Durian plant health and growth monitoring using image processing

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ABSTRACT

The demand for durians has increased considerably, gaining significant popularity in the market. Under the Industrial Revolution 4.0, precision agriculture is expanding globally, utilizing a range of digital technologies to provide the farming industry with crucial information for enhancing farm productivity. For durians to produce high-quality fruit, it is essential that the plants receive sufficient nutrients. Therefore, it is crucial for farmers to monitor the growth rate of durian plants to ensure they receive suitable nutrients for optimum growth. Manual growth monitoring often yields inaccurate results and is prone to human error. Thus, automatic systems for plant image analysis could prove highly beneficial for practical and productive agriculture. This research utilizes the you only look once version 5 (YOLOv5) model alongside an image referencing method for growth monitoring. It begins with the detection of the durian tree, segmenting the leaf area and computing tree size through image referencing. This method achieves a precision of 96% in detecting durian trees from images. Through these images, the growth rate of the durian is assessed through comparisons of canopy growth, stem size, and tree height.

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1. INTRODUCTION

The world of agriculture is currently undergoing a significant transformation, driven by the need for increased efficiency and sustainability. In this transformative era, the application of advanced technologies, such as image processing, is becoming increasingly important. The durian, often referred to as the 'king of fruits,' is a tropical fruit renowned for its distinctive taste, aroma, and nutritional value. Market research in Malaysia shows that the country exported approximately 448 thousand metric tons of durian, significantly contributing to its economy. In 2019, Malaysia's durian exports reached USD 22.3 million, a 172% increase from USD 8.8 million in 2011 [1]. This underscores the durian's substantial contribution to Malaysia's economy. However, the recent pandemic and economic challenges have caused a downturn in agricultural production compared to previous years, as highlighted in 2023 [2]. The pandemic in 2020, along with subsequent lockdowns, reduced plantation work as most activities in Malaysian plantations are performed manually. Traditional durian plantation methods, like those of other agricultural sectors, involve manual irrigation, fertilization, and pest control, all based on the farmers' observational data. Decisions are made based on these manual observations of plant conditions [3]. Studies indicate that a majority of farming time is dedicated to irrigation and fertilization [4]. Both activities can have serious effects if the plantation is exposed to either too much or too little water and fertilizer. Even within the same species, individual plants may require specific amounts of water and fertilizer [5]. Therefore, monitoring is a crucial aspect of agriculture to ensure viable decisions are made for various farming activities.

Based on previous researchers' research on the factors affecting durian production, it has been found that farmers' experiences and ages also affect the production of durian [6]. As the age of the farmer increases, durian production goes down by 0.479 tons on a year-on-year basis. This is due to their reduced ability to perform farming activities. Moreover, older farmers often had a hard time adapting to newer technology, which further contributed to the reduction of durian production. It is observed that increasing the number of workers will increase the durian productivity [7]. An additional worker increases the production by 4.903 tons. This shows that worker manual farming still plays a crucial role in durian plantations. The pandemic has prevented farmers from having additional workers as additional workers will cost additional burdens to their farming activity. The way to overcome this is to introduce an alternative way where a low number of workers could provide the same productivity outcome. This can be done by integrating technologies into farming workflows. Technologies like automated irrigation systems [8] and automated fertilization systems [9] are commonly implemented. These technologies have been used to reduce the number of workers needed for farming. As a result of automated farming activities, the production of the plantation can be maintained while reducing the workforce. However, its advantages are limited to reducing the manual workforce; the growth of the plantation still requires monitoring, which heavily depends on the farmer's experience.

In general, there are two types of monitoring systems for plantations. These monitoring systems are used to monitor the growth condition of the plantation. The first type of monitoring system features an internet of things (IoT) system which monitors the environmental parameters of the plantation. An example of an IoT monitoring system for farming was developed in [10], where an Arduino controller was used to collect temperature, humidity, soil moisture, air quality and light intensity. These collected data were transmitted via wireless fidelity (Wi-Fi) to a Raspberry Pi for further data storage and processing. These data are used to predict optimal soil conditions for plantations. On the other hand, a similar system was developed to collect water level, humidity, temperature, light and soil moisture data [11]. The system features a climate-based controller which computes the evapotranspiration rate of the plantation as monitoring data. The system uses these monitored data for plantation prediction analysis. Apart from collecting sensor data through Wi-Fi, there is also long range (LoRa) based monitoring system. The LoRa-based IoT monitoring system was deployed to monitor plantation and farmer health conditions [12]. A controller collects soil moisture, soil temperature, atmospheric temperature, and humidity, while another controller collects heartbeat data and the farmer's body temperature. Both controllers transmit the collected data through LoRa for data processing and storage. Through these systems, farmers can monitor their plantation conditions as well as their workers' health conditions. Another example deployed is a LoRa-based IoT monitoring system to monitor starfruit [13]. The system has three sensor nodes, with each of the nodes equipped with pH sensors and soil moisture sensors. These sensor nodes are deployed onto the starfruit plantation to collect the data and transmit it to the LoRa wide area network (LoRaWAN) gateway, which uploads the data into their server. Apart from static monitoring, there are also dynamic monitoring. A robotic vehicle equipped with multiple sensors to detect parameters such as soil moisture, rain, temperature, humidity and air quality sensors was developed [14]. The robot moves around the plantation site to collect these sensor data. Based on the data collected from these sensors, the robot will perform specific farming activities, such as targeted irrigation, focusing on the plants it has monitored. Finally, ground sensors such as soil moisture on multiple sites in the field were deployed [15]. These soil moisture sensors provide low moisture alerts to the robot and these robots will move to these locations with low moisture and capture images for soil content analysis.

The second method of monitoring the plantation is to observe the situation of the plantation instead of the environmental factors. This includes assessing the plantation fruits' condition and tree health conditions. An example is the applied image processing technique on pepper fruits, where the colour of the pepper was extracted for their feature classification [16]. This method enables the determination of the number of peppers growing on the tree and gives insights into their health conditions. Meanwhile, a fruit monitoring system was implemented at a mango farm [17]. This system deployed a Raspberry Pi with a camera at the mango tree. The camera captures the tree images and separates them into two processes where: the first process counts the number of mangos, and the second process extracts the size of the mango by using the image pixel as a reference to the mango width and height. Another example of such monitoring was deployed by a manned aircraft equipped with an infrared camera, a Lidar sensor, and a multispectral camera to obtain imagery in a Pinus radiata plantation [18]. They introduced a novel processing method which fuses three different images, enabling it to extract detailed information about the trees. This method classifies healthy trees and unhealthy trees from the plantation area. Another airborne method was proposed using the 3D canopy structure of trees as a reference to monitor their health [19]. A drone equipped with a Lidar

Sensor was set to capture the imagery of a forest, extracting images of the tree canopies were extracted. By comparing the size of the tree canopy between two imageries with different times of capture, the growth condition of the tree can be monitored. In addition to the Lidar sensors, digital cameras have also been used to monitor the growth of trees. A low-cost digital camera on an unmanned aerial vehicle to capture images of the canopy of the tree was proposed in [20]. The captured image underwent a process of multi-pyramid features extraction and had their texture and color extracted. These extracted features were then used to classify the trees as healthy or unhealthy. The greenness of the trees was also used to identify their health conditions. This method was applied to maize seedlings [21]. The image of the maize seedling was captured, and its background was segmented. The maize seedling's greenness colour will be determined by extracting the green colour from the hue of the image, indicating the seedling's health.

Each of the methods previously listed has its own unique strengths and weaknesses. The IoT method focuses on environmental factors, which, while crucial, do not directly reflect the health condition of the plantation but rather assist in maintaining optimum growth conditions. The image processing method, often employing airborne drones, provides accurate information about the health and growth conditions of the trees. However, the cost of data acquisition is often prohibitively high for many farmers. Therefore, we propose the development of a durian health and growth monitoring system that is accessible via a web platform. This proposed system allows for image capture using any device, such as a mobile phone or camera, with the images uploaded to the system's website for processing. It then processes these images to extract information about the health and growth conditions of the durian trees. This system could significantly reduce labour costs, as farmers would no longer need to manually monitor the trees. Additionally, by providing detailed insights into the growth and health conditions of the durian trees, the system enables more precise adjustments in irrigation and fertilization, ultimately optimizing the growth rate of the plants and enhancing both fruit production and quality.

2. METHOD

The proposed system consists of two main parts: the image processing components and web system components. Essentially, the proposed system integrates image processing into a web system. The web system includes a backend service that runs the tree extraction process and tree health and growth analysis process.

The image processing component is divided into two distinct sections. The first section is dedicated to tree extraction, while the second section focuses on the analysis of tree health and growth. These sections operate consecutively, where the durian tree image is first subjected to the extraction process before undergoing health and growth analysis. The image processing component is further broken now into four stages: data acquisition, model training and testing, post-processing, and result analysis. The data acquisition stages and model training and testing stages are essential for the tree extraction process, while the post-processing stage extracts the tree health and growth analysis data. The result stage is the result from the post-processing stage. Figure 1 shows the overall block diagram of the image processing part.

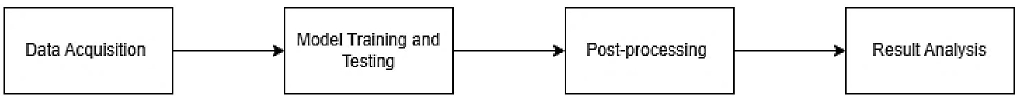

Figure 1. Block diagram of the image processing component

In the web system component, the image processing component is hosted in the web system. Users can upload durian tree image into the system. Then, the web system will load the image into the image processing component, and the result from the analysis will be displayed on the front end of the web system.

2.1. Data acquisition

The first step in the image processing component is data acquisition. This phase involves collecting data on durian trees. The images of the durian trees were captured using mobile phone cameras at a durian farm in Kedah, Malaysia. A total of 500 images of durian trees were collected for the system. These images were captured from various angles and under different lighting conditions, which cover a range of durian tree varieties, growth stages, and environmental conditions. This ensures a diverse representation in the dataset. The captured images are of a resolution of 1920×1080 pixels. Each image in the dataset is stored in a dedicated folder and is assigned a unique number as its ID. Figure 2 presents samples of the captured durian tree images.

Figure 2. Durian tree dataset

2.2. Model training and testing

The second step in the image processing component is model training and testing. This step is essential for the tree extraction process. Our proposed system employs the you only look once (YOLO) deep learning algorithm, a modern deep learning algorithm which specializes in object detection [22], introduced in 2015 [23]. YOLO interprets object detection in images as a task of regression [24]. It begins taking the input image and splitting it into a grid, with each cell responsible for detecting objects. Every grid cell predicts an imagery box that potentially contains objects. As multiple grid cells might identify the same object, YOLO used confidence scoring to determine how accurately the object was detected. YOLO used non-maximum suppression to filter out low-confidence overlapping boxes. The final box is presented with the object class and its confidence score, indicating the detected objects in the image.

The initial step in using YOLO algorithm requires the data collected from previous steps to be per-processed. In the pre-processing phase, there are two important processes. First, the images will go through image enhancement, such as median filtering, which suppresses the noise in the image, and image resizing, which resizes all the images into a constant size. Subsequently, all the images are labelled. This is done by drawing a bounding box in the durian tree image. The bounding box coordinates and its object class ID will be stored in a text file to indicate the object in the image. Figure 3 shows the sample labelled durian image.

Figure 3. Labelled durian image

Once all the durian tree images were labelled and their corresponding label file stored together in a folder, the dataset was then split into a training set and a testing set. In our proposed system, the split was composed of 70% training images and 30% testing images. A random selection of 350 durian images along their label file were used as training images, while the remaining images were used as testing images. Subsequently, the training of the YOLO model was started. We set the number of epochs of the training to 100, considering the relatively small size of the training dataset. After completing 100 epochs, the training stop and the model weights of the durian tree were stored in separate folders. This model was then used for inference with the test images.

In the testing stage, we use the trained model to predict the test images. The test images will have a predicted bounding box drawn on it. The bounding box also shows the confidence level of the object the model predicted. Figure 4 shows a sample of the predicted test image.

Figure 4. Labelled durian image

2.3. Post-processing

The subsequent step in the image-processing component is the post-processing phase. In this stage, information regarding tree health and growth is extracted from the detected tree images. Three types of information are extracted: tree details data, tree health data, and tree growth data. To initiate the extraction process, we propose an image reference method. This method relies on a constant size reference object, which serves as a point of reference for extracting tree data.

The reference object used in our system is a square-shaped red object with standardized dimensions of 30×30 cm. The shape and colour of the object ensure that it occupies a significant portion of the image, thus facilitating accurate reference. The object is constructed from robust materials, consisting of red cardboard attached to a cardboard base. Figure 5 shows the red reference object.

The reference object is strategically placed within the frame of the system input image. Figure 6 shows an example of a durian tree image that includes the reference object. The first step in processing this image involves extracting the coordinates of the reference object, which are essential for tree data extraction. Figure 6 shows one example of an input image.

Figure 5. Red reference object Figure 6. Labelled durian image

The process of extracting the reference object's coordinates involves four steps. First, the image is converted from the red, green, and blue (RGB) colour model to hue, saturation, and value (HSV), as HSV makes it easier to identify and isolate specific colours. Next, the colour ranges for identifying the red reference object are defined: the lower red range is set at [0,50,50], and the upper red range is at [10,255,255]. Colours outside these ranges are filtered out. The red areas are then processed to calculate their edges, and the largest red area is enclosed in a square box. The coordinates of this square box are subsequently used for further analysis.

2.3.1. Tree data extraction

Once the coordinates of the red reference object have been obtained, various tree data points can be computed, such as tree size, canopy size, and tree height. This computation is possible after the tree has been detected through the YOLO model and the coordinates of the red reference object have been extracted. The extraction of tree data involves three steps.

First, the width of the reference object is computed and measured in pixels. This is done by subtracting the x_1 coordinate of the top left corner of the object with the x_2 coordinate of the bottom-right corner of the object.

$$object_{width} = x_2 - x_1 \tag{1}$$

Next, this pixel width is converted to centimeters. This conversion is based on the known width of the red reference object, which is 30 cm. The conversion factor is obtained using (2).

$$conversion\_factor = \frac{30}{object_{width}} \tag{2}$$

Once the conversion factor is established, the tree data can be computed by referencing the bounding box of the tree detected by the YOLO model. The width of the tree stem in pixels is calculated by identifying the tree contour with the highest width-to-height ratio. The stem size is then calculated using this measurement.

$$stem\_size = \frac{stemwidth_{pixel} * conversion\_factor}{10} \tag{3}$$

The contour with the largest area in the tree image is selected to represent the canopy and compute the canopy size of the tree. The size of the canopy is then measured accordingly.

$$canopy\_size = \frac{canopywidth_{pixel} * conversion\_factor}{10} \tag{4}$$

The height of the tree is determined by measuring the vertical distance between the top and bottom of the tree's bounding box. The tree height can be obtained by (5):

$$tree\_height = \frac{treeheight_{pixel} * conversion\_factor}{10} \tag{5}$$

All this computed data, including stem size, canopy size, and tree height, is stored in a database for use in the web system.

2.3.2. Tree health

Leaf colour plays a crucial role in assessing the health of a plantation, as plants with diseases often exhibit yellow and brownish leaves [25]. In our proposed system, we aim to analyze the greenness index of durian trees to determine their health condition. Initially, the tree is detected using the YOLO model from the previous process. The background is then removed to focus on the leaves of the tree.

The initial step in leaf colour analysis involves converting the colour space of the input image from RGB to HSV, as HSV is more effective in colour analysis. This conversion allows for the filtering of colour intensity to a specific range. Based on feedback from local farmers and the HSV values of durian tree images under different health conditions, we have selected a green level range with a low threshold of [35,50,50] and a high threshold of [85,255,255]. This threshold enables the extraction of the green colour areas of the durian tree.

By extracting the green foliage, a mask is created and applied to the durian tree image. This filters out non-green areas, allowing the system to analyze the green leaves. Figure 7 shows the extracted green area from a durian tree image.

Figure 7. Extracted green area from durian image

Next, the greenness index algorithm was applied to the masked image to compute the greenness index of the durian tree. The greenness index is calculated using (6).

$$Greenness\ Index = \frac{Total\ Green\ Pixels}{Total\ Image\ Area} \tag{6}$$

Next, a greenness index algorithm is applied to the masked image to compute the greenness index of the durian tree. The greenness index is calculated by first determining the total number of green pixels in the image, identified through the mask highlighting green areas. The total number of green pixels is calculated by summing the values of the green mask, divided by 255, to normalize the pixel counts to a binary scale. The equation for the total green pixels is (7).

$$Total\ Green\ Pixels = \sum \frac{mask\_pixel}{255} \tag{7}$$

The total image area is the product of the image's width and height, accounting for all pixels in the image. By dividing the total number of green pixels by the total image area, the greenness index quantifies the proportion of the image that is green. This serves as an indicator of tree health. A higher greenness index value indicates a healthier tree with more green foliage, reflecting better overall plant health. Based on the greenness index, the health of the durian tree is categorized into three classes: unhealthy (greenness index lower than 0.2), moderately healthy (greenness index between 0.2 and 0.4), and healthy (greenness index higher than 0.4).

2.3.3. Web system

The proposed system operates on a local server using Flask, a Python web framework. The deep learning model required for tree detection, along with the image processing processes necessary for tree data extraction, runs on this local server. The Flask server manages incoming HTTP requests and routes them to the corresponding processes. Figure 8 illustrates the architecture of the web system.

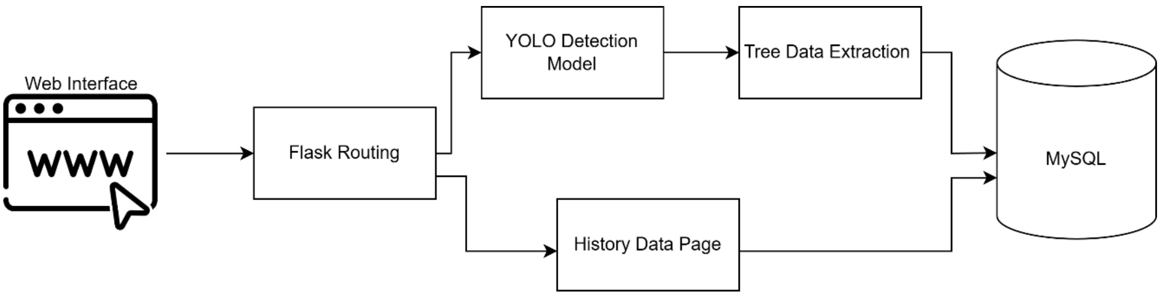

Figure 8. Web system architecture

Users access the system through an HTTP page hosted by the Flask server. There are two main routes available to users: the first route initiates the tree growth analysis process, which involves running the

YOLO detection model and the tree data extraction process. The second route leads to the history data page, where data previously stored in the database is retrieved and displayed on the webpage. Users opting for the first route need to upload an image of the durian tree. This uploaded image undergoes tree detection, and the extracted tree data is then stored in the database. The database used in this system is MySQL.

3. RESULTS AND DISCUSSION

The system was used by a farmer in a local durian farm in Kedah, Malaysia. This farm was managed by TW Megastart. The durian farm is in Muda Kuari, Tunjang Jitra, and Kedah, with a total farm area of 2.5 acres, as shown in Figure 9. The system was tested by the local farmers for two months, starting from June 2023 to August 2023. The system was running 500 times across the two months to determine the variation between trees.

Figure 9. Local durian farm location

3.1. Tree detection

The first part of the system is the tree detection process. Throughout the testing period, there were only two times failures where the trees could not be correctly identified out of 500 tries. This was recorded in the database, and the farmers were asked whether the detection was correct. Figure 10 shows the pie chart of the durian tree detection result. It has a 99.6% detection rate of the durian tree.

The YOLO model of the system has a mean average precision of 0.96 m, indicating 96% correct prediction of the intended object. Table 1 shows the training model output trained from 100 epochs. As the epoch increases, the training loss values decrease. This indicates that the model is learning to localize objects and detect them correctly. The precision, recall, and mean average precision also improve over time, which is a result of a 96% detection rate. Figure 11 shows the example of the detected tree through the system. There is a difference between the model accuracy and farmer recorded result, as the images taken by farmers might have more distinct tree features and less interference, which increased the accuracy.

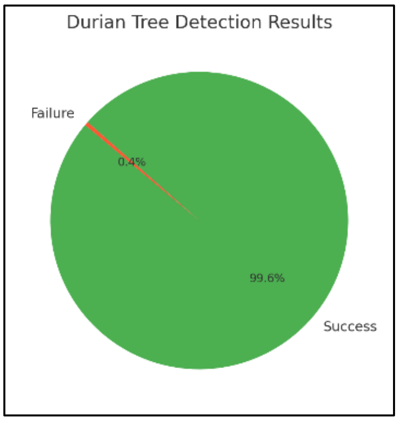

Figure 10. Pie chart of durian tree detection result

Table 1. YOLO training model output

Train/box loss	Train/object loss	Train/class loss	Metrics/precision	Metrics/recall	Metrics/maP_0.5
0.0896	0.0305	0.0304	0.3529	0.0268	0.0061
0.0685	0.0308	0.0228	0.7059	0.1693	0.0431
0.0581	0.0302	0.0178	0.2353	0.3515	0.1436
…	…	…	…	…	…
0.0051	0.0013	0.0009	0.9641	0.9873	0.9512

Figure 11. Pie chart of durian tree detection result

3.2. Tree health and growth information

Once the tree has been detected by the system, tree data such as stem size, tree height, canopy size, and the greenness index are extracted and stored in the database. To verify the system's accuracy, farmers recorded the actual measurements of 100 durian trees on the farm at the beginning of the test. These measurements were then compared with the data processed and stored by the system. Figure 12 illustrates the comparison between the farmers' measurements and the system's measurements of stem size and tree height. The system demonstrated an accuracy of 95%, with its measurements slightly differing from the actual measurements of the durian trees.

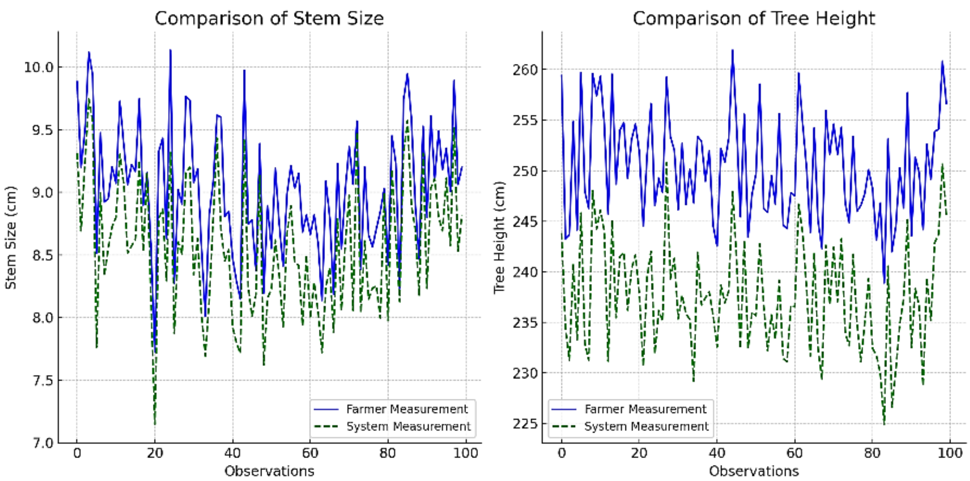

Figure 12. Difference between farmer measurement and system measurements

Throughout the testing phase, which included all 500 uses, the system consistently identified all the durian trees as healthy. This assessment was corroborated by the farmers' experience, which also indicated that all the durian trees were healthy. This result suggests that the system currently has a 100% accuracy rate in analyzing the health of durian trees. The web system also provides growth analysis for the durian trees. This analysis is conducted by comparing data from two different periods. The system stores all processed durian tree data in the database once their images have been uploaded. When a new image of a particular tree is captured and uploaded, the system compares the current tree data with the previous data. Table 2 presents an example of the growth comparison output generated by the system.

Table 2. Durian tree comparison data

Durian tree ID	Date	Stem size (cm)	Canopy size (cm)	Tree height (cm)	Stem growth rate	Canopy growth rate	Tree height growth rate
1	1/6/2023	6.76	201.76	223.72	-	-	-
1	1/7/2023	7.65	238.57	237.74	13.16%	18.24%	6.27%

3.3. Web system

The web system was deployed on a computer which was placed in the durian farm for two months. The computer port forwarded the local server to www.twm.ddns.net. The main page of the system prompts farmers to upload images into the system. Once the farmer uploads the images, the system will process the image and display the result in the following page. Figure 13 shows the main page of the system, whereas Figure 14 shows the result page of the system.

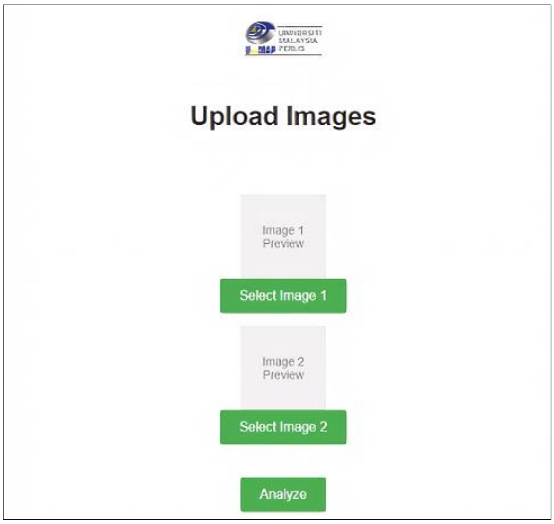

Figure 13. Main page of the web system

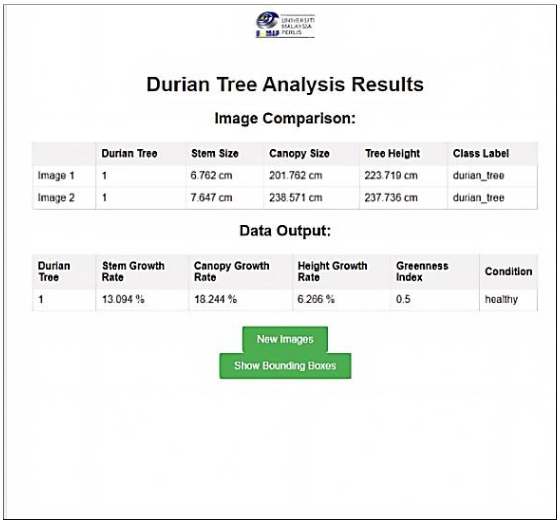

Figure 14. Result page of the web system

4. CONCLUSION

A real-time system capable of capturing and analyzing images of durian trees was designed and successfully tested at a local farm, demonstrating high accuracy. The system provided measurements for key growth parameters such as stem size, canopy size, and tree height with 95% accuracy. The durian tree detection model achieved 96% accuracy, and during practical tests, the system had a 99.6% success rate in detecting durian trees. This reliability highlights the system's precision in both identifying trees and extracting growth parameters, offering a highly automated solution for agricultural monitoring. Furthermore, the system exhibited 100% accuracy in assessing tree health, with results matching farmers' observations during the two-month trial. This shows that the system can effectively reduce the need for manual monitoring, minimizing reliance on farmers' expertise while improving decision-making for irrigation and fertilization, ultimately enhancing farm efficiency and productivity.

The potential to automate growth and health monitoring in this manner has significant implications for agriculture. By providing precise, real-time data, the system reduces the labour-intensive task of manual observation, allowing farmers to allocate resources more efficiently. This automation not only cuts down on time spent monitoring but also ensures more accurate and consistent tracking of tree health, which is crucial for optimizing durian production.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] S. Safari, A. Razali, W. Mahfuzah, W. Ibrahim, M. Sukri, and A. Rahim, "From farm to China: a case study of Malaysian frozen whole durian export supply chain (In Malay: *Dari ladang ke China: kajian kes rantaian bekalan eksport durian sejuk beku Malaysia dan bentuk biji*)," *Economic and Technology Management Review*, vol. 16, pp. 1–20, 2021.

[2] L. P. Onn, "Saleable and sustainable: Sabah takes the lead in palm oil certification in Malaysia," *Iseas Yusof Ishak Institute*, vol. 106, no. 2021, Aug. 11, 2021. [Online]. Available: https://www.iseas.edu.sg/articles-commentaries/iseas-perspective/2021-106-saleable-and-sustainable-sabah-takes-the-lead-in-palm-oil-certification-in-malaysia-by-lee-poh-onn/. (Accessed: Jan. 01, 2024).

[3] S. Navulur, A. S. C. S. Sastry, and M. N. G. Prasad, "Agricultural management through wireless sensors and internet of things," *International Journal of Electrical and Computer Engineering*, vol. 7, no. 6, pp. 3492–3499, Dec. 2017, doi: 10.11591/ijece.v7i6.pp3492-3499.

[4] M. Crowley, "Foreign labor shortages in the Malaysian palm oil industry: impacts and recommendations," *Asian Journal of Agriculture and Development*, vol. 17, no. 2, pp. 1–18, Dec. 2020, doi: 10.37801/ajad2020.17.2.1.

[5] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E. H. M. Aggoune, "Internet-of-things (IoT)-based smart agriculture: Toward making the fields talk," *IEEE Access*, vol. 7, pp. 129551–129583, 2019, doi: 10.1109/ACCESS.2019.2932609.

[6] S. Thongkaew, C. Jatuporn, P. Sukprasert, P. Rueangrit, and S. Tongchure, "Factors affecting the durian production of farmers in the eastern region of thailand," *International Journal of Agricultural Extension*, vol. 9, no. 2, pp. 285–293, 2021, doi: 10.33687/ijae.009.02.3617.

[7] O. Suriya, C. Jatuporn, P. Sukprasert, and S. Pattanakiat, "Factors affecting Cavendish banana production of farmers in Nong Suea district, Pathum Thani province (in Thai: *ปัจจัยที่ส่งผลต่อการผลิตกล้วยหอมของเกษตรกรในอำเภอหนองเสือ จังหวัดปทุมธานี*)," *Panyapiwat Journal*, vol. 9, no. 2, pp. 208–218, 2017.

[8] D. Kennedy, T. T. M. Delsy, and P. V. G. K. Rao, "Design and development of automated irrigation system," *International Journal of Pharmacy Research & Technology*, vol. 7, no. 1, pp. 8211–8220, 2015.

[9] C. Joseph, I. Thirunavuakkarasu, A. Bhaskar, and A. Penujuru, "Automated fertigation system for efficient utilization of fertilizer and water," in *2017 9th International Conference on Information Technology and Electrical Engineering (ICITEE)*, IEEE, Oct. 2017, pp. 1–6, doi: 10.1109/ICITEED.2017.8250474.

[10] R. Varghese and S. Sharma, "Affordable smart farming using IoT and machine learning," in *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, IEEE, Jun. 2018, pp. 645–650, doi: 10.1109/ICCONS.2018.8663044.

[11] S. Bouarourou, A. Zannou, A. Boulaalam, and E. H. Nfaoui, "IoT based smart agriculture monitoring system with predictive analysis," in *2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology, IRASET*, 2022, doi: 10.1109/IRASET52964.2022.9738367.

[12] N. Bandyopadhyay, P. Gaurav, M. Kundu, B. Misra, and B. Hoare, "IoT-based health and farm monitoring system via LoRa-based wireless sensor network," in *2020 4th International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech)*, IEEE, Oct. 2020, pp. 1–7, doi: 10.1109/IEMENTech51367.2020.9270055.

[13] A. F. Rachmani and F. Y. Zulkifli, "Design of IoT monitoring system based on LoRa technology for starfruit plantation," in *TENCON 2018 - 2018 IEEE Region 10 Conference*, Oct. 2018, pp. 1241–1245, doi: 10.1109/TENCON.2018.8650052.

[14] M. Hasan, K. N. W. Uddin, A. Sayeed, and T. Tasneem, "Smart agriculture robotic system based on internet of things to boost crop production," in *International Conference on Robotics, Electrical and Signal Processing Techniques*, 2021, pp. 157–162, doi: 10.1109/ICREST51555.2021.9331091.

[15] P. Senthil and I. S. Akila, "Automated robotic moisture monitoring in agricultural fields," in *2018 International Seminar on Intelligent Technology and Its Applications (ISITIA)*, Aug. 2018, pp. 375–380, doi: 10.1109/ISITIA.2018.8711348.

[16] Y. Song, C. A. Glasbey, G. W. Horgan, G. Polder, J. A. Dieleman, and G. W. A. M. van der Heijden, "Automatic fruit recognition and counting from multiple images," *Biosystems Engineering*, vol. 118, no. 1, pp. 203–215, Feb. 2014, doi: 10.1016/j.biosystemseng.2013.12.008.

[17] S. K. Behera, P. K. Sethy, S. K. Sahoo, S. Panigrahi, and S. C. Rajpoot, "On-tree fruit monitoring system using IoT and image analysis," *Concurrent Engineering*, vol. 29, no. 1, pp. 6–15, Mar. 2021, doi: 10.1177/1063293X20988395.

[18] L. Windrim, A. J. Carnegie, M. Webster, and M. Bryson, "Tree detection and health monitoring in multispectral aerial imagery and photogrammetric pointclouds using machine learning," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 2554–2572, 2020, doi: 10.1109/JSTARS.2020.2995391.

[19] Y. Zhang, H. Wu, and W. Yang, "Forests growth monitoring based on tree canopy 3D reconstruction using UAV aerial photogrammetry," *Forests*, vol. 10, no. 12, pp. 1–16, 2019, doi: 10.3390/F10121052.

[20] P. Barmpoutis, T. Stathaki, and V. Kamperidou, "Monitoring of trees' health condition using a UAV equipped with low-cost digital camera," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2019, pp. 8291–8295, doi: 10.1109/ICASSP.2019.8683128.

[21] W. Yang, S. Wang, X. Zhao, J. Zhang, and J. Feng, "Greenness identification based on HSV decision tree," *Information Processing in Agriculture*, vol. 2, no. 3–4, pp. 149–160, Oct. 2015, doi: 10.1016/j.inpa.2015.07.003.

[22] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma, "A review of YOLO algorithm developments," in *Procedia Computer Science*, vol. 199, pp. 1066–1073, 2022, doi: 10.1016/j.procs.2022.01.135.

[23] W. Zhiqiang and L. Jun, "A review of object detection based on convolutional neural network," in *2017 36th Chinese Control Conference (CCC)*, Jul. 2017, pp. 11104–11109, doi: 10.23919/ChiCC.2017.8029130.

[24] T. Diwan, G. Anirudh, and J. V. Tembhurne, "Object detection using YOLO: challenges, architectural successors, datasets and applications," *Multimedia Tools and Applications*, vol. 82, no. 6, pp. 9243–9275, Mar. 2023, doi: 10.1007/s11042-022-13644-y.

[25] R. A. D. L. Pugoy and V. Y. Mariano, "Automated rice leaf disease detection using color image analysis," in *Third International Conference on Digital Image Processing (ICDIP 2011)*, Apr. 2011, doi: 10.1117/12.896494.

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