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An artificial intelligence technology for promoting hom-thong banana agriculture system

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ABSTRACT

The hom-thong banana, being a high-value Thai export variety, is facing significant risk from disease outbreaks affecting crop yield and quality. Traditional visual inspection methods in detection of diseases are labor-consuming, error-prone. This research addresses these limitations by developing a new artificial intelligence (AI)-based automatic disease detection system for the hom-thong banana industry on top of cutting-edge computer vision technology. The study employed deep learning object detection models, contrasting Roboflow, you only look once (YOLO)v11, and YOLOv12 architectures, which were trained on a large dataset of 2,576 images of Thai banana plantations. With systematic data augmentation techniques, the dataset was augmented to 6,184 images of seven types of disease under varied environmental conditions. The method entailed extensive preprocessing and evaluation of performance through precision, recall, and mean average precision (mAP) metrics. Outcomes indicated that YOLOv12 outperformed with 93.3% accuracy, 83.3% sensitivity, and 86.3% mAP@50 compared to standard inspection schemes. This research is applicable to Thailand's smart agriculture initiative by providing farmers with low-cost, accurate, and effective disease monitoring equipment. The application of this AI system has the ability to enhance the yield of crops, reduce losses, and enhance the competitiveness of Thai banana exports in the global market, in support of sustainable agricultural development.

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1. INTRODUCTION

The hom-thong banana, renowned for its golden hue, aromatic fragrance, and superior taste, stands as a significant high-value crop for Thailand [1]. Commanding a premium in both domestic and international markets, particularly in Japan, this cultivar presents a lucrative opportunity for Thai farmers and is a key contributor to the nation's agricultural economy [2]. However, the full potential of hom-thong banana cultivation is currently hampered by a multitude of challenges, ranging from inconsistent yields and vulnerability to pests and diseases to inefficiencies within the supply chain. To address these critical issues and secure a sustainable and prosperous future for this prized commodity, a paradigm shift towards more innovative and intelligent agricultural practices is not just an option, but a necessity [3].

The path to elevating hom-thong banana production lies in the adoption of cutting-edge, innovative agricultural systems, with artificial intelligence (AI) technology at their core. Traditional farming methods, while valuable, often fall short in providing the precision and real-time data needed to optimize cultivation and mitigate risks effectively [4], [5]. Farmers grapple with issues such as the devastating impacts of Panama disease and other pathogens, the complexities of nutrient and water management, and the laborious process of monitoring crop health and predicting yields. These challenges frequently lead to significant pre- and post-harvest losses, inconsistent fruit quality, and an inability to consistently meet the stringent demands of export markets [6].

Traditional disease diagnosis methods such as visual examination through horticultural experts or farmers are typically human-error susceptible, tedious, and labor-intensive when disease has similar visual features [7]. In recent years, AI and computer vision have seen significant advancements that have been identified as potential tools for monitoring plant health in real-time. Object detection algorithms, in particular, have shown high promise in identifying plant diseases from images captured under varying field conditions [8].

One of the best-known AI solutions for computer vision within agriculture is the series of object detection models you only look once (YOLO). YOLO is especially well-known for high-speed and high-accuracy real-time object detection, and it is thus very well-suited for applications at the field level, where rapid decision-making is required [9], [10]. Experiments have established the performance of YOLO models in agricultural use cases, such as detecting tomato leaf blight [11], monitoring apple orchard pests [12], and detecting diseases in grapevines [13]. Contrary to the single-pass detection mode provided by conventional convolutional neural network (CNN) classifiers, YOLO's single-shot detection mode offers simultaneous classification and localization of multiple disease symptoms in a single image irrespective of complex backgrounds [14].

Research into YOLO with banana disease detection has become trendy in recent years for example, used deep learning object detection to diagnose banana bunchy top virus with much accuracy under field light illumination [15]. With the more recent YOLO versions, such as YOLOv5 and YOLOv8, the detection accuracy increases, computational capacity decreases, and portability and mobility to smart devices also improves to the extent where they can be deployed in portable configurations or drone-based monitoring [16], [17]. These and subsequent issues provide hom-thong banana farmers with the possibility of early-warning disease detection, thus generating less crop loss and less over-use of pesticides.

In Thailand, where the hom-thong banana is both a staple food and an export crop, the use of AI-based to keep disease detection systems on farm would supplement the national smart agriculture agenda. Combined with affordable imaging acquisition tools, smartphones, drones, or IoT cameras, the farmer can image the crop repetitively and receive feedback in reparable time to respond to issues causing potential loss of yield. It provides a promising, sustainable farming approach and includes other benefits outlined in the national agenda productivity, minimizing environmental impact, and income of the farmer [18], [19]. Therefore, the current study proposes the development of AI technology for promotion of hom-thong banana agriculture system using the YOLO object detection algorithm for early detection and accurate recognition of the key banana diseases. The proposed system is hoped to be an efficient and deployable tool for farmers, cooperatives, and agricultural agencies to ultimately support the competitiveness and resilience of the hom-thong banana industry in local and global markets.

This research proposes the development and implementation of an innovative agriculture system designed to specifically promote the cultivation of the hom-thong banana through the strategic integration of AI. This system will leverage AI-powered tools for the early detection and diagnosis of diseases through image recognition, enabling timely, and targeted interventions [20]. By bringing predictive analytics into play, we'll sharpen our yield forecasting, letting us plan earlier, plan smarter, and sync better with market needs [21]. In parallel, intelligent systems paired with deep data analysis will fine-tune our use of resources, especially when it comes to fighting disease while still driving down the bottom line of operational costs. Leveraging AI, the project seeks to weave a production network for the hom-thong banana that's not just leaner and more resilient, but also more profitable. The goal from the outset and at every step is to lift the competitiveness of Thai agriculture in the global arena and, just as crucially, to boost the incomes of the farmers whose work makes that agriculture possible.

2. METHOD

In this section provides an enhanced machine vision system with a deep learning approach to determine the diseases in hom-thong bananas as shown in Figure 1. RGB images obtained from hom-thong banana plantations in Thailand are annotated to form a training dataset and testing dataset. These images are taken in both optimal and suboptimal weather conditions. As mentioned in the previous section, the deep learning models are developed using the training dataset, and the performance analysis of the segmentation instance was conducted on the testing dataset. Following processing, the information was gathered to support the management of hom-thong banana farming by gathering disease data.

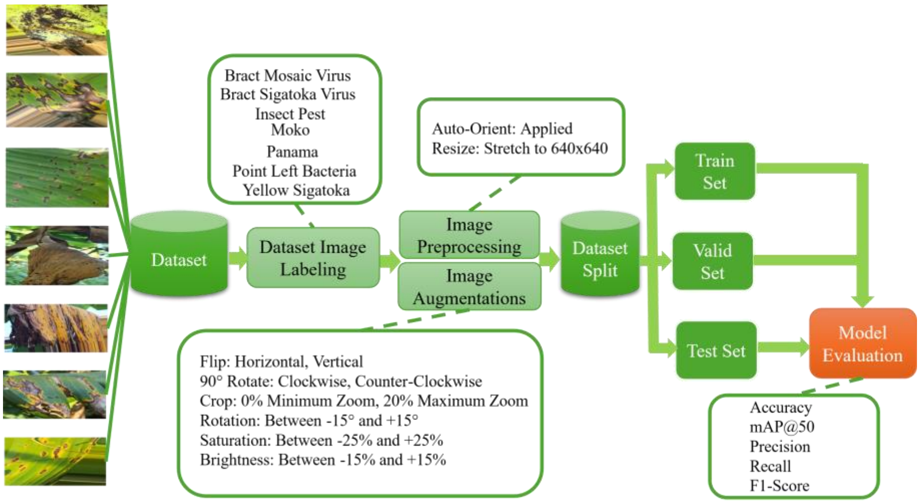

Figure 1. The methodology of the model of our work

2.1. Data collection

In this data collection in this study, we collected data on banana disease phenotypes from Thai hom-thong banana growers from the time of planting until they were ready for market demand, which is approximately 9-10 months before the crop could be harvested. In addition to recording banana density, as illustrated in Figure 2, banana phenotype data collection can be carried out in a variety of settings, including those with various light and weather conditions. Data is essential to machine learning. Gathering, labeling, and analyzing data are one of the deep neural networks (DNN) algorithm's primary pre-processing responsibilities. Figure 1 illustrates its seven illness features. In this step, images are used as data. Every picture is from an orchard of bananas. The main goal of the system described in this paper is to recognize objects in this case, the disease phenotypes of hom-thong bananas from the obtained photos. The automatic identification of these items in computer vision presents this difficulty. It follows that this stage may involve the use of some AI algorithms. For this strategy to work effectively, a lot of data is needed. As illustrated in Figure 2, we used Roboflow labeling software for analysis of seven illnesses, a program that can manually annotate these objects, to gather and annotate 2,576 photos of hom-thong banana disorders in order to accomplish this goal.

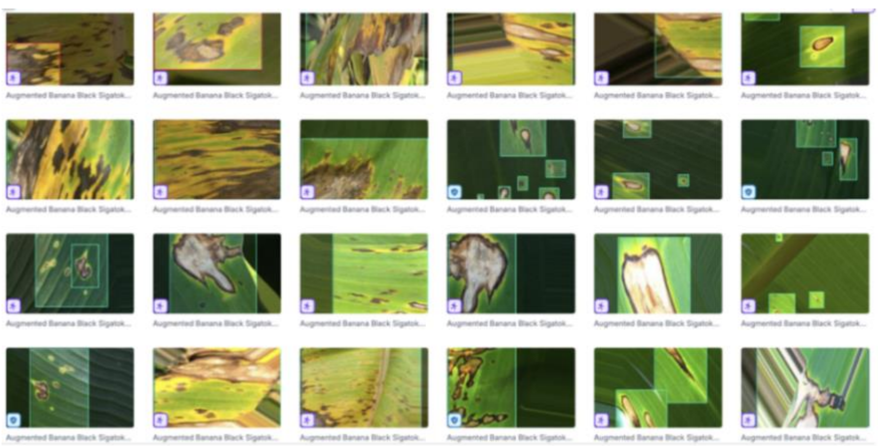

Figure 2. The data of annotation

In this instance, we have decided to use a labeling platform. This makes it possible to store annotations in a variety of formats. All completed annotations in the common objects in context (COCO) format must be saved in a suitable file format for later viewing in order for the training process to generate predictive models [22]. The software programs selected for DNN modeling and testing are compatible with this format. A corresponding JSON file including a framework for recording the object category and location of each annotation is included with every collection of annotated photos in the COCO format. As will be covered in the results section later, the COCO standard also offers important metrics required to assess the accuracy of the model [23].

2.2. Data preparation

Important steps in this section include confirming that there is enough data for model training, organizing the data, and augmenting the data with the Roboflow tool [24]. A snapshot of Roboflow shows an overview of the dataset. The pre-processing carried out for this investigation is also illustrated in Figure 3.

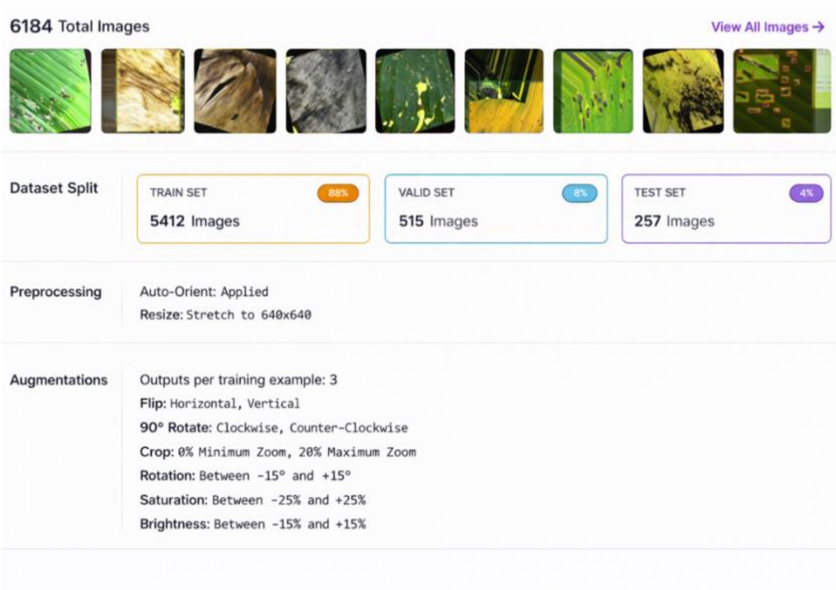

Figure 3. The data preparation for augmentation

The Roboflow platform facilitates every aspect of data, including pre-processing, augmentation, annotation, organization, model training, and deployment. This study's pre-processing step was concerned only with resizing any source images to follow the specifications of the target dataset. In terms of pre-processing, the source images underwent automatic orientation correction and rescaling to achieve a normalized size of 640×640 pixels to match the other normalized images in the dataset, which aided in ensuring a better performance in terms of computational time. In terms of augmentation, we applied a variety of techniques to increase the dataset size. This included all of the images being flipped both horizontally and vertically, as well as being rotated 90 degrees in either direction to assist the model in identifying objects at angles. We modified the brightness of the images by ±15% in order to create diversity in lighting situations that could increase the model's overall performance regarding different lighting environments. In terms of color, we adjusted saturation by ±25% to enhance the resiliency of the model to color changes. Finally, we randomly cropped 20% away from all of the images to try and teach the model to detect objects that were only partially visible. By using augmentation, we increased the original dataset of 2,576 images to 6,184 images. Although the free version of Roboflow limits your dataset size after augmentation, 6,184 is still a good number for training a model.

Roboflow organization capabilities made it easier to annotate the images and group them into a control system to create a comprehensive dataset of augmented and annotated images. Furthermore, the platform also simplified the workflow of machine learning because it separated the processed dataset into training, validation, and testing subsets automatically. Figure 3 shows a snapshot of a Roboflow interface showing the dataset overview and the preprocessing configurations that we used in the research. After we collected, annotated, preprocessed and augmented the dataset, our dataset was ready for machine learning experimentation and the development of an object detection model.

2.3. Application of artificial intelligence hom-thong banana diseases

The YOLOv12 model was trained on an NVIDIA Jetson Orin Nano development kit with 8 GB of RAM. The model was trained with PyTorch, a backend framework that runs on Linux. To give less chance of overfitting, the model was trained with 0.001 learning rate, batch set to 32 and dropout set to 0.5. The model was trained on for over a thousand epochs. Training was stopped when 162 epochs were reached if the validation set did not see improvement for 20 more epochs. Such a step was introduced in order to enhance generalization and avoid overfitting the training set. In both models, the learning rate was initially set to 0.01. Momentum and dropout weight parameters for both models stood at 0.937 and 0.0005, respectively. A learning rate is essential in such models in order to avoid overfitting in the training dataset. In fact, it can independently decide upon optimal values for trainability in order to avoid such problems. Adding a warm-up step can be essential in order to avoid settling in a local minimum point. At the moment, there is a momentum of 0.8 and bias learning rate of 0.1 and this section will continue to summarize the tools specified within the context of making a model to make a prediction.

Python is one of the most used programming languages and widely used for machine learning. Reasons for this include simplicity, packages available for efficiency in solving problems, and the number of developers [25]. Many libraries are available that are valuable to build DNN when developing in Python. The study's main focus is on object detection issues, with a particular focus on banana disease analysis. Because of this, many excellent Python modules are available. We decided to use Detectron2, which utilizes the PyTorch module. A greater variety of machine learning issues may be solved with the PyTorch library, which is extensively utilized in research. Advantages of the library include simplicity and flexibility. Often PyTorch is compared in some way with other programs that perform similar functions. In particular, both TensorFlow programs are used to build AI solutions because there is no concrete way to demonstrate which program is superior or best [26]. Detectron2 also has very modern object detection and segmentation algorithms [27].

The Detectron2 package's installation and setup are environment-dependent and not necessarily simple. Because it is so simple to upgrade from free to premium, we came to the conclusion that the Google Colab environment was a good choice for research and exploratory testing [28]. Google Colab has a number of tools that facilitate and speed up the configuration and installation process of the package. The premise of this technology is that individuals can run a virtual machine for a designated period of time, variable within the free version, and the developer is not notified how long, until their eventual disconnection. The pro version is eligible for the longer term. The virtual machine session can terminate, and the results might not be saved, depending on the model training. By implementing a very tiny piece of code to save the model checkpoint at different stages of the training process, this issue can be fixed. Technically speaking, if we are aware of and comprehend the restrictions of Google Colab's free edition, we consider the fantastic instrument at your disposal to assist you in completing the task at hand.

2.4. Performance evaluation

Five different criteria were used for evaluating the performance of the instance segmentation task for the Roboflow, YOLOv11, and YOLOv12 models. Accuracy was considered as the ratio of the correctly predicted positive events to the total positive events predicted, as clarified in (1). The recall measure, shown in (2), was used for computing the percentage of correct identifications for the positive events. These criteria were mean average precision (mAP) at 0.5 intersection over union (IoU), accuracy, recall, area under the curve (AUC) in (3) for the receiver operating characteristic (ROC), and inference time. As shown in (4), mAP is the average of the AP values over k object categories. A 50% overlap criterion between the predicted and actual item boundary/bounding boxes was utilized for AP computation. As shown in (5), the AUC for each model was calculated. The AUC takes into account all possible cut-off values. The speed of inference, or the amount of time required to analyze each individual image, also appears to be a measure of the model's capacity to produce prediction outputs. These metrics are calculated using:

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$IoU = \frac{Area\ Overlap}{Area\ Union} = \frac{TP}{FP+TP+FN} \tag{3}$$

$$mAP = \left(\frac{1}{K}\right) \sum_{i=0}^{k} (AP)i \tag{4}$$

$$AUC = \int_0^1 TPR(FPR)^{-1}(u)du \tag{5}$$

which indicates instances of true positive, false positive, and false negative using the letters TP, FP, and FN. $(AP)i$, where k is the total number of object classes, is the average accuracy for the i is class among these k classes. The area under the precision-recall curve for a class is known as the average precision (AP). FPR stands for false positive rate, TPR for true positive rate for a particular (single) image, and t for the model's inference time (in seconds).

3. RESULTS AND DISCUSSION

3.1. Comparative performance model for hom-thong diseases evaluation

The images of 2,576 photos in the complete RGB image dataset were taken by Thai banana growers in hom-thong. Ten percent are used for validation, seventy percent are used for training, and twenty percent are used for testing. In order to detect hom-thong banana illness, the model was trained across 162 epochs on the complete dataset in about 7.6 hours. Using a variety of metrics, including box loss (box_loss), segmentation (seg_loss), classification (cls_loss), and focal diffusion (dfl_loss), the training and validation set graphs in Figure 4 of Roboflow, Figure 5 of YOLOv11, and Figure 6 of YOLOv12 show how the model's performance improved. By controlling layer imbalance during training with a target loss function, these measures evaluate the model's ability to locate illness in hom-thong bananas by layer.

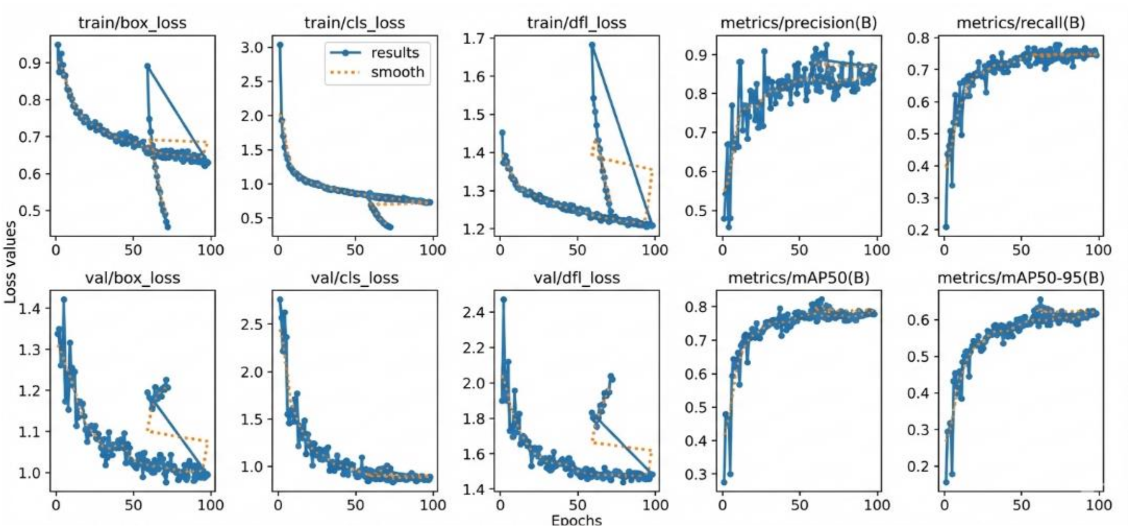

Figure 4. Training and validation sets are plotted using Roboflow to display epochs

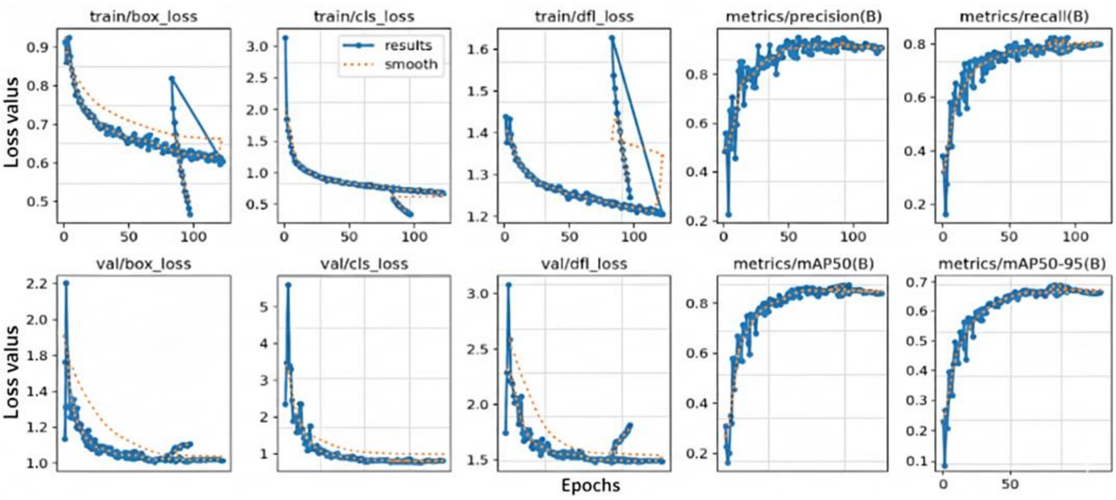

Figure 5. Training and validation sets are plotted using YOLOv11 to display epochs

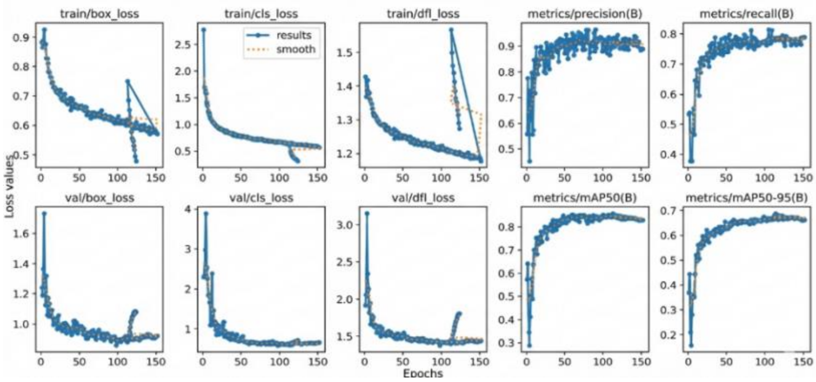

Figure 6. Training and validation sets are plotted using YOLOv12 to display epochs

The results from the Roboflow architecture in Figure 4 show steady convergence throughout the training run. Loss curves steadily decline with little variance, signaling established, stable learning. Both training and validation losses advance in parallel, keeping just the right amount of distance, which confirms the system is learning correctly without veering into overfitting. The convergence pace, though, is noticeably more gradual than with YOLO, and the architecture only manages expected baseline scores. Turning to the YOLOv12 results portrayed in Figure 5, the performance eclipses the Roboflow steady baseline in learning speed. The model sets records for swift initial convergence, reflected in steeper, earlier declines of the loss. There is mild elevation in curve oscillation, yet the downward trend remains tighter, and performance metrics outpace those from Roboflow. The training and validation losses, meanwhile, do not diverge excessively, and the networks finish suggesting wider generalization and improved efficiency in computation all in a fraction of the time the original architecture required. The YOLOv12 architecture, illustrated in Figure 6, clearly exhibited the highest overall performance across the range of assessed metrics. It realized the fastest convergence speed, finishing with the best terminal loss of any model examined. Curves from the training process showed steady, tight behavior during the final epoch, a sign that optimization reached a strong, final plateau. The small gap between training and validation losses further underscores the architecture's ability to generalize, which makes it particularly attractive for integration into agricultural disease detection applications.

Table 1 highlights how precise and memory-efficient the YOLOv12-based thermal imaging model for detection is, with scores of 0.933 and 0.893 for YOLOv11, and 0.873 for Roboflow. Figures 4 to 6 lay out two ways to grasp mAP. The first, mAP50, measures average accuracy at an IoU threshold of 0.5 on the given image set. Here, YOLOv11 averages 0.832, while Roboflow's model averages 0.817. The second measure, mAP50-95, computes across IoU values from 0.5 to 0.95 in 0.5 steps. Values above 0.863 show how quickly the YOLOv12-based model can detect banana leaf disease across a range of lighting conditions. The models based on YOLOv12 were relatively more challenged on some metrics, reflected in lower performances on train/box_loss, train/seg_loss, train/cls_loss, and train/dfl_loss, as shown in Figure 6. This implies that it takes not only sufficient data, but also data appropriate for facilitating effective and precise detection, to solve the problem presented successfully. To describe why some new models based on YOLOv12 were developed, in this research, there were two ways for image augmentation for the model utilizing the mosaic approach and using the conventional approach, as listed in Table 1. With continuing training, there is a steady decrease in classification loss on training (train/cls_loss) on each epoch. Starting from around 4.5, it ends around 0.21, based on Figure 6. This compares with val/cls_loss, where it oscillates from around 3.1 to around 0.6, being roughly three times higher than train/cls_loss, indicating a significant role for augmentation in isolating a considerable difference in loss values for training and validation.

Table 1. The performance of comparison results augmentation techniques of model

Model	Precision (%)	Recall (%)	mAP@50 (%)
Roboflow	87.3	75.7	81.7
YOLOv11	89.3	82.5	86.2
YOLOv12	93.3	83.3	86.3

3.2. Results of development

The optical camera can produce a more accurate and accurate model to calculate disease occurrence in hom-thong banana than the one produced using YOLOv12 in optical closed-circuit television (CCTV).

Light intensity affects image quality obtained. The difficulty in trying to detect objects under varying lighting was a problem with the previously built models. An optical camera having the ability to capture images under a lot of lighting and weather conditions can be utilized to gain a wider field of view to image more objects. Therefore, the performance of the imaging device depends on how the algorithm is trained shown in Figure 7. Therefore, the merged images form the image dataset, which in this research is used to establish a real-time image YOLOv12 model that provides different views of the disease status of hom-thong banana. The major reason why optical cameras are used is in the provision of having more accurate images in order to obtain best quality of hom-thong banana farming. This process is crucial for the suggested model to predict disease incidence more accurately in various local or sub-climatic conditions. Rough photographs of hom-thong bananas taken from various perspectives and orientations. Figure 8 displays the model outputs, which demonstrate image and light detection in every hom-thong banana species.

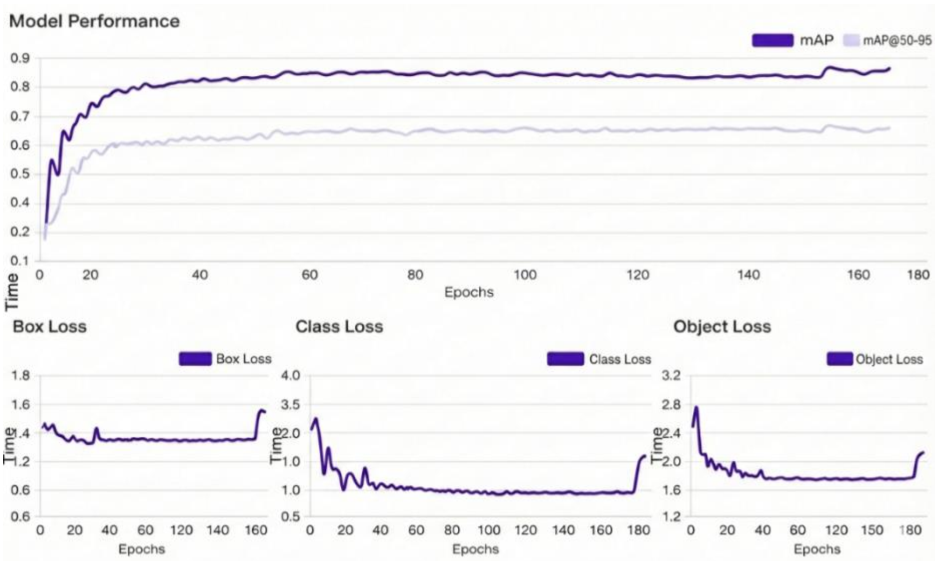

Figure 7. YOLOv12 plots of classification loss of model

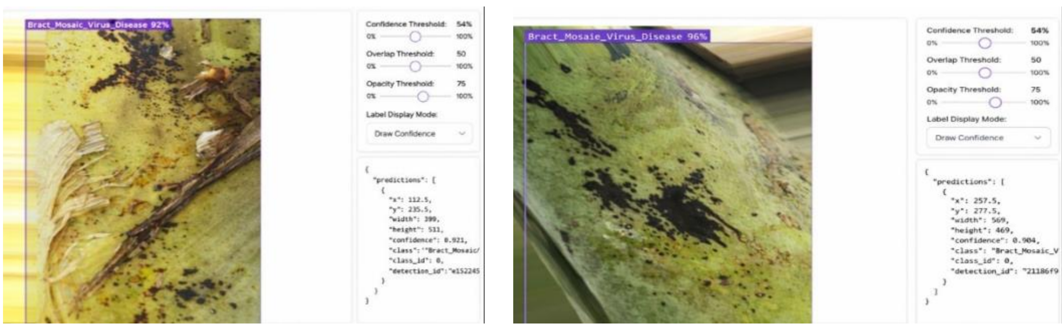

Figure 8. Result of YOLOv12 deploy model

3.3. Discussion

The findings from the study suggest that there is great potential for disease detection models based on AI to improve the farming of hom-thong bananas in Thailand. The three replacement models that were compared - Roboflow, YOLOv11, and YOLOv12 - have varying performances with significant real-world implications for use on farms. The best performing model was YOLOv12 with the best precision (93.3%) and recall (83.3%) values, as well as mAP@50 (86.3%) values. Improved performance may be justified on several grounds. To start with, YOLOv12 boasts a higher architecture that integrates the quality of feature extraction and superior anchor box mechanisms tasked with dealing with the complex visual features of banana diseases. The precision capability of the model without affecting recall rates is particularly beneficial in agriculture production environments where false positives will lead to additional sprays of pesticides and production costs.

The tendency of converging training in Figures 4 to 6 provides insightful information regarding the model's behavior. Steep initial decrease in loss and convergent trends of YOLOv12 indicate good learning processes, and that the model is learning efficient features from the augmented dataset. While the comparatively low training and validation losses of all the models relative to each other represented good generalization performance, YOLOv12 exhibited the most implicit performance. The data augmentation method used in this experiment, which allowed the original dataset to expand from 2,576 to 6,184 images, effectively strengthened model robustness. The different augmentations: horizontal and vertical flip, rotation, brightness (±15%), saturation (±25%), and random cropping (20%), better prepared the models to deal with different environmental conditions in the field. This is critical when implementing the systems into real-world settings, where illumination, viewing conditions, and ambient conditions vary significantly.

It is important to note disparity classification loss between the training and validation set, is most acutely seen in YOLOv12 (train/cls_loss: 0.21 vs. val/cls_loss: 0.6). An actual threefold difference in disparity indicates, while augmentation techniques typically improve model generalizability, they also mean that dimensionality and complexity has increased, meaning it must be tamed through hyperparameter tuning. Future research will try to move beyond augmentation techniques to minimize such a disparity without compromising detection performance. The ability of the model to operate under varying lighting conditions addresses one of the biggest hurdles to AI use at the farm level. The practical real-world effect of such findings is enormous. According to the accuracy of YOLOv12, agricultural farmers can rely on the system to identify disease accurately without undue worry of false alarms. Although the 83.3% recall rate is worse compared to precision, it is still significantly better than that possible through human inspection and carries early warning capacity with the ability to avert huge losses in crops.

There are certain constraints that need to be mentioned, however. The study specifically tackled the performance of seven specific disease types of the hom-thong bananas, and it is necessary to go back and check with the model on the performance regarding other banana varieties or other types of diseases. Additionally, YOLOv12's computational load, although reasonable on today's hardware, may be cumbersome to deploy on hardware-constrained rural environments. Implementation of this technology in existing agricultural practice must consider farmer training, infrastructure requirements, and cost assessment. It must be researched in the future with a focus on exploring the possibility of creating lightweight model implementations for mobile and edge computing platforms to improve access.

4. CONCLUSION

This research effectively developed and validated a unique AI-based system for enabling hom-thong banana cultivation on the basis of automatic disease identification. The extensive comparative analysis of three different deep learning models Roboflow, YOLOv11, and YOLOv12 provided valuable information about the application of computer vision technology in the agriculture sector in real life. The key results indicate that YOLOv12 performs significantly better than other approaches, achieving 93.3% accuracy, 83.3% recall, and 86.3% mAP@50 in detecting seven banana diseases. These performance results are much better than manual inspection methods, providing farmers with a fast, reliable, and objective method of disease detection. Moreover, the model's capability to generalize under changing environmental factors and the use of robust data augmentation methods support its potential applicability in practical field applications in Thai banana farms. The research contributes to some of the key challenges that presently hinder the hom-thong banana industry, including erratic yield, susceptibility to diseases and pests, and inefficient supply chains. By facilitating early detection of diseases, the system can help a farmer to timely intervention, reduce crop loss, and lessen pesticide use, which can also contribute to a more sustainable and profitable agricultural practice. This AI system can be implemented successfully and indicates a shift towards precision agriculture in Thailand's banana industry. The technology's potential also lies beyond disease detection, for example, with wider applications in crop monitoring, yield prediction and quality inspection, as a complement to Thailand's national policies for smart agriculture. Future research should investigate how to widen the system's scope to include other categories of diseases and types of bananas, develop mobile-friendly apps so farmers can access them easily, and commence longitudinal field studies to assess long-term effectiveness and economic payback.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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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 that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

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

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

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

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