Tree diameter at breast height measurement based on computer vision

Mohamad Razmil Abdul Rahman[1], Ishak Suleiman[2], Mohammed Al Haek[2], Yee Kit Chan[3]
[1]Centre for Robotics and Sensing Technologies, TM Research and Development Sdn. Bhd., Cyberjaya, Malaysia
[2]Centre for Artificial Intelligence, TM Research and Development Sdn. Bhd., Cyberjaya, Malaysia
[3]Faculty of Engineering and Technology, Centre for Remote Sensing and Surveillance Technologies, Multimedia University, Melaka, Malaysia

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ABSTRACT

Diameter at breast height (DBH) is a crucial metric in forestry, serving as a key input for estimating timber volumes and biomass, assessing forest health, and aiding in biodiversity and climate change studies. However, traditional measurement methods practiced today are time-consuming and labour-intensive, while many advanced methods introduced in recent years require high upfront costs, limiting wide adoption by small-scale institutions and projects. This research paper aims to explore innovative approaches to DBH measurement that balance accuracy with cost-effectiveness, ultimately contributing to the broader goals of sustainability and environmental protection. In this paper, the authors propose an automated DBH measurement method, extracting the value from smartphone RGB images through the utilization of computer vision techniques and mathematical algorithms. By incorporating tree distance data in Phase 3 of the study, the proposed method achieved accuracy comparable to manual tape measurements while significantly reducing the time and resources required for fieldwork. Specifically, 74 out of 143 trees (51.7%) had an estimated DBH that fell within 1 cm of the actual measurements, resulting in an absolute mean error (MAE) of 1.10 cm, root mean square error (RMSE) of 1.80 cm, and relative root mean square error (RRMSE) of 6.0%. Thus, this hybrid approach offers a promising solution for forestry applications, enhancing both the efficiency and accessibility of DBH data collection.

Corresponding Author:

Mohamad Razmil Abdul Rahman
Centre for Robotics and Sensing Technologies
TM Research and Development Sdn. Bhd., Cyberjaya, Selangor, Malaysia
Email: razmil@tmrnd.com.my

1. INTRODUCTION

Accurate measurement of trees is essential for effective forest management, conservation efforts, and urban planning. One commonly used method is measuring the diameter at breast height (DBH), which serves as a standard indicator for assessing tree size, growth, biomass, and carbon content in forest management and ecological studies [1]. However, traditional DBH measurement techniques can be labour-intensive and costly, often requiring long hours in the field, while modern methods of measurement come with high upfront investment [1], [2]. As the demand for sustainable forestry practices and urban greening initiatives increases, there is a pressing need for improved measurement methods that are both accurate and affordable.

The measurement of DBH is a crucial aspect of forest management and ecological studies. The traditional method usually used by forest researchers to measure tree DBH is with a diameter tape or a caliper [3]. In the last 5 years, various innovative methods have been developed to improve the accuracy, efficiency, and cost-effectiveness of DBH measurement. These methods can generally be divided into two categories: contact methods; such as using an electronic tree measuring fork, an electronic bar, a draw-wire displacement sensor, or an electronic caliper; and non-contact methods, which include close-range photogrammetry (CRP), simultaneous localization and mapping (SLAM) and terrestrial laser scanning (TLS) using light detection and ranging (LiDAR) [4]. Both of these method categories have their advantages and disadvantages.

While reported to give the most accurate results, contact methods for measuring DBH are typically time-consuming. Nevertheless, these manual approaches have seen recent innovations that move beyond traditional diameter tapes and calipers. This includes an innovation proposed by replacing the traditional tapes with electronic sensors, estimating the DBH by measuring the inflection of an elastic wire. Sun *et al.* developed a new handheld device equipped with an electronic measuring tape that is able to upload data directly to a smartphone application, thereby replacing traditional paper-based recording methods. The device was reported to be cheap to produce and achieved high accuracy, reporting a DBH measurement bias of 0.05 cm and an RMSE of 0.36 cm [5]. Li *et al.* improved their version of electronic caliper-like device that can measure tree diameter and tree position by combining angle sensors and Ultra-Wideband (UWB) modules, together with a computer software that allows direct data import and analysis [5]. This contact-measurement method achieved good RMSE of 0.13 cm with 0.60% relative RMSE (RRMSE) when compared to actual measurement with diameter tape and 0.46 cm RMSE (0.175% RRMSE) when compared to caliper measurement results. However, the application of contact measurement methods is limited to accessible tree trunks. When the tree trunks are surrounded by obstacles like thick understory consisting of saplings, shrubs, vines and other ground cover plants, the DBH measurements using contact methods will be more challenging and require longer time to complete.

To overcome the limitations of contact methods, many non-contact methods have been developed over the years. Unlike contact methods, DBH measurements using non-contact methods can be conducted at a distance from the target trees without having to come in contact with the trunks. In general, these methods involve capturing either 2D or 3D image data of the tree using suitable devices and perform post processing to estimate the DBH. 3D image data can be captured using passive sensors and active sensors. In one study, a binocular vision method was proposed to achieve non-contact and efficient DBH measurement. This method involves the use of a calibrated passive binocular camera to capture images, which are then processed to generate point clouds for DBH extraction [6]. The proposed method demonstrated an RMSE of 3.13 cm and a MAE of 3.11 cm, indicating its accuracy and efficiency. A slightly better RMSE was obtained in another study using passive cameras and structure from motion (SfM) photogrammetry, providing high precision in DBH measurement [7]. The Auto-DBH software developed integrates SfM reconstruction and automatic DBH estimation, achieving RMSEs as low as 1.41 cm in plots with mostly round-stem trees. Unmanned aerial vehicles (UAVs) with passive cameras were also utilized in DBH measurement studies. UAV images have been used to extract values for crown width and tree height. The DBH information was subsequently derived from these measurements using inversion models, achieving a coefficient of determination (R^2) of 0.85 and an average relative error of 4.3% [8]. This method provides a quick and precise means of obtaining stand factors in forest surveys. However, its reliance on regression models may limit the applicability of the findings to different forest types or conditions. Moreira et al. used UAV-based photogrammetry and SfM techniques to measure DBH but found that the accuracy can vary significantly based on survey design parameters such as flying altitude, camera tilt and image processing methods [9].

Active sensors, such as LiDAR, work by emitting their own energy and measuring the time it takes for the signal to return from the target object. These returning signals are used to create a detailed 3D profile of the environment. In methods like TLS and mobile laser scanning (MLS), the 3D data is combined with deep learning algorithms to improve the accuracy of DBH measurements in complex forest environments. The proposed methods achieved high precision and recall rates, with RMSEs of 2.5 cm in natural forests and 1.65 cm in urban forests, demonstrating robustness against noise [10]. Xu *et al.* used a combination of backpack laser scanning (BLS) and UAV laser scanning (ULS) technologies to extract DBH and tree height information [11]. This study employed LiDAR360 software for data processing and demonstrated high accuracy in individual tree segmentation and parameter extraction. While achieving a good R^2 value of 0.904 for DBH, they acknowledged the limitations in the DBH precision, particularly in understory areas where the canopy may obstruct the laser scanning. Although they produce more accurate results, measurements acquired via LiDAR systems typically face two primary barriers: they are not a cost-effective solution for general application, and they require complex operational procedures and processing.

A cheaper solution for non-contact method is by using 2D image processing. This method works by first identifying the tree trunk in a 2D image and then calculating the scale between the image and the real-world object. Recent research has advanced the use of 2D images for estimating tree parameters. Studies have shown that standard smartphone cameras can effectively extract DBH values through deep learning and photogrammetry techniques. For instance, recent methods using deep learning models like YOLOv5 or single-image scaling have achieved accuracies with RMSE values as low as 0.73 cm [12], [13]. Additionally, SfM techniques have been successfully applied to reconstruct 3D sparse points from 2D images to calculate tree dimensions [7]. However, these 2D-based methods often face limitations, such as the need for manual reference objects in the field of view or challenges in identifying objects due to lighting and complex forest backgrounds [1].

To address these issues, this study investigates a reference object method in Phase 2, followed by a Phase 3 approach that replaces physical reference objects with direct distance measurements using built-in smartphone LiDAR sensor. The main hypothesis is that accurate DBH estimates can be obtained using smartphone images to replace traditional measurement methods, which are often slow and labor-intensive. In this paper, the authors introduce an automated DBH measurement method that utilizes computer vision techniques and mathematical algorithms to extract trunk diameter values directly from smartphone RGB images. This solution aims to make forest surveys faster, less labour-intensive, and safer, as well as to greatly enhance efficiency. By streamlining the measurement process, the proposed approach is able to reduce the time and effort required for data collection while minimizing risks associated with fieldwork. Ultimately, this innovation will enhance the overall effectiveness of forest management practices and contribute to more sustainable environmental care.

2. METHODOLOGY

2.1. Data collection

2.1.1. Study area

The study areas are shown in Figure 1, located in Peninsular Malaysia in Figure 1(a), specifically in the state of Selangor (Figure 1(b)). There were 2 main locations where the image data were collected as shown in Figure 1(c). The first area is in the Permanent Reserved Forest of Bukit Belata Tambahan in Hulu Selangor (3º33'031z.1" N, 101º27'24.1" E). Hulu Selangor is a district located in the north of Kuala Lumpur. The second area is in the urban park of Cyberjaya Lake Garden (2°56'17.16" N, 101° 38' 31.2" E), in the district of Sepang, south of Kuala Lumpur. The average temperature in Selangor remains relatively stable year-round, typically ranging between 23 °C (73°F) and 33 °C (91°F). The warmest months are generally March and April, with average highs reaching around 33 °C (91°F). Sample images were purposely collected from natural forest and urban forest areas to ensure the trained model will be able to segment individual trees out in varying forest (dense) and urban (sparse) backgrounds, as can be seen in Figures 2(a) and 2(b). There were variations of species and shapes of trees in both environments as well. These variations are good to be included in the training data as they would help to familiarize the segmentation model further with a variety of tree species and shapes.

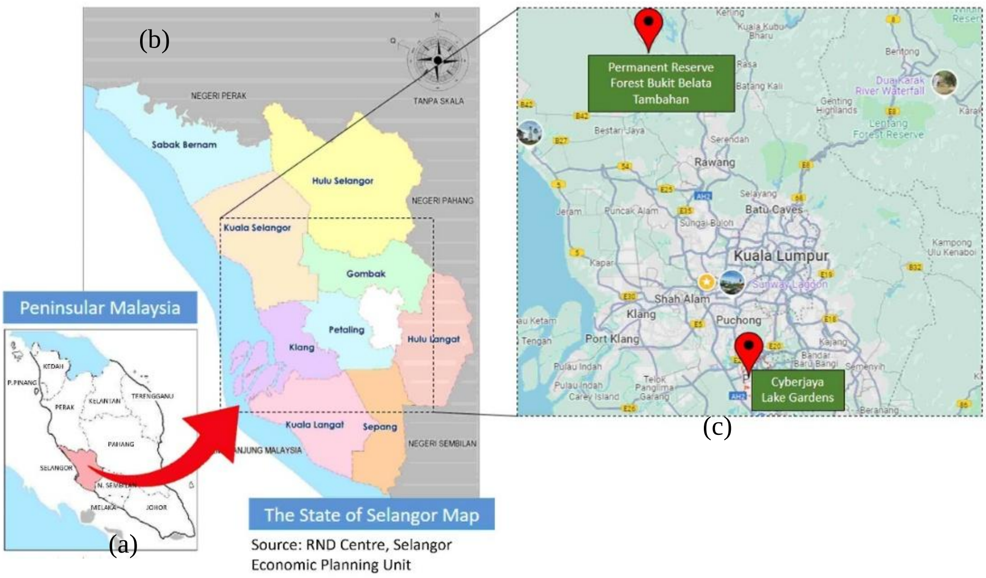


Figure 1. Location of the study area (a) Malaysia Peninsula, (b) State of Selangor, and (c) the collected image data

(a) (b)

Figure 2. Sample images of trees in (a) plot 1: reserved forest and (b) plot 2: urban park

2.1.2. Hardware for image collection

In this study, the images required for artificial intelligence (AI) model training were collected using global positioning system (GPS) enabled smartphone cameras, a reference object and tree-diameter tapes. It is important to enable the GPS function in the smartphone settings before performing image collection so that all the images acquired will be geographically tagged. The geolocation information (GPS coordinates) of where each image was taken was stored in the metadata of each image file. Geolocation information is one of the important data required by forest researchers and it is used to correctly identify each tree. The reference object used was a white rectangular piece of board mounted on a long stick with a sharp end, to enable it to be driven into the ground and stand independently beside trees during image capture. The white colour was ideal for making the reference object to be highly visible in each image. The purpose of the reference object is to provide length measurement reference during post-processing to find the DBH. For that reason, the horizontal length of the reference object must be known and recorded. For visual clarity, the reference object can be seen beside the urban trees in Figure 2(b). The tree diameter tapes were used to measure the actual DBH values of each tree captured as our sample image. These actual DBH were used to validate the DBH results obtained by our model.

2.1.3. Data acquisition

In the reserved forest plot, tree image collection for training and test data were collected in teams of 2 or 3 persons. Besides safety reasons, it was also to make data collection faster and tasks were carried out efficiently. One of the requirements of the images collected is to have the base of the targeted trees to be visible in the images for DBH measurement purposes, thus thick bushes and shrubs around the base of trunks need to be reduced before images are taken. Proper personal protective equipment (PPE) was used by each person as a safety precaution against hazards when working in the forest. The PPEs were safety jungle boots, hats for head protection, long sleeve shirts, long pants and gloves. The image collection activity in the forest was quite challenging and took longer time compared to data collection in the urban park due to the undulating terrain and thick vegetation. In the urban park, image collection was faster as the terrain was rather flat and easily accessible. In the beginning phase, the authors collected images of only straight trees for the segmentation model training data. As the accuracy of the segmentation improved, the authors included branched trees and leaning trees as well to further enhance the segmentation model capability. The authors later developed a new method for the auto calculation of DBH values specifically for branched and leaning trees. Overall, more than 2000 tree images were collected in several phases and used as training data and test data.

2.2. Methods

The data source for this study was tree images captured by normal smartphones, which also recorded geolocation data at the time of the picture. The developed DBH estimation model will perform the DBH calculation from the tree images in cm, based on the reference object in the image that provides the cm/pixel information. To achieve that, the collected images were first used to train the segmentation model using YOLOv8 deep learning model. The segmentation model's purpose is to detect and identify the central tree image in the image samples. The model was trained with more than 1700 annotated images of trees from forests and urban backgrounds to increase its accuracy in tree detection. To enhance the model's ability to accurately detect various tree shapes, the training dataset included not only images of typical straight trees but also those with leaning and branched trunks. After the tree has been identified in the image, the DBH Estimation Model will be used to extract the tree DBH values. This model was developed based on standard DBH measurement methods for various tree shapes as outlined in the Forest Research Institute Malaysia's (FRIM) Technical Information Handbook No. 59 titled "Manual Kerja Lapangan: Survei Karbon Hutan

(Field Work Manual: Forest Carbon Survey)" [14]. The DBH values were derived from the images using key points and pixel-counting methods. The model was improved further in Phase 2 so it can correctly measure the DBH of leaning and branched trees as well. The measurement methods for odd-shaped trees are slightly different, and modifications were made to the algorithm. The overall flow of the process is shown in Figure 3.

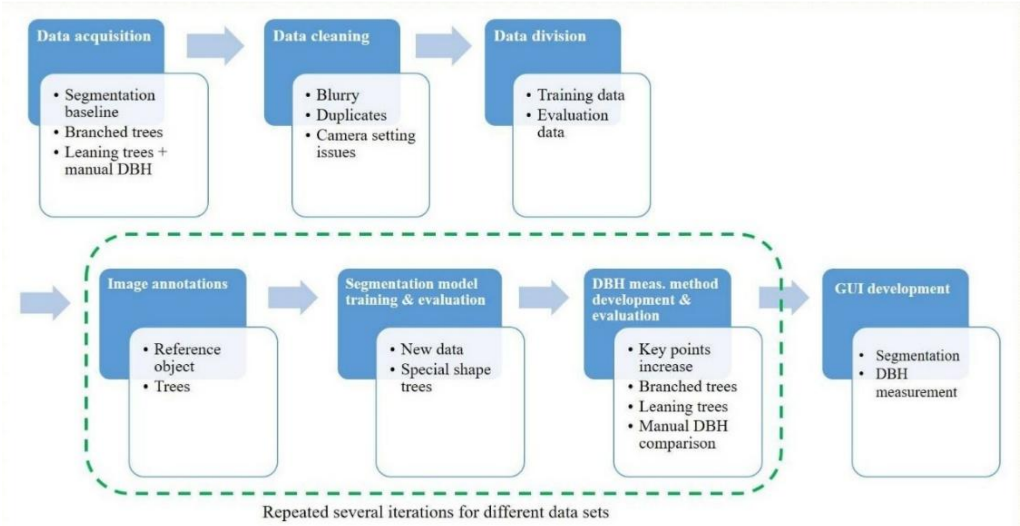


Figure 3. Process flow of the tree DBH estimation model development

2.2.1. Image annotation

Image annotation in computer vision refers to the process of labeling or tagging images with descriptive information, such as tags or descriptions, to facilitate the training of machine learning models. This process is crucial for developing accurate models in various computer vision tasks, including image classification, object detection and semantic segmentation. In this study, the image annotations were performed manually to accurately identify and label trees with various shapes in the collected images. The annotations were carried out using LabelMe, an open-source image annotation tool [15]. LabelMe was inspired by MIT's web annotation tool with the same name. LabelMe allows the creation of annotations for object detection, classification, and segmentation of computer vision datasets. It allows users to draw annotations using polygons, rectangles, circles, lines, and points. To properly outline the shape of trees, the authors used the polygon function during annotations, instead of simple bounding boxes normally offered by other annotation tools. Besides annotating the trees in the images, the reference object in the images was annotated and given a dedicated label as well. This was done to enable automatic DBH measurement based on the size and pixel count of the reference object. It is important to properly annotate the base of the trees without including the sprawling roots to prevent miscalculation of the DBH. Figure 4 shows an image example of a tree with the reference object, annotated by using LabelMe tool.

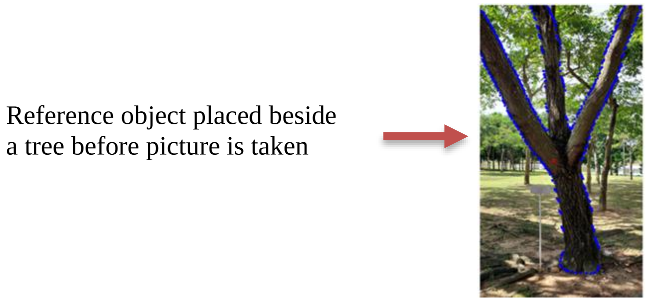


Figure 4. Sample of annotated tree using LabelMe tool

2.2.2. Segmentation model training and evaluation

Segmentation in computer vision involves partitioning an image into distinct regions to identify and classify objects [16]. Challenges in segmenting trees include overlapping branches, varying lighting conditions, and complex backgrounds. Solutions for these challenges include adjusting algorithm variables in high-density areas to narrow the object recognition range [17]. These methods improve the accuracy in distinguishing tree components within complicated scenes like in a thick forest. In this study, YOLOv8 deep learning algorithm was used for developing the tree segmentation model due to its significant advancement in object detection and segmentation processes within computer vision [18]. YOLOv8 demonstrates improved speed in object detection, which is crucial for real-time applications. Performance tests indicate that YOLOv8 can process images faster than YOLOv7, achieving a higher frames-per-second (FPS) rate while maintaining accuracy [19]. YOLOv8 outperforms YOLOv7 in terms of accuracy too, especially in detecting small objects. The introduction of a dynamic head network enhances the model's ability to accurately identify and localize objects, leading to improved mean average precision (mAP) scores [20]. With YOLOv8, users can achieve better performance with less manual tuning due to its anchor-free architecture. The backbone network of YOLOv8 also has been optimized for better feature extraction, contributing to its overall performance improvements. This enhancement allows the model to leverage deeper learning capabilities, resulting in more robust detection and segmentation outcomes. YOLOv8 was also selected due to its versatile design, which made it easier to train on different datasets without extensive modifications required.

In this study, the segmentation model training was done in 2 phases. In Phase 1, the model was trained with 1335 annotated images of trees from forests and urban backgrounds to increase its accuracy. In this initial phase, only trees with somewhat vertical trunks were used, focusing on the main objective which was to accurately detect the trees in each image. The model performance was then evaluated with 150 new test images, and the mAP was calculated at an intersection over union (IoU) threshold of 0.50 (mAP50), at varying IoU thresholds ranging from 0.50 to 0.95 (mAP50-95) and F1 score were recorded. The F1 score is a key metric in machine learning, balancing precision and recall for optimal AI model performance. In Phase 2, the model was further trained for improvement with an additional 406 newly collected tree images of various shapes, including ones with branched and leaning main trunks before being evaluated again with the same 150 test data. The new mAP50, mAP50-95 and F1 scores were recorded for comparison.

2.2.3. DBH estimation method development and evaluation

The DBH estimation module was developed to extract the trunk diameter measurements from still tree images. The module was developed using Python programming language and algebraic mathematical calculations involving coordinates and linear lines. The diameter of the trees was measured at 1.3 meters height from the ground as practiced by forestry researchers [21], [22]. The estimation method developed in Phase 1 worked well only for vertical-standing trees. In Phase 2, the method was improved to cater DBH estimations for leaning and branched trees as well. The output of the tree segmentation model is a masked area predicted to be the tree in focus for DBH estimation. These masked areas have outlines consisting of pixel dots with x and y-coordinates for each of them, which were later used in the DBH estimation process.

The overall steps and flow of the algorithm is shown in Figure 5. Figure 6(a) shows the marking used for DBH measurement of a single trunk tree, while Figure 6(b) shows the DBH measurement markings for trees with multiple trunks. The DBH estimation module consists of three main processes. The first process is to check if the tree in the image has a single trunk or multiple trunks. This step is important because the method of DBH estimation will slightly differ between a single-trunk tree and one with many trunks (multi-stemmed). According to [23] who studied the measurement and management methods of multi-stemmed trees by various forest practitioners, forest researchers have always identified them as particularly challenging regarding consistency in measurements across space and time. Many different but accepted methods were practiced around the world for measuring the DBH of multi-stemmed trees. One of the most widely accepted methods is to measure the individual DBH of each stem and the DBH for the tree is found by taking the square root of the sum of all squared stem DBHs, rounded to the nearest whole number [24].

$$DBH = \sqrt{(D1^2 + D2^2 + D3^2)} \quad (1)$$

where DBH is the overall tree DBH, D1 is the diameter of the first trunk, D2 is the diameter of the second trunk and D3 is the diameter of the third trunk. The second process embedded in the DBH estimation method is identifying the tree incline and the bottom point. The incline is important to correctly measure the DBH at a perpendicular angle to the trunk incline, and the bottom point provides the starting point for the 1.3 meters height where the DBH is measured. The final process is to measure the DBH itself after all guiding parameters have been identified.

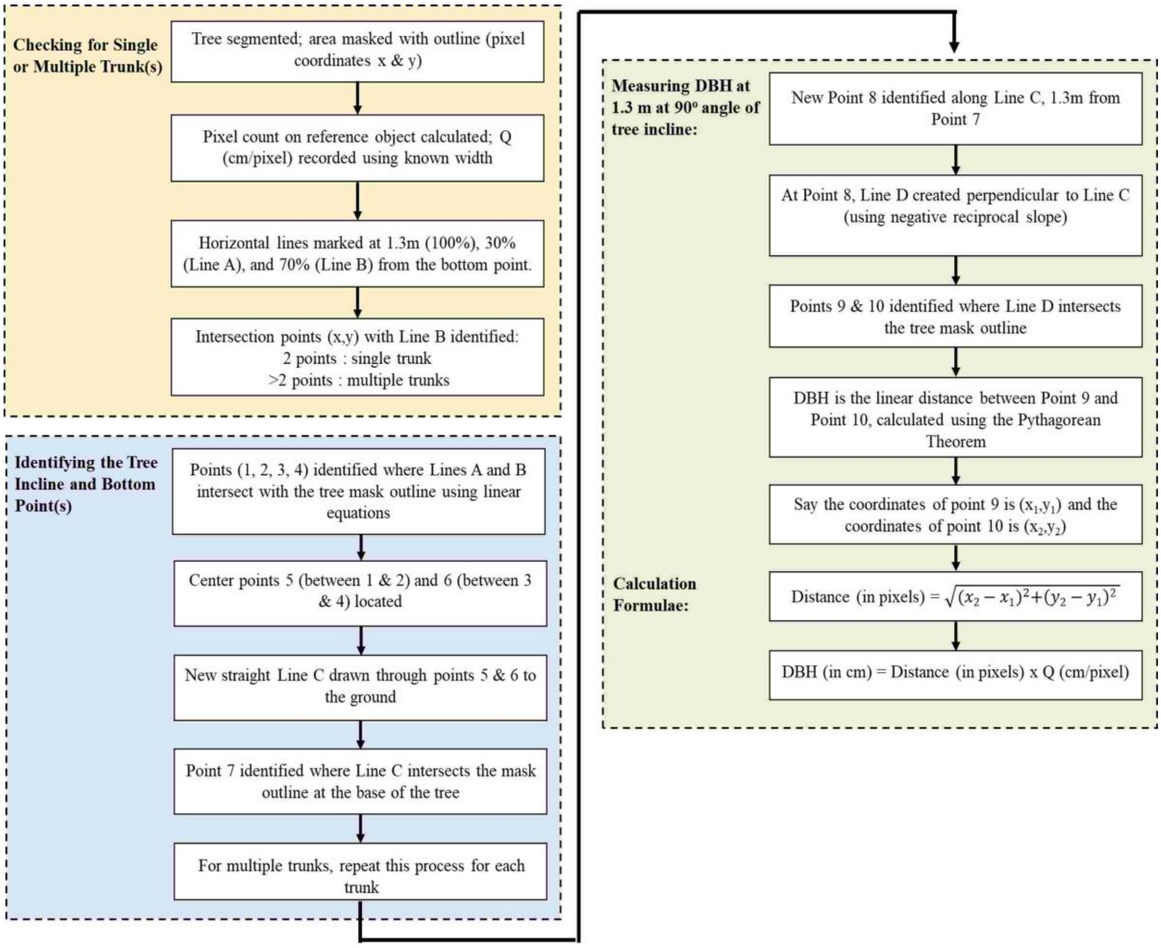
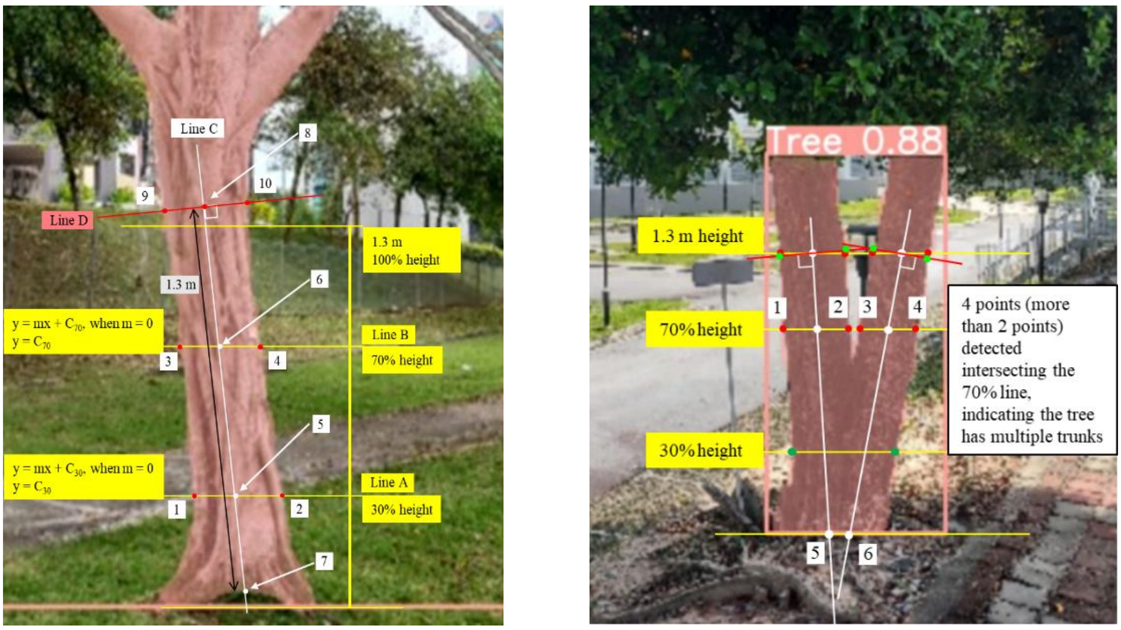


Figure 5. Flowchart of DBH extraction algorithm



(a) (b)

Figure 6. Markings to extract DBH value from still images (a) measurement of DBH for single-trunk tree and (b) measurement of DBH for multiple-trunk tree

Phase 3 of the study involved the acquisition of mobile devices featuring LiDAR sensors (specifically the iPhone 16 Pro) to facilitate the collection of new set of test images. The existing Tree Segmentation model from Phase 2 was retained because its segmentation accuracy was considered sufficient. The use of built-in LiDAR sensors enabled the direct measurement of the smartphone's distance from the tree during image acquisition, which replaced the previous reliance on external reference objects. The DBH estimations were calculated using a simplified in (2). This was done by first calculating the angle for the field of view (***FOV***) as shown in Figure 7 using 12 image samples of a reference object in the laboratory with known width. Images of the reference object were captured using three different iPhone 16 Pro smartphones, with four images per phone, recorded at each of four designated distances of 1 m, 2 m, 3 m and 4 m.

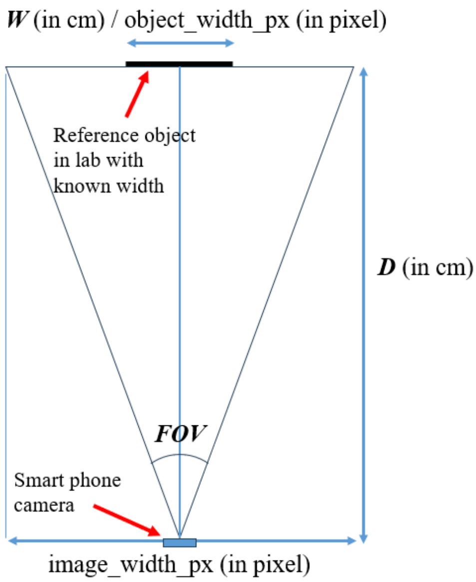


Figure 7. Calculation of ***FOV*** angle using a known-width object as reference

$$FOV = 2 * \arctan\left(\frac{W * image\_width\_px}{2 * D * object\_width\_px}\right) \quad (2)$$

where:
- FOV is the field of view angle (deg),
- W is the physical width of the reference object (cm),
- D is the distance of smartphone from the tree (cm),
- image_width_px is the width of the image (px),
- object_width_px is the width of the object (px).

The average value of FOV was then used as a constant in (2) with values from collected tree images to calculate the DBH, represented by W in the equation.

2.2.4. GUI development

The main function of the graphical user interface (GUI) was to showcase the capabilities and features of this low-cost DBH estimation tool. At the same time, it provided a practical platform for testing and fine-tuning the solution. The GUI was developed using Streamlit, a Python-based open-source framework that enables the creation of web applications with minimal code. Streamlit is widely used in data science and machine learning projects because it is easy to use and ideal for rapid prototyping projects.

The GUI was designed to be simple and practical. It allows users to browse and upload data images directly from their device's storage, with file size limit of 200 MB per file. Compatible image formats include PNG and JPEG. Figure 8 shows a snapshot of the measurement results on the automated tree DBH measurement GUI.

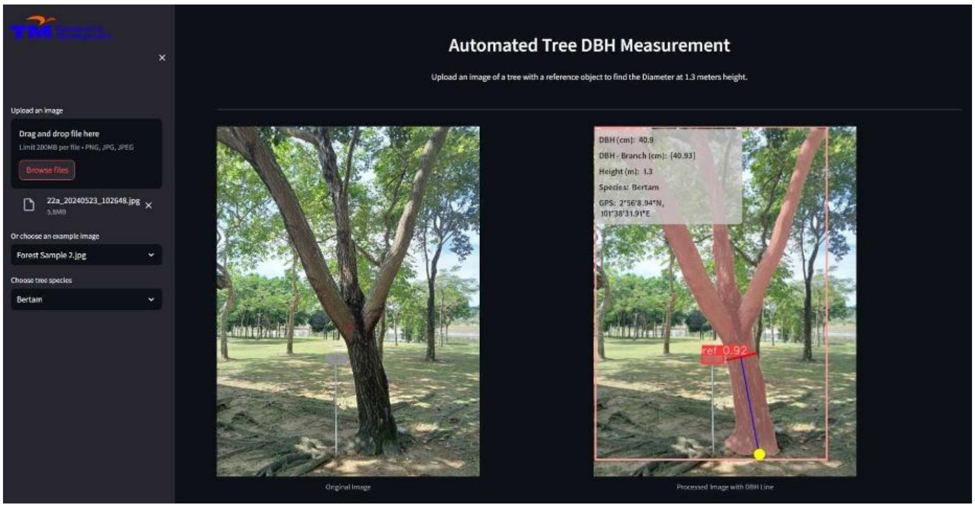


Figure 8. GUI of the tree DBH measurement solution

3. RESULTS AND DISCUSSION

3.1. Tree segmentation model results

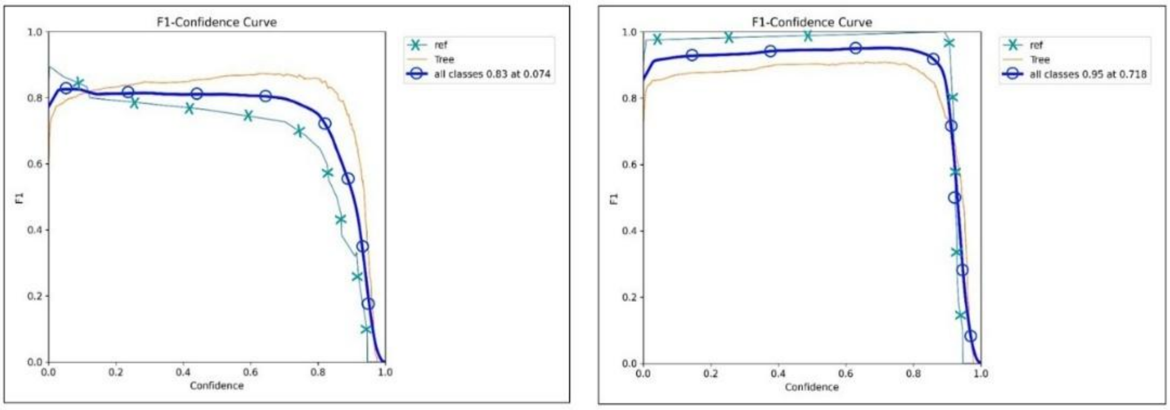
The tree segmentation model was trained with the objective of detecting and masking a single tree in focus in still images collected using smartphone cameras. The model was trained with 1335 training data in Phase 1 but the results showed some partial detections on some trees, as shown in Figure 9. With some areas detected as false negative and not properly masked, the DBH estimation will not be accurate or not possible at all, if the unmasked area is at the DBH estimation region. Table 1 shows the Tree Segmentation Model results comparison between Phase 1 and Phase 2 models. The Phase 1 segmentation results achieved mAP50 of 88.3%, mAP50-95 of 64.0% and the F1 score was at 83%. To improve the segmentation model, more training data were collected both from reserved forest and urban forest areas. In this second phase, data collection included images of trees with various shapes, including leaning and branching with multiple trunks. Annotation techniques were refined further especially around the base area of the trees in every image. In total, an additional 406 images were included in the training data set for Phase 2. The test results showed improvement of mAP50 to 96.0% and mAP50-95 to 74.9% while the F1 score improved by 12% to 95%.

Figure 9. Tree segmentation model results for Phase 1 and Phase 2

Figure 10 shows the F1 score curve for tree segmentation model improvement from 10(a) Phase 1 model to 10(b) Phase 2 model. Figure 10(a), the model recorded peak F1 score of 0.83 at Intersection over Union (IoU) 0.074. The result of Phase 2 model in Figure 10(b) achieved higher peak F1 score of 0.95 and better IoU of 0.718. This means the model in Phase 2 has a better balance of high precision and high recall, leading to a more accurate segmentation.

Table 1. Tree segmentation model results comparison for Phase 1 and Phase 2

Metrics	Phase 1 Model	Phase 2 Model
Training data set	1335	1741 (1335 + 406)
Test data set	150	150
mAP50	88.3%	96.0%
mAP50-95	64.0%	74.9%
F1 Score	83%	95%

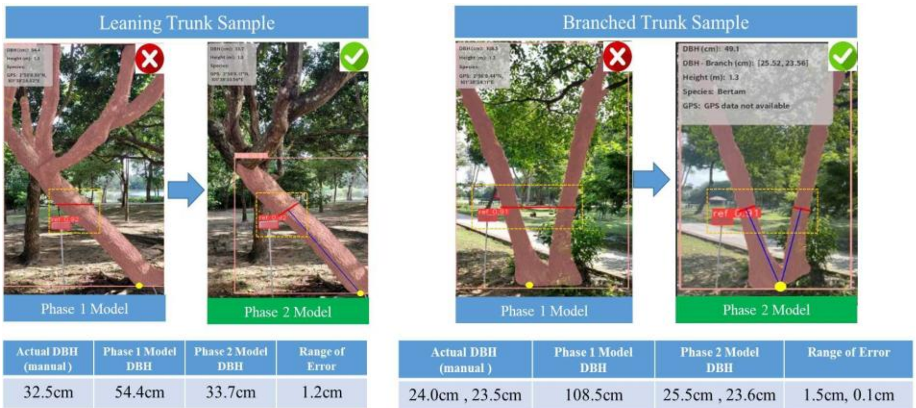


(a) (b)

Figure 10. F1 score curve for tree segmentation model improvement from (a) Phase 1 to (b) Phase 2

3.2. DBH estimation model results

The DBH estimation model in Phase 1 gave accurate results for vertical trees but could not properly measure the DBH of leaning trees or trees with multiple trunks. In Phase 2, the calculation method was reviewed and improved to cater for also leaning and multi-stemmed trees. The results obtained were compared with the DBH values measured manually using diameter tapes and the range of error calculated were found within the acceptable limits which are below 2.0 cm, but for a small test sample. The summary of the results is shown in Figure 11. Figure 11(a) shows a leaning trunk sample image and how the Phase 2 model measured the DBH values perpendicular to the center line of the leaning tree trunks, producing accurate reading. Figure 11(b) shows a branched trunk sample image and how the Phase 2 model is capable of detecting multiple trunks and gives correct diameter measurements of every trunk.



(a) (b)

Figure 11. Phase 2 results of the DBH measurement model showed improved results and acceptable range of errors for (a) leaning trunks and (b) branched trunks

The Phase 3 model was tested with 143 tree image samples. Table 2 summarizes the key statistical characteristics of the traditionally measured DBH and the estimated DBH results from images acquired using iPhone 16 Pro smartphones with LiDAR sensor. The average DBH of the latter method was 29.8 cm, with a standard deviation (Std. Dev.) of 13.5 cm. The minimum estimated DBH was 12.9 cm, and the maximum estimated DBH was 92.7 cm.

Table 3 shows the Phase 3 method performance metrics. Estimated DBH results were within 1 cm of the actual DBH values for 74 out of 143 measured trees (51.70%). An overall RMSE of 1.80 cm (6.0% RRMSE) was achieved using this Phase 3 model which uses the distance between smartphone camera and trees to estimate the DBH. The MAE was 1.10 cm, and the standard deviation of errors was calculated to be 0.77 cm.

Table 2. Key statistical characteristics of the estimated DBH for Phase 3 DBH estimation model

Parameter	Mean (cm)	Std. Dev. (cm)	Min. (cm)	Max. (cm)
DBH (traditional)	29.82	13.62	12.73	92.31
DBH (application)	29.76	13.52	12.93	92.71

Table 3. Performance metrics achieved using Phase 3 method

DBH within 1 cm error (%)	RMSE (cm)	RRMSE (%)	MAE (cm)	Std. Dev. Of Errors (cm)
51.70	1.80	6.0	1.10	0.77

3.3. Discussion

Tree DBH data is a critical metric in forestry and ecological studies, serving multiple purposes across various domains. DBH is a standardized measurement taken at 1.30 meters above ground and is used extensively in forest inventories, ecological management, and urban planning. The data collected from DBH measurements provide insights into tree growth, forest health, biomass content and ecosystem services. In this study, the authors reported a method to measure and record the tree DBH that is faster and less labour intensive compared to the traditional method, as well as a lower-cost alternative compared to MLS, TLS and SLAM methods. The study included a diverse range of tree sizes, as evidenced by the high standard deviation (Std. Dev. = 13.52 cm) around the mean DBH of 29.76 cm (Table 2). This ensures that the accuracy analysis presented in this study is applicable across various tree sizes.

The accuracy assessment of the Phase 3 model, which utilizes smartphone camera-to-tree distances for DBH estimation, revealed good performance metrics suitable for forestry applications, as shown in Table 3. Over half of the measured trees (74 out of 143 trees, or 51.70%) produced DBH estimates within a 1 cm margin of error, indicating a moderate level of measurement precision for individual trees. The overall RMSE was calculated to be 1.80 cm with RRMSE of 6.0%, demonstrating strong typical accuracy across the varied sample. Furthermore, the MAE was 1. 1 cm, suggesting the model is largely unbiased in its estimates. The low standard deviation of errors (0.77 cm) confirms high consistency and repeatability in the model's performance. These results jointly validate the efficiency of using integrated distance capture devices for reliable, large-scale DBH inventories.

The results of this study show an accuracy (RMSE) that is consistent with those reported in previous literature. It is slightly higher than the 1.5 cm RMSE DBH accuracy reported in a study in Canada, conducted using an iPad Pro LiDAR to collect point cloud data of trees in a natural Boreal forest [22]. The 1.80 cm RMSE achieved is however lower than a few other studies; for example, the study in an urban park of Slovakia (RMSE 2.8 cm), comparing DBH estimates from a variety of parameter combination settings in the scanning application (3DScannerAPP 1.9.1) [25]. Similar to [22], this study also utilized an iPad Pro LiDAR, point cloud data and a circle fitting algorithm to estimate the DBH. A prior study in Türkiye reported an RMSE of 2.3 cm for smartphone-based DBH estimates from 105 trees when compared to caliper measurements [26]. Higher DBH accuracy (RMSE 0.7 cm) can be achieved using professional-grade TLS and MLS methods compared to consumer iPhone LiDAR (RMSE 1.7 cm) [2], but the related equipment acquisition costs are substantially greater.

Before further discussion, it is essential to acknowledge several key limitations in this study. The first limitation that the authors discovered was that the proposed method will not give accurate results if the tree trunk does not have a round cross-section, or, in other words, the trunk's width is of different lengths when viewed from different sides of the tree. When the tree trunk is not perfectly round, the DBH measured might be slightly different depending on which side of the tree the image was taken from. In this case, for improvement of the estimation, the authors suggest capturing the images of such trees from 2 or 3 different directions around the tree. Doing that will provide several DBH estimation values of the tree and the estimated DBH value can be calculated using (1). The second limitation identified is the vast diversity of tree shapes, which may reduce the effectiveness of this method for certain types. In this study, the authors focused only on straight, leaning and upright trees with multiple trunks. However, future work can include training the model further for other shapes of trees if sufficient data are available. The third limitation found is the accuracy of GPS location data obtained from smartphones. Modern smartphone GPS modules currently can provide accuracy up to 2 meters. While this is rather impressive precision, it may not be enough to guide foresters in identifying single trees in dense forests.

Notwithstanding these limitations, the author's study introduces a fast and cheap method to estimate tree DBH accurately. Forest researchers can simply upload new images of trees in the GUI and the DBH values will be assessed and calculated automatically by the trained model. In the field, the method proposed would help users to spend on average only around 10 to 30 seconds per tree, much quicker compared to around 2 to 15 minutes per tree using the traditional method. This faster data collection can allow users to cover more trees and more plots in a day's work. While traditional methods of measuring DBH require at least 2 or more persons to perform data collection effectively, this solution can be operated by a single person, leading to reduced manpower costs. If multiple manpower is available, each person can operate individually using their smartphones covering different plots and maximizing productivity. Using this method, collected data will be handled digitally and saved on the cloud, thus minimizing errors and hassles arising from manual data handling using pencils and paper. The proposed method also provides a safer alternative for forest researchers, not having to climb tall ladders to measure the DBH of large trees.

Like other studies and methods discussed in the literature review, the author's solution effectively addresses the limitations associated with traditional surveying methods, which are often characterized by high labour intensity, time consumption, and high manpower costs. Traditional techniques typically require extensive manual effort and can take significantly longer time to complete field surveys, particularly for large or complex forest sites. For instance, a study indicated that traditional methods could take 2 to 3 times longer than modern alternatives like laser scanning, leading to increased labour costs and extended project timelines [27]. In contrast, the proposed approach not only maintains acceptable accuracy but is also significantly more cost-efficient compared to most complex solutions like laser scanning as in [10], [11], [21], [28]. While LiDAR technology excels in speed and precision, it involves substantial initial investment costs for equipment, post-processing software and training. The cost of a LiDAR scanner can range from USD50,000 to over USD100,000, making it less accessible for smaller projects [29]. By implementing this solution, a balance is achieved between efficiency and affordability. The proposed solution reduces the overall project costs by minimizing labor requirements and shortening field survey durations.

To further enhance this study, several avenues for future work can be explored. Firstly, to improve user experience and operational efficiency, the authors suggest embedding the tree segmentation and DBH estimation models discussed in this study into a mobile application. This would make the process more accessible and user-friendly, allowing users to perform measurements conveniently on their smartphones and getting immediate DBH results. Some studies have been done to compare the performances of such mobile applications, namely Arboreal, Katam and Trestima with traditional data collection methods and concluded that the DBH measurements by the applications were accurate, but each application has different levels of performance based on different forest terrains [30], [31].

Secondly, the authors would like to propose combining the image and distance measurements trigger into a single button in the mobile application. This is to ensure the distance where the image is captured is the same as the distance recorded. The authors found that the use of two separate buttons for image and distance capture introduced inaccuracies in the measurement of the smartphone's distance from the tree, which will consequently affect the estimated DBH result. Lastly, if higher accuracy in GPS information is required, the authors recommend integrating the mobile application with a global navigation satellite system (GNSS) receiver, such as the Trimble DA2 or the Leica GG04 Plus. These receivers utilize real-time kinematic (RTK) technology to provide exceptional GPS accuracy of up to 1 cm. This level of precision would be helpful for researchers to accurately locate and identify individual trees within forest plots based on geolocation information. By pursuing these enhancements, the authors aim to make the proposed method more practical and effective for users in various forestry applications.

4. CONCLUSION

In this study, the authors have explored a new method that can estimate the tree DBH by using computer vision techniques and mathematical algorithms. Specifically, a tree segmentation model was trained to detect and mask trees in still images, and a tree diameter measurement algorithm was programmed using Python language on Streamlit to come up with an interactive and easy-to-use DBH estimation interface. The experimental results have shown that this method can be used to accurately estimate tree DBH and reduce the time, manpower and overall cost of forest surveys in the field. For future work, the authors aim to embed the tree segmentation and DBH estimation modules into a mobile application for faster results. Secondly, the authors propose to combine the image and distance measurements trigger button in the mobile application to prevent distance measurement inaccuracies. Lastly, the authors intended to incorporate a GNSS receiver with RTK technology to improve GPS accuracy, ensuring more precise data collection in various environments.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mohamad Razmil Abdul Rahman	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ishak Suleiman		✓	✓	✓	✓	✓		✓		✓	✓			
Mohammed Al Haek		✓	✓	✓	✓	✓		✓		✓	✓			
Yee Kit Chan				✓	✓					✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
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

The authors declare no competing financial, personal, or professional interests that could have influenced the findings of this study. This research was conducted with full academic independence and integrity.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Mohamad Razmil Abdul Rahman is a senior researcher at the Centre for Robotics and Sensing Technologies, TM Research and Development Sdn. Bhd., in Cyberjaya, Malaysia. He holds a bachelor of science in electrical and electronic engineering and a master's in engineering management, both from Universiti Tenaga Nasional (UNITEN), Selangor, Malaysia. In his role, Razmil focuses on advancing research in areas such as the internet of things (IoT), sensing technologies, robotics, process automation, computer vision, UAV photogrammetry and EMC compliance. Among the projects he has led is the smart forestry AI tools project, which was honored with the Gold and Special Award at the Malaysia Technology Excellence Awards 2025 and the Sustainable Development Goals International Innovation Awards 2024. His work aims to develop innovative solutions that enhance efficiency and functionality across various applications. For further inquiries, he can be contacted at razmil@tmrnd.com.my.

Ishak Suleiman is an associate principal researcher at the Centre for Artificial Intelligence, TM Research and Development (TM R&D) Sdn. Bhd., Cyberjaya, Malaysia. He holds a Master of Electrical Engineering (MEE) and a Bachelor of Electrical Engineering (BEE) from Universiti Teknologi Malaysia (UTM), obtained in 2002 and 1999, respectively. With over 20 years of experience in AI research and digital signal processing, he specializes in machine learning, deep learning, and computer vision. His recent projects include developing disease prediction models for eHealth applications, creating AI tools for smart forestry, and implementing image analytics for infrastructure verification systems. He holds multiple patents in the field of MIMO-OFDM communication systems and has published extensively in international conferences and journals. His accolades include a Bronze Award at the International Invention, Innovation and Technology Exhibition (ITEX) 2007. He can be contacted at ishak@tmrnd.com.my.

Mohammed Al Haek is a researcher at the Center for Artificial Intelligence, TM Research and Development (TM R&D) Sdn. Bhd., where he has been contributing since 2018. He is currently pursuing a Ph.D. in computer science at Multimedia University, Malaysia (MMU), focusing on artificial intelligence and computer vision applications. Holding a master's degree in computer science from the International Islamic University Malaysia (2016), he brings deep expertise in artificial intelligence, machine learning, and data science. His research portfolio includes significant contributions in areas such as eye-tracking technology for cognitive assessment, energy optimization strategies for swarm robotics, and modeling immune system responses for adaptive systems. At TM R&D, he applies his expertise in AI and machine learning to a range of impactful projects, including predictive modeling, time-series forecasting, computer vision, large language models (LLMs), visual language models (VLMs), and satellite image analysis, utilizing advanced algorithms and innovative data solutions to address complex challenges. He can be contacted at mohammedalhaek@tmrnd.com.my or alhaek@tmrnd.com.my.

Yee Kit Chan received his B.Eng. (Hons) in electrical engineering from the University of Malaya. He obtained his M.Eng.Sc. and Ph.D. in microwave engineering from Multimedia University, Malaysia. He is the deputy dean and professor at the Faculty of Engineering and Technology, Multimedia University, Malaysia. He is a registered Professional Engineer with the Board of Engineers Malaysia and a Professional Technologist with the Malaysia Board of Technologists. His research interests include synthetic aperture radar design, remote sensing, radar sensor development, and precision farming. Prof. Chan is presently the honorary treasurer of the IEEE Geoscience and Remote Sensing Society Chapter, Malaysia Section. In 2021, he was awarded the Top Research Scientists Malaysia (TRSM) by the Academy of Sciences Malaysia (ASM) and admitted as a Fellow of the ASEAN Academy of Engineering & Technology in 2022. He can be contacted at ykchan@mmu.edu.my.