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Original research article

Drone Approach for Remote Sensing The Intercrop On Durian Plantations Using YOLOv5 Model

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ABSTRACT

This paper proposes a potential solution for monitoring the durian plantations which apply intercropping by using drones equipped with RGB and spectral cameras. Currently, farmers mainly rely on their naked eyes to estimate whether a density of papayas around a durian tree is suitable. This eye estimation is time consuming and often not accurate enough, especially when trees reach the heights above the human head. To help the farmers, the proposed method used drones to create the ortho-mosaic map of the monitoring areas then YOLOv5 model is used to detect and locate durian and papaya trees. These results were used to evaluate the durian growth conditions. The trained model result showed a high accuracy at over 95% in detecting and locating trees which is reliable enough to apply to the practice. Furthermore, in the validating process, durian growth conditions also correctly evaluated and detected regions where density of papaya trees must be adjusted.

Keywords: Drones; Deep learning; Durian tree; Intercropping; Papaya; YoLov5

1. Introduction

Intercropping is defined as the agronomic practice of growing two or more crops on the same field at the same time. Farmers often use intercropping with perennial and short-term crops because it allows them to maximize land use efficiency by growing multiple crops in the same area. However, intercrops sometimes grow randomly and inconsistently. Farmers typically monitor their gardens manually and rely on experience, which is no longer suitable for relatively large garden area and reduced workloads nowadays. Therefore, a technical solution that allows farmers to have an overall view of their

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orchards, as well as the density of intercrops and giving recommendations, is necessary.

In the literature, it is often found that crops are selected so that they don't compete with others when utilizing the available resources for growth. Since different crops have different behaviors in regard to their responses to physical and environmental conditions, crops must be very carefully selected so they can be intercropped together [1, 2]. Based on growth characteristics and compatibility, intercropping can be divided into three classes: parallel cropping, companion cropping and multistoried cropping.

This study focuses on the application of multistoried cropping in Vietnam, especially in the Mekong Delta, where two selected crops are the durians and papayas.

Durian is a native fruit tree typical of the rainforests of Indonesia and Southeast Asia. Due to their flavors and nutrients, durians are currently in high demand in several Asian countries, and create high incomes for farmers. For adapting climate change as well as increasing the values of crops, under the instruction of local authorities in several regions in Vietnam, farmers have turned thousands of hectares of farmland into fruit orchards with a large part of them devoted to cultivating durians. One of the most noticeable challenges for farmers in switching to durian cultivation is that the process from planting the seedling to finally harvesting and reaping can take several years. It often takes 5 to 6 years from planting to the first harvesting in durians. Instead of waiting for the trees to finally bear fruits during the initial cultivation stage, it would be ideal to try their hands at intercropping. In the Mekong Delta, where this study is conducted, papaya is the most common choice of the famers. Consequently, this study focuses on monitoring the durian plantations using UAV where papaya is used for intercropping. During the durian growth process, the number of papaya trees around a durian tree must be carefully controlled and papaya crowns also require monitoring. These actions ensure that durians can fully develop and do not have to compete for light, water, and nutrients resources with papayas.

Currently in the Mekong Delta, monitoring the large durian plantations is still implemented manually which requires extensive labor and easily creates mistakes especially when papayas grow high. This manual implementation decreases the competitiveness of Vietnam durian due to labor costs increasing. Remote sensing, Internet of Things (IoT), drones, and artificial intelligence are promising solutions which can create a giant leap in how technologies can be implemented to alleviate farmers' workload [3, 4]. Of these approaches, the drone system has proved itself as a breakthrough technology with remarkable capability in modern agriculture [5]. The prominent advantages of drones in monitoring large areas, such as mobility, low-cost operation, and easy maintenance, are undeniable.

Although remote sensing is the most common drone application [6], its application in intercropping has been rarely reported in the literature [7]. Intercropping encounters more challenges than conventional planting classification tasks in remote sensing monitoring due to the complexities of spatial distributions. The first challenge comes from the spectral overlap of different crops at different growth stages. Under such conditions, distinguishing and locating different intercropping objects from a single image is a relatively difficult task. The second challenge derives from differences in the sizes and shapes of tree crowns. To overcome these challenges Culvenor [8] applied tree identification and delineation algorithms to delineate tree crowns from 0.8 m resolution imagery. Mayossa et al., [9] introduced a semi-automatic classification method based on a QuickBird texture analysis to differentiate coconut palms from oil palms in Melanesia. Other works include [10-13].

The fast development of deep learning techniques has created a giant leap in plant phenotyping research. With powerful tools derived from deep learning and machine learning, the actions of extracting and comparing information from plant phenotype data have become much more convenient. Some applications of deep learning in plant phenotyping research include object detection [14-16] and image segmentation [17-19]. These capabilities were shown in the work of [20] which aimed to count sugar beets, maize, and strawberry plants in the field automatically using fully convolutional networks. A U-Net network with Vgg16 were used as the backbone in the study of Yu et al., [21] to segment maize tassels. However, this model still encountered challenges in distinguishing individuals within the same category. Cauliflower and Arabidopsis leaves were two subjects to be detected in the work of [22]. The selected model used in the study is You Only Look Once (YOLO)v3 network. To detect the leaves of eggplants, tomatoes, purslane, and orchids in greenhouses, the CenterNet network was used in work of [23]. YOLOv5 was used to detect sweet potato leaves in the field [24]. It was also applied to detect and count soybean plant leaves and flowers based on the soybean phenotype perception method [14]. Later a corn leaf counting model which used the backbone of YOLOv5 was proposed by [25]. Two prominent advantages of YOLOv5 model when compared with other networks are the high detection accuracy and quick inference response [26, 27]. Furthermore, according to [28], YOLOv5 demonstrated superior performance in object detection compared to YOLOv7. Additionally, the authors of [29] indicated that while YOLOv8 may achieve a higher number of epochs than YOLOv5, it necessitated significantly more extensive hardware architecture utilization. Since this study aimed to serve farmers, whose investment budgets are limited, the authors decided to adopt YOLOv5 as the main approach.

It can be seen that a drone is an ideal choice to help farmers alleviate the monitoring workload in the large durian plantations which apply intercropping. Through saving labor costs, these plantations can gain more benefit and improve their product competitiveness worldwide. The rest of the study is organized as follows. Section two provides information about the device and data acquisition. Section three describes how the approach is implemented. These models will ease the hardship of monitoring large areas and free farmers from tedious work. Finally, the solutions are drawn in Section four.

2. Device and data acquisition

2.1 Observation area

The observed area in this study is a 4-year-old durian plantation with papaya intercropping. Data acquisition was conducted in August 2023. The observed area, designated by the yellow rectangle in Fig. 1, is located at latitude of 9’53’05.4 N and longitude of 105’49’01’E, in Dong Phuoc, Chau Thanh district, Hau Giang province.

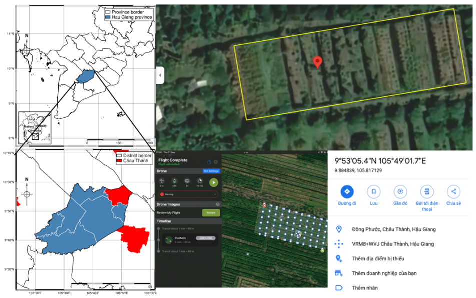


Fig. 1. Plantation’s top view and its coordinates.

2.2 Data acquisition

In this study, we use spectral images which are minimally affected by sunlight. Flight time was conducted between 9:00 AM and 11:00 AM, and from 2:00 PM to 3:30 PM. At that time, output images can avoid direct sun glittering from water surfaces. Additionally, flights should not be conducted before or after rainfall, as GPS signals can be loss unconditionally.

To obtain the remote images, a Phantom Pro 4 drone is adopted. This device has one RGB camera and one Sentera Double 4K multispectral camera. The RGB camera supports 3-axis (roll, pitch, yaw) rotations and can provide images whose resolution is 4800×3600. The multispectral camera can provide 4000×3000 resolution images (4000×3000 pixels). This camera can capture 5 narrow spectral bands including: Green, Blue, NIR, RED and Red-edge bands.

While the camera system is capable of capturing three distinct images, namely RGB, NDVI, and NDRE spectrum images, the quality of RGB images is significantly influenced by light reflection. Conversely, NDVI and NDRE spectral images are relatively unaffected by this issue. Moreover, since NDVI and NDRE spectral images share similar physical properties, this study predominantly utilizes NDVI images for analysis, reserving RGB images solely for observational purposes. Data are acquired through FieldAgent software. During the flight, both cameras was set vertically downwards. UAV are operated at velocity of 2.5 m/s and 3 different altitudes of 20, 25 and 30 meters. At these heights, ground with ground distance sample (GSD) resolutions are 0.57, 0.72 and 0.86 cm/pixel respectively. Images are taken with 60% overlap to ensure the accurate mapping. The main parameters of data sources are given in Table 1.

Table 1. Main parameters of data source.

Altitude	Number of images	Velocity	Ground distance sample (GSD)
20	NDVI: 205	2.5	0.57
	NRE: 205	2.5	0.57
25	NDVI: 140	2.5	0.72
	NDRE: 140	2.5	0.72
30	NDVI: 80	2.5	0.86
	NDRE: 80	2.5	0.86

3. Methodology

3.1 System overview

The flowchart illustrating the methodology employed in this study is shown in Fig. 2. In this chart, the data preparation stage contains three main steps: data collection, mapping, and labelling. In the first step, data collection was implemented through the utilization of drone.

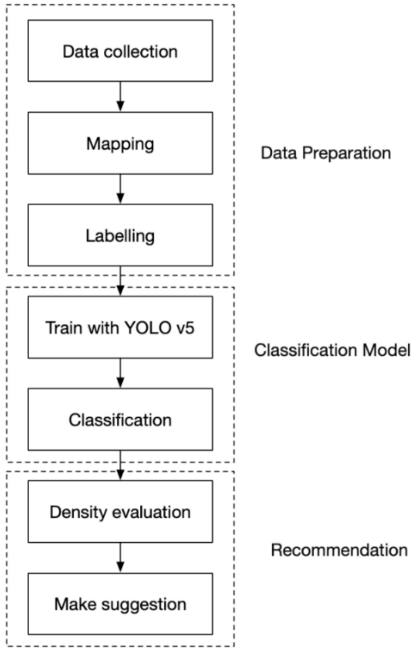


Fig. 2. The approach procedure.

3.2 Data preparation

With these photos, it is necessary to construct an ortho-mosaic map to accurately evaluate the density throughout the orchard. An Ortho-mosaic map is an image with high detail and resolution, and it is formed by combining several smaller images which are called orthophotos. An orthophoto is an aerial photo that has been corrected for lens distortion, camera tilt, perspective, and topographic relief, which is changes in the elevation of the earth's surface. These corrected orthophotos have no distortion and a uniform scale across the image. Due to the uniform scale, the distances can be interpolated easily through the number of pixels in the map. In this study, the Agisoft Metashape Professional software was employed to generate ortho-mosaic images from the drone's returned images. The process of ortho-mosaic map creation is summarized in Fig. 3.

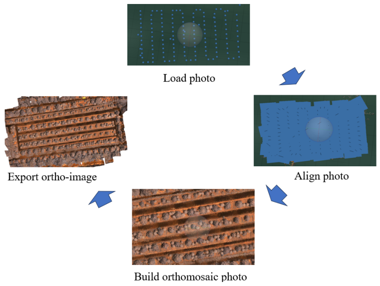


Fig. 3. Construct orthomosaic steps.

Fig. 4 shows a successfully returned ortho-mosaic map of the monitored area in the plantation from the software. This map has no distortion and owns the uniform scale which can be served for density evaluation.

3.3 Fruit plants classification

In order to handle the challenges of the spectral overlap between durian and papaya trees, this study adopts YOLO V5 model [29] for object detection and localization. In general, the YOLO algorithm aims to predict a class of an object and the bounding box that defines the object location on the input image. It recognizes each bounding box using four numbers, including coordinates of center of the bounding box, width of the box and height of the box. In addition, YOLO also predicts the corresponding number for the predicted class as well as the probability of the prediction. In this study the predicted class and the bounding box of object are prepared manually with the help of the MakeSense tool. MakeSense is a widely-used tool that aids in annotating and labeling objects in images. Users can accurately label objects by drawing rectangular bounding boxes around them, ensuring precise delineation of their boundaries. Additionally, labeled objects are associated with their corresponding image names or identifiers, as illustrated in Fig. 5. This meticulous manual labeling and annotation process is the foundation for training machine learning models to accurately recognize and identify objects in images. Using the MakeSense tool in this study allowed researchers to generate high-quality labeled data sets, which serve as valuable resources for subsequent analysis and model development.

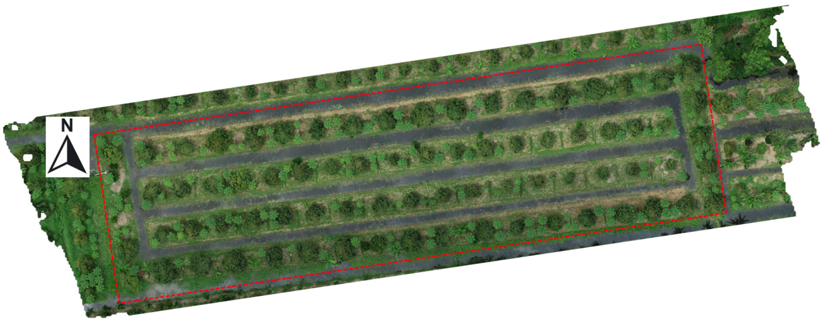


Fig. 4. Ortho-mosaic map of the observed area.

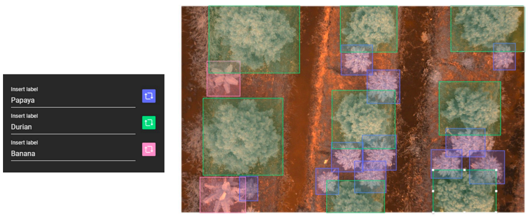


Fig. 5. Labelling with MakeSense tool.

4. Result and discussion

4.1 Intercropping classification

After being preprocessed, 80% of the dataset was used for training, and the rest was used for testing and validating. Fig. 6 displays the results of the detections and locations on the ortho-mosaic map after the model had been trained.

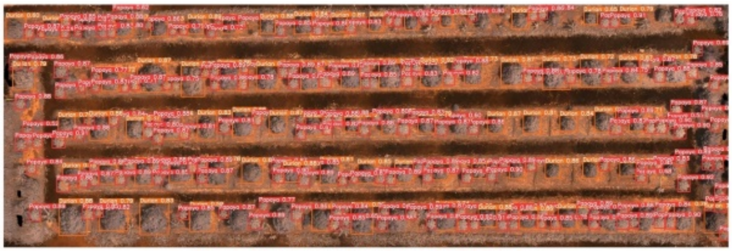


Fig. 6. Location and detection results from trained model.

Table 2 synthesizes the classification results from the trained model.

Table 2. Results from trained model.

Plants	Number of trees	YOLOv5 results	Percentage
Durians	82	85	96.47%
Papaya	175	184	95.11%

It can be seen that the obtained result has very high accuracy and can be used as a reliable monitoring method for supervising the orchard. In order to supervise this orchard, the entire area is divided into 5 subsections. The area of each subsection is about 6×100 m^2. In each subsection, papayas and durians were numbered from left to right. This process is illustrated in Fig. 7.

The white lines which serve as boundaries of subsections are positions of irrigation channels. In order to automatically supervise, these locations were obtained through Hough line transform [30], after the photos had been processed with binary quantization techniques. This process is shown in Fig. 8

Fig. 7. Organization of the supervised orchard.

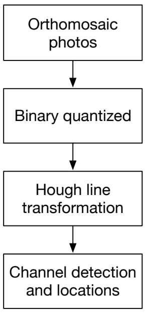


Fig. 8. Channel detection and locations.

4.2 Evaluate intercropping density

To monitor individual trees as well as to evaluate the durian growth condition, position and image of each tree were extracted and saved as in Fig. 9. From the extracted images, the size of the tree can be interpolated through the total number of involved pixels, due to no distortion and uniform scale properties of ortho-mosaic map.

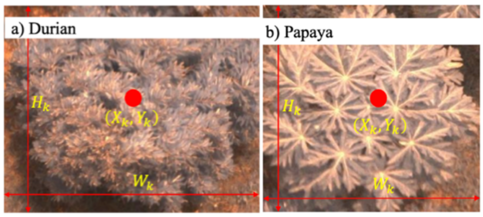


Fig. 9. Information extraction.

The plantation is monitored periodically, i.e. once a week. After that the state vector of each tree is recorded and updated. The state vector of tree k is presented in Eq. (4.1)

$$S_k = (T_k, R_k, N_k, X_k, Y_k, H_k, W_k), \tag{4.1}$$

where T_k represent type of tree k, T_k=1 if the tree is papaya, otherwise, T_k= 0. R_k is the region number that the tree belongs to $R_k \in \{1, 2, 3, 4, 5\}$. N_k is the ordinal number of the tree in the sub area. X_k, Y_k are the x and y coordinates of tree k. H_k, W_k *are* the height and width of rectangle boundary associating with tree k returned from YOLO.

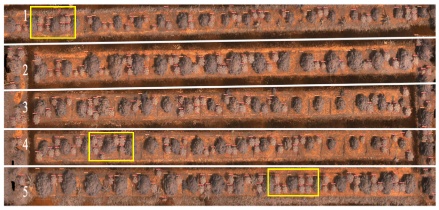
As mentioned earlier, due to durian long-time growth periods, intercropping papayas with durians plays a significant role in raising the farmer incomes. Papaya trees have a relative short growing period and can be harvested two to four times per year depending on the cultivar and weather conditions. However, the papaya tree can sprout on its own without the farmer knowing. Unexpected and uncontrolled papayas produce low yields as well as compete for nutrients and decrease growth of surrounding durians. In current practice, one durian tree will be surrounded with 4 papaya trees, so that the durian has enough light and nutrition for its development. However, this approach has some limitations when it does not consider the effect of crowns when both durians, papayas develop gradually. Furthermore, in orchards with limited area, the durian densities are often higher which allow smaller number of surrounding papayas. Papayas are also uprooted if their total crown areas exceed some certain level in the controlled area. These requirements create several challenges for traditional supervising method. In order to handle these challenges effectively, this study applied the following approach in evaluating the state of individual durian tree.

Let α, β, γ be three consecutive durian trees that belong to the same sub region and β is the tree located between α and γ. The area A_β of region around the tree β is defined as Eq. (4.2)

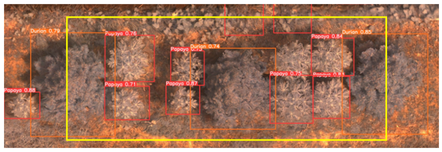
$$A_\beta = (|X_\gamma - X_\alpha|) \times \text{Channel width}. \tag{4.2}$$

Inside this region, the total number of inside papayas trees, i.e. I_β, and the total crown area from other trees, i.e. C_β, indices are used to measure whether the density is acceptable

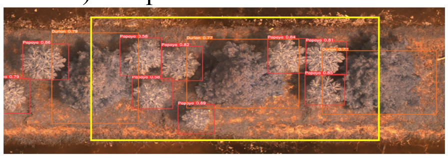
A papaya k is located inside the region around tree β if and only if $X_\gamma \le X_k \le X_\alpha$. The total crown area from other trees, C_β is equal to the sum of overlapped areas between the region and other returned bounding boxes. C_β also considers the overlapped areas of durian α and γ. With I_β and C_β, the density can be properly evaluated after each flight.



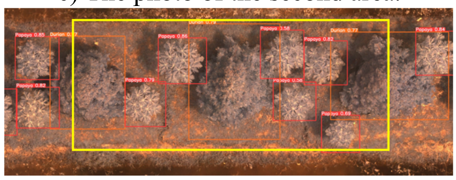
a) Three detected areas with high papaya density.



b) The photo of the first area.



c) The photo of the second area.



d) The photo of the third area.

Fig. 10. Detected regions with high papayas density style.

4.3 Discussion

In various state of art, [31] investigated the applicability of using cameras mounted on UAV to evaluate the height of various kinds of plants. This research shows that the correlation coefficient between the proposed method and the truth value for cabbage, pumpkin, barley, and wheat were 0.86, 0.94, 0.36, and 0.49, respectively. In addition, [32] shows a tool that can classify various kinds of vegetation in an area of 2.45 ha by using a drone. This tool is based on a support vector machine with the accuracy reaching 77-91% depending on the multispectral data and 67-80% for data from RGB sensors. [33] succeeded in designing and developing an autonomous drone for leaves diseases by using YOLOv5 on the Roboflow platform. The drone is highly accurate on autonomous flight with 95% of accuracy at 100 meters far at 5-meter height to 74% accuracy at 10-meter height far at 5-meter height. In case of classification, because of the drone hovering, the accuracy is just at 64.55%. [33] designed a method to evaluate land clearing and preparation process for a smart durian orchard farm by using RGB and thermal cameras mounted on a drone. This research shows that thermal sensors provided a better image resolution on evaluation variations in soils and irrigation systems, which can affect crop yield.

We propose a method to monitor orchid with intercropping plantations. This process will help farmers observe the density of various kinds of plants so they can adjust their planting strategies as well as optimize the use of available resources. According to our records on this study and a former study [32], the ideal operating height for a drone to obtain clear and crisp images of the observed surface will vary from 20 to 30 meters. If the height is greater, the captured images will be blurred and not suitable to form the ortho-mosaic images.

5. Conclusion

Durian is a important economic crop variety and contributes a large proportion to Vietnam's agricultural exports. Due to the long period from planting to the first harvesting, most plantations have to apply intercropping to reduce the economic burden during the waiting process. To properly monitor intercropping, and release farmers from the tedious workload of monitoring large plantations, as well as early detection of abnormal states during crop periods, this study proposed an approach using drones combined with the YOLO v5 model. Through the high-resolution images obtained from drones, individual durian and papaya trees can be detected and located. For each durian tree, the subregion around the tree and two evaluation indices are identified and computed. Through these indexes, farmers can obtain essential information about the density around each durian tree and take further action. The results from the trained model have very high accuracy and can be used as a reliable monitoring method for supervising the orchard. Although this study is conducted on intercropping of durians and papayas, this approach can be extended to other cases where the density is not too high.

However, some technical limitations remain that we cannot yet overcome, such as the bandwidth and the coverage area of Wi-Fi hotspots. Additionally, to monitor individual trees, ortho-mosaic images should be generated from the captured images. This process is time-consuming and requires significant computation time, making it unsuitable for providing real-time video streams from drones.

In future work, we suggest that with our method, it will be possible to monitor an orchid plantation. By using spectral images, we can calculate vegetation indices and better understand plant health. These values allow farmers to use IoT systems for autonomous irrigation, fertilization, and pH control, either for individual plants or localized areas.

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