing a conclusion.

II. RELATED WORK

A. APPLYING DEEP LEARNING TO AGRICULTURAL INSPECTION

The growing popularity of artificial intelligence applications in various industries has promoted the application of deep learning in many fields. Among these applications, image recognition technologies have been widely used in agricultural applications, such as farmland mapping, crop image segmentation and target detection of pasture animals. Image recognition is mainly used in training neural network models to identify categories and to use convolutional neural networks (CNN) to extract target areas in images, segment objects and determine the numbers and types of pests on the leaves.

Yang *et al.* [1] have proposed a litchi picking robot which is an important tool for improving the automation of litchi harvesting, with a binocular camera to collect the litchi images. They have also improved the YOLOv3 network in the YOLO (You only look once) series; YOLOv3 is currently the most widely used technology for object detection. They designed the YOLOv3-DenseNet34 litchi detection network. The Results have shown that the YOLOv3-DenseNet34 has enhanced the detection accuracy and speed. Based on the triangulation principle of binocular stereo vision, the average precision (mAP) of the litchi's coordinates was calculated.

The binocular stereo vision-based litchi pre-positioning method has a maximum absolute error of 3.66cm, an average absolute error of 2.30cm and an average relative error of 0.836% at a detection distance of 3m, which fulfills the requirement of the picking robot. In a large area, the visual pre-targeting requirements of the YOLO network perform regression directly without RPN to detect targets in the image. Hence, the method is fast and can be implemented for real-time applications.

The latest version (YOLOv3) [2] not only has higher detection accuracy and speed but also performs well in the detection of small targets. However, the YOLOv3 model has a more complex architecture which requires more processing, rendering it less suitable for real-time applications such as the harvesting robots. Conversely, the layer optimization and parameter reduction in the Tiny-YOLOv3 [3] model reduces the computational complexity, making it suitable to incorporate the edge devices, Jetson and Raspberry Pi, applying the object detection model for edge intelligence with real-time pest identification.

With the rapid development of deep learning methods, the neural networks constructed with these methods require significant Graphics Processing Unit (GPU) performance. The GPU is a processor that is specially designed to handle intensive graphics rendering tasks. The deep learning model has recently been improved so that a lightweight model can be implemented on the embedded platform for real-time operation. We compared the most commonly used YOLOv3 and the Tiny-YOLOv3 network models for object detection, analyzing the recognition accuracy and speed of these two methods to balance the recognition accuracy and speed in deep learning.

B. APPLICATION OF EMBEDDED SYSTEMS TO DEEP LEARNING

Jetson is a potent GPU embedded platform for computing mass data. Deep learning computations can be performed on the GPU, and the CPU can compute the benchmarking algorithms. Hulens *et al.* [4] have presented a survey of different embedded processing platforms, regarding their computing abilities and the influence on the system's battery life. The results have shown that the CPU performance of Jetson TK1 (the predecessor of Jetson TX2) is lower than the average of the same rank of embedded systems.

There are two ways to configure the devices for mobile edge computing and the internet of Things (IoT) on the Jetson TX2; one is to compress the training model for deep learning and the other is to train a relatively smaller model. Examples of model compression include the optimization of convolution or operations [5], the quantization of the parameters [6], [7], and the simplification of the model structure [8]–[11]. These approaches assume that a pre-trained model already exists and compressing it would speed up the operation without significantly affecting the accuracy. However, most of these well-trained models tend to be used for general-purpose applications. For example, the AlexNet [12], [13] can accurately classify the 1000 classes in ImageNet, which is approximately a 37.5% top-1 error rate.

To perform the UAV's object detection and positioning, we need to classify the different instars of *T. papillosa*. Although the pre-trained model could be used as a feature extractor, the resultant model would overload the embedded devices even through fine-tuning and increase the operational costs. This work proposes a method to reduce the input images' recognition rate and increase the model's convolutional layers to resolve the issues with the embedded devices.

C. THE ROUTE PLANNING FOR THE AGRICULTURE DRONE FOR SPRAYING PESTICIDE

Distance is an essential factor in our route-planning algorithm for the pesticide-spraying drones, since accurately-determined GPS coordinates of the detected pests are required to reduce both the flight distance over the 3D-sloped terrain and the energy requirements of the drones. Saxena *et al.* [14] have published a novel approach to construct a 3D depth model from a single image. Chahal *et al.* [15] have proposed combining machine learning techniques to generate a depth image from a single image. However, the depth image can only indicate whether object A is closer to or farther from the camera than object B. The distance from A to the camera cannot be calculated from the depth image alone.

To overcome these difficulties, we have navigated the drones close to the pests' locations to improve positioning accuracy and reduce measurement errors. We have used triangulation methods to identify similarities for image depth measurement and calibrated the optical sensors according to the distance and scale of a known object. The in-depth image generates a reference point between the object and the camera. The following formula describes the method:

$$F = \frac{P \cdot d}{w} \tag{1}$$

Equation (1) yields the focal length of the system, which is used to calculate the distance of a detected object, where F is the focal length of the camera, P is the resolution (in pixels) of the object, d is the distance from the camera to the object and w is the width of the object.

D. APPLYING EDGE COMPUTING TO DEEP LEARNING

The image recognition in deep learning focuses on the efficiency of real-time recognition and timely data acquisition mechanisms to support delay sensitive. Edge intelligence processing which is dependent on the hardware performance, the ability for a quick response, and the availability of ample storage capacity. Past pest recognition methods used embedded devices to acquire images upon pest detection and transmit the acquired images to the cloud, where the deep learning architecture was deployed to recognize the pests. The recognition results were then returned to the embedded device. This study overcomes these problems by incorporating edge computing with the GPU of the embedded hardware, which has low power consumption, high performance and quick transmission time, to provide highly accurate and real-time recognition of *T. papillosa*.

NVIDIA's Jetson is a well-known embedded hardware with small size, light weight, and low power consumption. It is a widely-used accelerator for machine learning algorithms to speed up complex machine learning computations [17], [18]. However, to fully utilize the Jetson's performance in real-time, it is necessary to optimize both the Jetson hardware and the Neural Network (NN) algorithms.

In recent years, Jetson has developed the TK1, TX1 and TX2 versions. They all use YOLOv3 for target detection [19], [20], indicating that the YOLO and SSD have better accuracy and transmission speed. Among the different versions, Nvidia TX1 has been applied to tennis ball collecting robots using deep learning [21]. TX2 is an embedded device suitable for deep learning training. Luo *et al.* [22] have used the Kinect-V2 vision sensors to detect and locate targets using robots with Tiny-YOLOv3 on the TX2. The Cascaded-CNN (C-CNN) model has been implemented with the TX2 and applied to the classification of weeds in multi-spectral images in intelligent agriculture. These studies [23]–[26] have shown that the embedded hardware of the Jetson series is effective in target detection and has the advantages of having high efficiency and low power consumption.

III. METHODOLOGY

T. papillosa has one generation per year. The life cycle includes three stages: eggs, nymphs, and adults. The mating season is from February to August. Peak egg-laying by females is from April to May. Nymphs emerge from April to October; the insect overwinters in the adult stage, and the overwintering adults appear in January to August the following year.

In this study, a detecting drone is used for real-time photography of *T. papillosa* in the orchard before spraying pesticides from an agricultural drone. The pest images captured by the detecting drone are sent to the orchard's TX2 embedded system via the network. The TX2 recognizes the *T. papillosa* life stages and locations in real-time. It considers each tree's height on the slope and the pest's position, to calculate the 3D flight path for the agricultural drone. The flight sequence and the optimal path's total

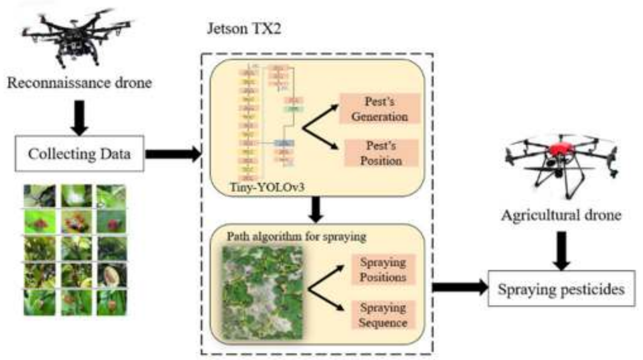

FIGURE 1. **The system architecture flow chart.**

distance are transmitted to the agricultural drone for spraying pesticides.

This study aims that the agricultural drone applies pesticides only where needed and apply novel applications for edge intelligence to agricultural control. The pesticides can be applied in a timely fashion, effectively preventing pest dispersion, reducing pesticide use and minimizing damage to the environment. Fig. 1 shows a flowchart of the system's architecture.

A. YOLOv3 MODEL AND TINY-YOLOv3 MODEL RECOGNIZE TESSARATOMA PAPILLOSA

The purpose of this study is to provide immediate feedback when the drone performs pest identification in the orchard. However, *T. papillosa* is physically very small and the drones need to be capable of detecting small targets with high recognition accuracy. To fulfill these requirements, a lightweight and fast artificial intelligence model is essential. Therefore, the YOLOv3 [2] model and Tiny-YOLOv3 [3] model have been selected as the identification models for this study.

1) SAMPLE COLLECTION AND LABEL

Deep learning models need to have sufficient training samples to avoid overfitting the training data and negatively affecting the recognition rate of *T. papillosa*. We collected images of *T. papillosa* at different instars and different angles (such as side view, front view, etc.), as well as from the orchard and the Internet to increase the number of training samples for the YOLOv3 model and Tiny-YOLOv3 model (as shown in Fig. 2).

We collected about 700 images of different stages and instars of *T. papillosa* from the Internet and the orchards. We used the image expansion method to expand the data of these 700 images to more than 5000 as training samples. An additional 473 untrained images were used as test samples.

The samples are manually labeled for the training of the YOLOv3 and Tiny-YOLOv3 models to avoid negatively affecting these models' recognition of *T. papillosa*. Before training the YOLOv3 and Tiny-YOLOv3 models, it is necessary to label *T. papillosa* within each image. We used the tool LabelImg to label the collected sample images to establish the

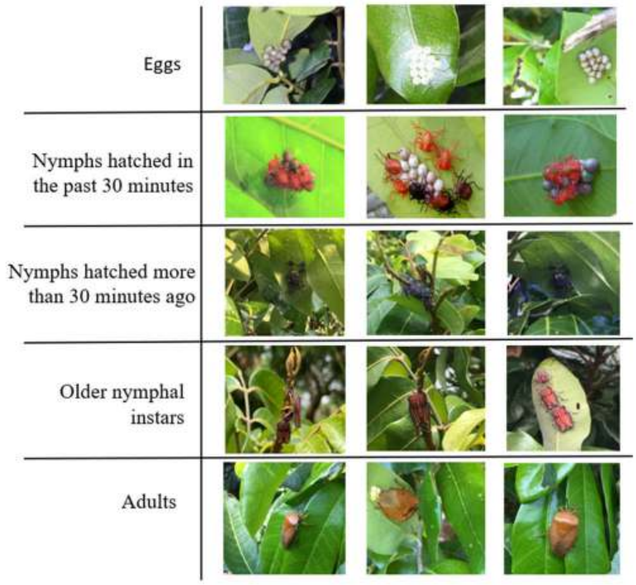

FIGURE 2. **The different life stages and instars of *T. papillosa*.**

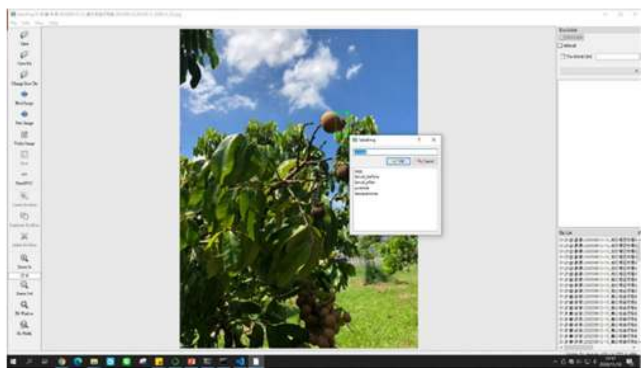

FIGURE 3. **The interface of Labelimg for target pixel information of label image.**

target pixel information (as shown in Fig. 3). The information is tagged to the images containing the eggs, nymphs or adults, and this is stored in XML format.

2) DATA AUGMENTATION

Many studies [27] have found that data augmentation can increase the accuracy of model recognition. Therefore, we have collected many samples in this work. After labeling the images, we used an Imgaug library for image augmentation in the machine learning experiments for data augmentation. The operations performed to augment the images include cutting, rotating, contrast enhancement, noise addition, edge sharpening and so on. The corresponding label information is automatically generated to increase the amount of training data and improve the recognition by the YOLOv3 and the Tiny-YOLOv3 models.

We refer to the reference [28] to perform image augmentation with fewer data samples.

The study created five categories of life stages and instars of *T. papillosa* (Figure 2). However, the number of samples of the two categories of eggs and nymphs hatched in the past 30 mins was only about 50-80, far less than the

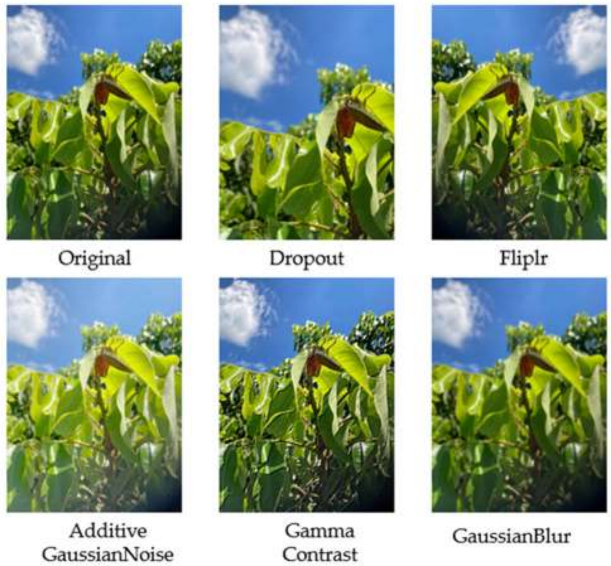

FIGURE 4. Examples of augmented images.

other categories – nymphs hatched more than 30 mins ago, older nymphal instars, and adults – which had more than 200 samples each. To improve the accuracy of YOLOV3 and Tiny-YoLov3 models in identifying the five categories of stages and instars of *T. papillosa*, the images of eggs and nymphs hatched in the past 30 mins were increased by the image augmentation method [28] to make them equivalent in number to the other three categories. Then we used the sample compensation method to reach a total number of training samples of about 5000 images, which included all five categories. Finally, we used the YOLOv3 and Tiny-YoLov3 models, training the samples to recognize the different categories of *T. papillosa*.

The research results show that the average number of training sets for each recognition category will improve recognition accuracy.

Imgaug is a Python library. It calls upon Python to perform data augmentation, process the sample images, and revise the label information. The Imgaug library has a total of 98 image augmentation functions. In this study, we have used the dropout, rotation, fliplr, edge sharpening, gamma contrast, additive Gaussian noise, and Gaussian blur (as shown in Fig. 4) functions to augment the training samples for both the YOLOv3 and the Tiny-YOLOv3 models.

3) TRAINING YOLOV3 MODEL

The YOLO (You only look once) series are neural network algorithms for object detection. They are implemented in the Darknet architecture. Although the author, Joseph Redmon, has not used any famous deep learning framework, the algorithms' highly effective object detection models are extremely suitable for industrial applications, such as pedestrian detection, industrial image detection and so on. The basic idea of the YOLO algorithm is as follows. First, use the feature extraction network to extract features from the input image to obtain a feature map of a certain size, such as 13 by 13, and divide the input image into 13 * 13 grid cells. The grid cell is used to predict the object's coordinates. YOLOv3 uses multiple scales to make predictions. It uses the upsample and fusion methods similar to the FPN (where the last three scales are fused, and the other two scales are 26 * 26 and 52 * 52, respectively). Detection performed on the feature map obtains a high recognition rate for small targets, which is suitable for the detection of *T. papillosa* and the recognition of small objects of small insects of different stages from the images taken by the drone.

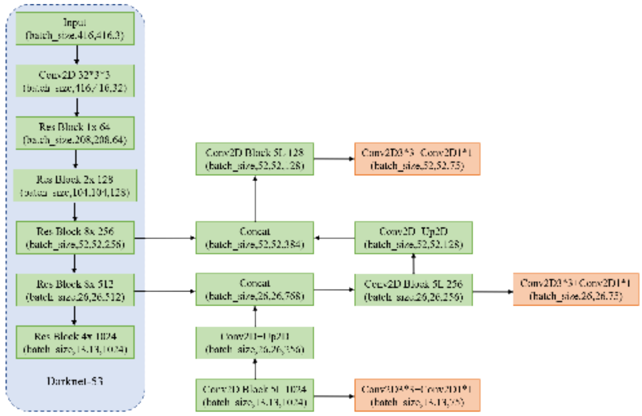

FIGURE 5. YOLOv3 Architecture diagram [2].

The darknet-53 network structure is based on full convolution and introduces the residual structure at the same time. Many layered models have descending gradients during the training and Darknet-19 has 19 convolutional layers. ResNet's residual structure reduces the difficulty in the training of deep networks and Darknet-53's 53-layer network can significantly improve the accuracy. When deeper networks are required for convergence, they may degrade the coverage as the network layers become deeper and more complicated, and the accuracy also suffers. The ResNet is implemented to avoid the network performance degradation caused by the deepening of the network. We used the YOLOv3 network architecture [2] for training and recognition, as shown in Fig. 5.

4) TRAINING TINY-YOLOV3 MODEL

Although many trained Tiny-YOLOv3 models are available on the Internet, the models are not trained to recognize *T. papillosa*. Therefore, we have redesigned the Tiny-YOLOv3 model and readjusted the parameters of the model during training to set *T. papillosa* as the recognition target. The hardware equipment used in this work includes a GIGABYTE Z370M motherboard, an Intel i7-8700 3.2GHz CPU, a NVIDIA GeForce RTX 2070-8G GPU with 16G DDR4-2666 internal memory, and the Docker container environment, which is established on Ubuntu. TensorFlow (with CUDA support) is used in the container to train the Tiny-YOLOv3 model. The Docker container is a typical virtual machine. It utilizes a virtualization technology and does not require a separate operating system to execute programs. The programs and operating systems can be executed without

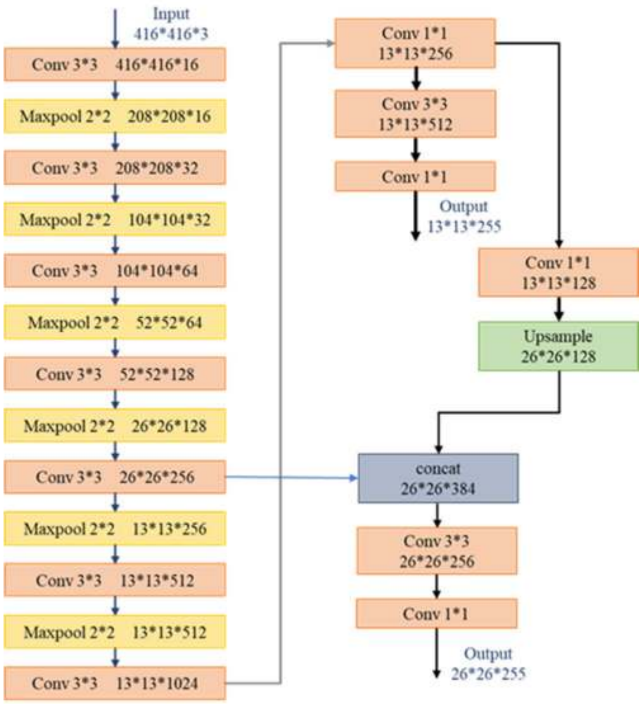

FIGURE 6. Tiny-YOLOv3 Architecture diagram [3].

affecting each other when the device is running. Docker containers can be used to avoid damage to the core of the operating system due to manual errors during experiments and can be quickly used to establish the environment required for testing on different operating systems.

In this work, we utilized the Tiny-YOLOv3 network architecture for training and recognition, as shown in Fig. 6.

B. THE POSITIONING OF AERIAL IMAGES

We have stitched multiple aerial images into a large aerial view as an informative map for positioning. The error of the coordinates will be calculated when the drone detects *T. papillosa*. We used the ground features' relative coordinates to stitch the image and utilized the ground control points to correct the absolute coordinates of all the surveyed areas. In this work, the orchard's Digital Surface Model (DSM) data (as shown in Fig. 7) and aerial images acquired by the drone are used to calculate the absolute coordinates of *T. papillosa's* locations, to plan the agricultural spray paths.

Fig. 7 shows the UAV hovering over the orchard. From the figure, we can see that there is a difference in the height of the trees. The pests to be detected are not directly underneath the UAV and need to be located using the proposed methods. Fig. 8 shows the 3D model reconstructed from the aerial images acquired by the UAV. The model is used later to determine the absolute coordinates of *T. papillosa.*

C. ROUTE PLANNING OF AGRICULTURE DRONE FOR SPRAYING PESTICIDES

T. papillosa is currently the most important pest in the longan industry. Since most of the longan trees are planted on hillsides and hilltops, these trees are difficult to prune, so they can

FIGURE 7. DSM data with a resolution of 1.42cm/pixel generated from the aerial images acquired by the UAV.

FIGURE 8. UAV hovering over the orchard.

grow to more than 13 meters in height. As a result, farmers have to spray pesticides by hand to control pests and diseases. With the aging of the rural workforce and shortage of farmers, the number of abandoned longan orchards increases. Therefore, if drones are used to detect where *T. papillosa* occurs and agricultural drones are then employed to spray pesticides to prevent and control *T. papillosa* infestations, the aforementioned problems could be alleviated.

In this work, it is proposed that the drone plans the pesticide spraying route on the slopes after identifying the pests in the orchards. The planning involves three steps: 1. defining the target area, 2. setting the takeoff and landing points, and 3. optimizing the route.

1) Defining the target area: The locations of the pests identified by the drone and the effective spray radius of the agricultural spraying drone are used to plan a complete route. The target area is then divided based on the time required by each pesticide spraying drone.
2) Setting the takeoff and landing points: After the target area has been set, the takeoff and landing positions in the orchard are determined to estimate the UAV's flight time, which includes the takeoff and landing positions in the planned route.
3) Optimize the route: An ant algorithm is used to accommodate the UAV's limited range when optimizing the pesticide spraying route.

We recognize the pests' locations through the reconnaissance aircraft, in which the positions are recorded to plan the shortest path. Figure 9 shows the area that needs to be

FIGURE 9. Locations where pesticide treatments are needed. The yellow-dashed circles represent the agricultural drone's range for spraying pesticides; the red stars are the positioning points for calibration before each drone flight.

sprayed with pesticides based on a radius of 5 meters from the pests' location, as indicated by the yellow dotted circles. The positions and sequence of where pesticide sprays are needed are transmitted to the flight controller of the plant protection machine. The red stars in Fig. 9 are used as coordinate points for positioning and calibration during each flight.

D. EMBEDDED PLATFORM

Since the Tiny-YOLOv3 model needs to be implemented with the CUDA kit, a GPU computing platform is required. However, the weight, size, and power of the current GPU embedded devices are limited. For example, the NVIDIA GTX 1080Ti has a TDP of 250W and 1.3TFLOPS. Although the GPU is able to perform the training smoothly in offline situations, it is not suitable for a drone due to the GPU's power requirements. We need to find a system with low power requirements, efficient processing and lightweight features to enable the drones to fly safely and take clear images of the pest locations in real-time. Equation (2) is used to determine whether the weight or power is suitable for the embedded platform on a UAV. In Equation (2), r is the radius of the drone propellers (meters), m is the weight of the aircraft (kilograms), P is the power (watts), g is the acceleration of gravity (9.80665 m/s^2), and K is the air density Q_{air}. K can be obtained from Equ2tion (3), where at 20°C and at pressure of Latham, í is 0.363562254.

$$P = K \cdot \frac{(m \cdot g)^{3/2}}{r} \tag{2}$$

$$K = \sqrt{\frac{1}{2\pi \cdot Q_{air}}} \tag{3}$$

A computing platform for embedded applications typically has a payload of less than 15W (for example, the Intel NUC board NUC5I3MYBE is 15W, and the Raspberry Pi 3 is about 6.7W). In this work, we consider embedded systems that are lightweight with multiple CUDA and low power consumption to assemble the embedded platform for the UAV. We have selected the NVIDIA Jetson Tx2 with a weight of 85 grams, 256 CUDA cores (1.5TFLOPS), 7.5W (peak efficiency) and 15W (peak performance) as the embedded system to be used on the drones for edge computing and the recognition of *T. papillosa*.

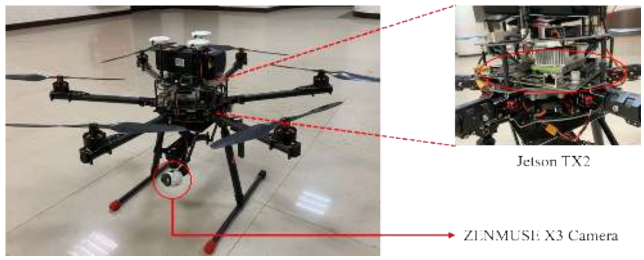

FIGURE 10. Self-assembled reconnaissance drone.

FIGURE 11. APD-616X Agricultural spray drone.

NVIDIA Jetson TX2 is an ARM-based, high-performance and energy-efficient embedded computing device, which is built around a NVIDIA Pascal^{TM}-family GPU and loaded with 8GB of memory and 59.7GB/s of memory bandwidth. It has dedicated units for accelerating neural network calculations for image processing and can be operated on Ubuntu 16.04 LTS [29]–[32]. We have installed the NVIDIA Jetson TX2 on a reconnaissance drone (shown in Fig. 10) and experimented on the longan trees on the slopes of Nanhua in Tainan, Taiwan.

The deep learning model of Tiny-YOLOv3 built on TX2 is used to perform *T. papillosa* recognition and locate the pest. TX2 will plan an optimized pesticide spraying path for the agricultural drone according to the pest position, while considering the tree heights on the sloping land. The optimized path is transmitted to the flight controller (Pixhawk 4) of the APD-616X agricultural spray drone through a wireless connection. We flew the entire path before spraying pesticides to verify the optimized path's correctness with a pesticide-spraying drone (as shown in Fig.11) under full water conditions.

E. CNN OPTIMIZATION ON THE EMBEDDED PLATFORM

1) REDUCING IMAGE RESOLUTION

A disparity map computes the horizontal displacement between each pair of corresponding pixels in two images. Wang *et al.* [33] have presented a technique for disparity estimation, which achieves a balance between accuracy and speed. The technique passes the input image pair through a feature extractor, which computes feature maps at different resolutions (for example, at scales of 1/16, 1/8 and 1/4).

Their technique improves accuracy through the following steps: using an image size of 1024*1024 pixels as an example, to ensure the image transmission speed, the first step uses 1/16 of the image size, that is, 64*64 pixels for feature recognition; the second step increases the image size to 128*128 pixels, to improve and correct the accuracy of the recognition from the first step; the third step is to increase the image size to 256*256 pixels and perform similar actions as the second step; and finally in step four, to use a spatial propagation model to simplify all used parameters obtained to reduce the storage space of the model, to achieve the effect of recognition in TX2 real-time. The detailed operational steps are as follows:

1) Compute the features at 1/16 of the original scale and generate a low-resolution disparity map from the disparity network. The first stage has low latency since low-resolution features are used.
2) If enough time is available, the technique enters step 2, where features at 1/8 of the original scale are obtained. In this step, only a correction of the map from step 1 is computed since these errors can be detected at a higher resolution.
3) If time is still available, step 3 is conducted, which is similar to step 2 except that the scale is 1/4, which doubles the resolution.
4) The map of step 3 is refined using a spatial propagation model. This technique reduces the number of parameters by several orders of magnitude and achieves a frame rate between 10 and 35 frames per second on TX2.

2) INCREASING THE NUMBER OF NEURAL NETWORK LAYERS

We have experimented on a computer with an Intel i7-6700K CPU and a NVIDIA GTX 1080Ti GPU (11.3TFLOPS). When processing a single video stream, the frame rate is 40FPS and the GPU load is about 42%. If two parallel video streams are processed at the same time, the frame rate exceeds 35FPS and the GPU load is about 65%. For successful pest recognition using the Tiny-YOLOv3 model on the drone, we have increased the number of layers in the Tiny-YOLOv3 model to reduce the number of parameters in each layer of convolution, however, the overall number of parameters is doubled and the memory required by CUDA is maintained at less than 11Gb.

IV. EXPERIMENTAL RESULTS

This section describes the process and results of the experiment. First, we have implemented different models of YOLOv3 and Tiny-YOLOv3 with the embedded computer Jetson TX2 to compare their speed and accuracy in the recognition of *T. papillosa*. Data augmentation is performed on the *T. papillosa* data sets and the parameters are adjusted to improve the models' learning rates. Finally, based on the pest recognition results from the TX2 embedded on the drone, the route for the pesticide-spraying drone is planned by the TX2 to compare the flight distances of the ant algorithm and the top-down sequential algorithm.

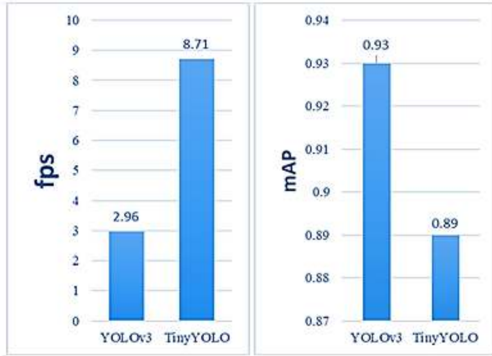

FIGURE 12. Comparison of YOLOv3 and Tiny-YOLOv3.

A. COMPARING THE PERFORMANCE OF YOLOv3 AND TINY-YOLOv3 MODELS

This experiment used TensorFlow as the environment for the TX2. The mean average precision (mAP) is calculated to evaluate the performance of the YOLOv3 and Tiny-YOLOv3 models from 473 images of *T. papillosa* taken by the drone with a resolution of 416*416 pixels. Fig. 11 shows the frames per second (FPS), and the mean average precision (mAP) of the YOLOv3 and Tiny-YOLOv3 models.

The results in Fig. 12 show the accuracy and performance of the YOLOv3 and Tiny-YOLOv3 models. The recognition speed of the Tiny-YOLOv3 model is more than three times faster than that of the YOLOv3 model. Therefore, this work uses the Tiny-YOLOv3 model based on the TX2 embedded device for the effective recognition of *T. papillosa* in the orchard.

The value of Intersection over Union (IoU) has a great influence on target detection. If the IoU value is too high, it will cause the test results to show that the marked ones are correct, but many correct ones will be lost and not marked. If the IoU value is too low, the test results will show that all correct and many incorrect ones will be marked. Based on the above reasons, in this study we experimented with the influence of the IoU value on the recognition of *T. papillosa*, as shown in Fig. 13-15, We used the 473 images as the test samples, and each image contains more than one *T. papillosa* individual. The Tiny-YOLOv3 model was trained with T. papillosa image samples to recognize the five categories of stages and instars. The red parts in Figures 13-15 are the numbers of target identification errors, and the green parts are the numbers of correct identifications.

In addition, the IoU settings also affect pest recognition accuracy in the images. If the IoU is set too high, the pest recognition accuracy is affected, resulting in lower accuracy. If the IoU is set too low, a pest may be labeled by many bounding boxes and the precision will be higher, but the recall rate will be low. Based on the experimental results in Fig. 15, IoU = 0.5% has been selected as the IoU for this work.

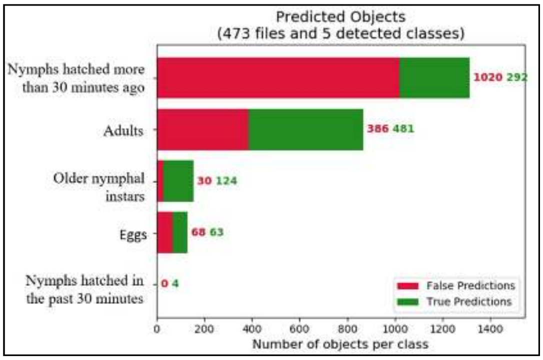

FIGURE 13. Predicted objects when IoU = 0.3%.

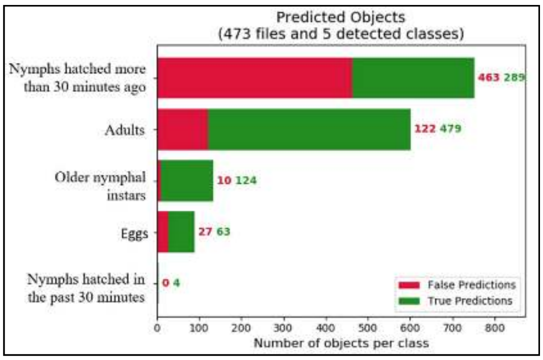

FIGURE 14. Predicted objects when IoU = 0.45%.

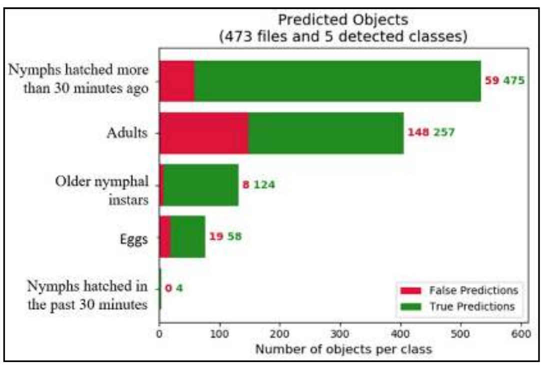

FIGURE 15. Predicted objects when IoU = 0.5%.

B. RESOLUTION AND RECOGNITION ACCURACY OF THE INPUT IMAGS

The input image resolution of the Tiny-YOLOv3 model is 416 * 416 pixels. To improve the pest recognition accuracy from the drone, we revised the resolution of the input image to 512 * 512 pixels and 640 * 640 pixels for the experiments. We have found that as the resolution increases, the frame rate (frames per second) decreases, but the accuracy of pest recognition increases. Fig. 16 shows the recognition results of different input image resolutions. Figs. 16 (a) and (c) have resolutions of 416 * 416 pixels, and the mAP for these figures are 50.12% and 38.12%, respectively. Figs. 16 (b) and (d) have resolutions of 640 * 640 pixels, and the mAP for these figures are 95.33% and 89.72%, respectively. These results show that when the image resolution is low, the identification

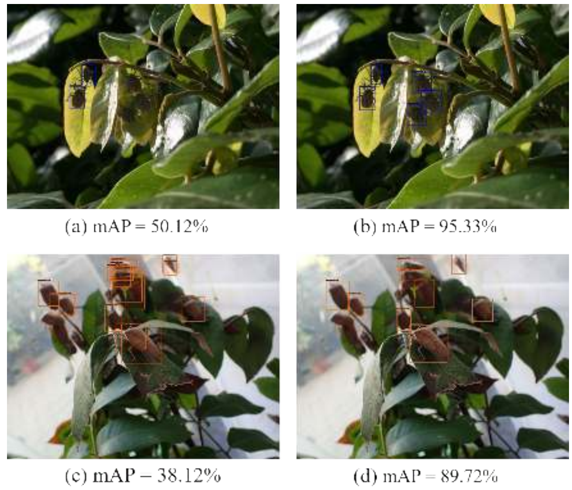

FIGURE 16. Comparison between different detectors.

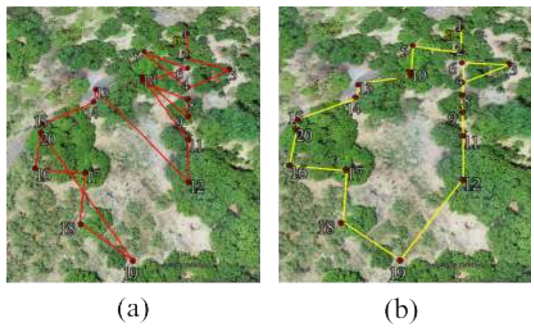

FIGURE 17. (a) The path planning from high to low based on the altitude. (b) The path planning based on the ant algorithm.

accuracy is also low, and the system is unable to distinguish between some pests and non-pests.

C. COMPARISON PATH ALGORITHMS

This study compares the route-optimizing method based on the identified pest positions to a traditional method, in which the entire orchard is sprayed. The route-optimizing method not only shortens flight time by 19% but also reduces pesticide use. In this study, we improved the ant algorithm by considering the earth's ellipse phenomenon, and used the Haversine formula, Equation (4) to calculate any two task points' distance in the ant algorithm. We compared two pesticide spraying routes for the drones; one route is performed by spraying from high to low based on altitude, as shown in Fig. 17 (a), and the other is the shortest distance based on the ant algorithm, as shown in Fig. 17 (b). Results show that for the agricultural drone to spray pesticides in a sloped area, the path based on the ant algorithm is shorter than the path based on high to low altitude.

$$hav\left(\frac{d}{r}\right)=hav\left(\varphi_2-\varphi_1\right)+\cos\left(\varphi_1\right)\cos\left(\varphi_2\right)hav\left(\lambda_2-\lambda_1\right) \tag{4}$$

We adopted the Deep Q-Learning algorithm (DQN) of enhanced learning to improve the optimization pesticide

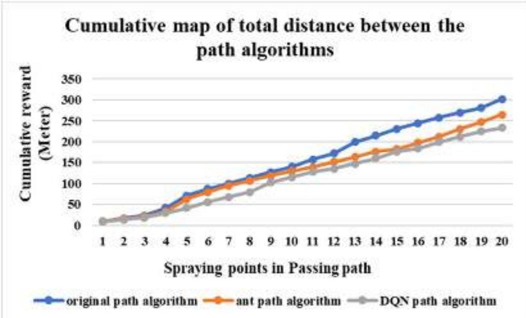

FIGURE 18. Comparison of accumulated flight distances between the original flight path and the ant algorithm, DQN path algorithm.

application route and set the environmental parameters through the edge computing server, including the orchard's terrain height and the pests' location. Then we used DQN to plan the optimal pesticide application route automatically. Figure 18 compared three path planning methods the DQN algorithm, the ant algorithm, and high to low based on the altitude. The figure showed that the DQN algorithm is better than the other two methods and the pesticide application route can be intelligently planned through the edge server. In the future, we will continue to research to consider more environmental variables to achieve an intelligent pesticide application route algorithm for pesticide-spraying drone tailored to local conditions.

D. RECOGNITION OF *T. PAPILLOSA* IN ORCHARDS BY DRONE

Fig. 19 shows the results of *T. papillosa* recognition in a longan orchard in Nanhua by a drone and TX2. When TX2 recognizes the pest, it records the life cycle stage and the position of the pest and plans the optimized route for the pesticide spraying drone. Figure 19 shows that the implemented system on the drone is able to recognize the different stages of *T. papillosa* even under different lighting and background conditions.

E. ASSESSING THE EFFECTIVENESS OF AGRICULTURAL SPRAY DRONES AGAINST *T. PAPILLOSA*

We overcame the difficulties with agricultural drones flying on sloped terrain by using a drone equipped with high-resolution optical cameras to take orthophotos, thereby creating 3D terrain data. We used the reconnaissance drone to photograph *T. papillosa*, and these data were provided to the TX2 embedded system that planned the optimal flight route based on the pests' positions and the variable heights of longan trees on slopes. In turn, all this information was provided to the agricultural drone spraying pesticides. The drone adjusted its flight height according to tree heights, as it followed the optimized path to precisely perform pesticide spraying.

Results show that use of the drone to prevent damage from *T. papillosa* can provide over 95% control of this pest *T. papillosa*, reduce water volume use by 12.5% for spraying pesticides, save more than 50% of farmers' labor, and reduce pesticide usage by 70%. Fig. 20 shows the variations in the numbers of *T. papillosa* in the sloping orchard of Nanhua,

FIGURE 19. Recognition results by the Tiny-YOLOv3 model in the TX2 for the images acquired by the drone's camera.

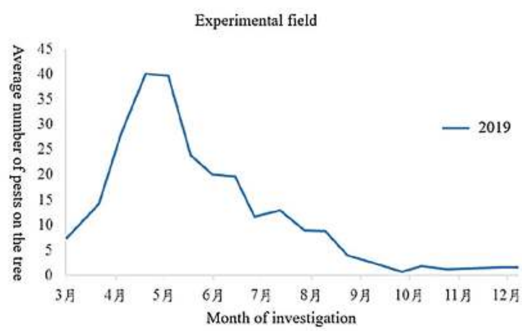

FIGURE 20. Variations in the numbers of *T. papillosa* in the experimental field.

Tainan, Taiwan, to confirm that this study is effective for controlling this pest *T. papillosa*.

V. CONCLUSION

This study uses edge intelligence applications to detect *T. papillosa* and plans routes for the pesticide spraying drone in real time. It shows that the combination of the drone with the TX2 is able to provide real-time pest detection in the orchard. The FPS and mAP values suitable for practical field applications are initialized on the embedded device TX2. Edge computing is performed with the Tiny-YOLOv3 to plan the optimized route to reduce pesticide use and provide the shortest flight route for the agricultural spraying drone. This work has proposed a feasible method for edge operations on embedded systems to recognize *T. papillosa* in real-time. We have found that the Tiny-YOLOv3 algorithm based on neural networks has excellent performance about the FPS and mAP. In this study, we have used input images of different sizes and IoU values to adjust the parameters of the Tiny-YOLOv3 model. We have also used the disparity map to optimize the image detection time by the TX2, resulting in increasing the frame rate and reducing the RAM requirement, and an overall improvement of the Tiny-YOLOv3 model's recognition performance.

Once the TX2 has identified the pests, it uses DQN path algorithm to plan an optimal route based on the pests' positions and tree heights. We compared two routes for the pesticide spraying drone. We have demonstrated that the planned path based on the ant algorithm is 19% shorter than the high to low path based on the altitude. Through this work, edge computing has been successfully applied to smart farming, and farmers can reduce pesticide use while effectively controlling pest dispersal. This research cooperates with the Tainan District Agricultural Research and Extension Station, Council of Agriculture (COA) of Taiwan government unit. Experts have determined that the research results used edge intelligence to automatic precision spraying.

This study uses the APD-616X agricultural spray drone, which can be sprayed pesticides for an area of 1000m2 when fully loaded about 25-35L. It reduces the consumption of water by 87.5% compared with the traditional manual spraying of pesticides. The pesticide-spraying drone takes an average spraying time of 5.3 minutes/1000m2. The manual pesticide sprayer is 11.4 minutes/1000m2. The pesticide-spraying drone's operating time is 53% less than the manual method. Besides, manual knapsack spraying requires two people operators to pull the tube and one to drive the sprayer, which differs from a pesticide-spraying drone that requires only one person to operate, pesticide-spraying drone reduces 50% of the workforce. The research that reduces workforce consumption, lower pesticide costs and decreased environmental damage has achieved precision agriculture.

In the future, we will use environmental sensors to analyze and predict whether climatic factors, such as temperature, humidity and light intensity, influence the occurrence of pests, and to help farmers take timely preventive actions.

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