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Short Paper

Analysis of Image Recognition Algorithms for Detecting Common Calamansi [*Citrofortunella microcarpa* (Bunge) Wijnands] Diseases in the Philippines

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Abstract

Purpose – Plant diseases are a major challenge for agriculture in the Philippines, particularly for calamansi [*Citrofortunella microcarpa* (Bunge) Wijnands], a key citrus crop. This study addresses this issue by employing image processing and machine learning techniques to enhance the detection of calamansi diseases.

Method – The research analyzed three image recognition algorithms—YOLOv5, Faster R-CNN, and MobileNetSSDv2—using a dataset of 2,990 images of calamansi leaves and fruits collected from farms in Victoria, Oriental Mindoro. The images were processed, and the models were evaluated based on precision, recall, and mean average precision (mAP).

Results – YOLOv5 outperformed the other models with a precision of 96%, recall of 96.2%, and mAP of 98.1%. This model was deployed in a mobile application, achieving a field-testing accuracy of 77.5%. The findings highlight the potential of using machine learning for real-time detection of plant diseases.

Conclusion—The study demonstrates the feasibility of integrating advanced algorithms into mobile technology to assist Calamansi farmers in monitoring crop health effectively.

Practical Implications – Adopting mobile-based disease detection systems can significantly improve crop management, productivity, and sustainability. However, the research is limited to specific diseases and data from a single region, underscoring the need for broader datasets and extended testing.

Keywords – calamansi, image recognition algorithms, agricultural innovation, YOLOv5

INTRODUCTION

According to the Food and Agriculture Organization of the United Nations, between 20 and 40 percent of global crop production is lost to pests. Plant diseases, on the other hand, cost the global economy around $220 billion annually. According to the Food and Fertilizer Technology Center for the Asian and Pacific Region, citrus greening is the main reason why citrus production fell by 60% between 1961 and 1970 in the Philippines.

As the diseases of plants are inevitable, being able to detect and classify them plays a major role in the field of agriculture. Nowadays, the eye observation of specialists is the main method implemented in practice for the detection and identification of plant diseases (Malathi et al, 2018). With continuous monitoring, this might be excessively expensive in large farms.

With image processing technology and machine learning, one can analyze the image of the plant leaves by extracting the features according to color, texture, and other characteristics from a quantitative point of view. Thus, it can be adopted in the prediction of plant diseases.

Fernandez (2018) reported in Philstar that over the years, Oriental Mindoro has been named the "Calamansi King" of the MIMAROPA (Mindoro-Marinduque-Romblon-Palawan) Region or Region IV-B due to its large contribution to the industry. Oriental Mindoro is the top producer of calamansi, accounting for 99 percent of the MIMAROPA calamansi output and 59 percent of the national necessity.

Calamansi [Citrofortunella microcarpa (Bunge) Wijnands] is a prized citrus plant that is abundant in the Philippines. Its fruit has a multitude of uses such as the source of marmalade, juice, and other medicinal purposes. It is one of the most important citrus species in the Philippines. Its potential lies in its varied uses. Once familiarity with the fruit is established in other countries, the scope for increasing export and production is large.

With the above-cited problems and opportunities, "Analysis of Image Recognition Algorithms for Detecting Common Calamansi [Citrofortunella microcarpa (Bunge) Wijnands] Diseases in the Philippines" was done to analyze selected algorithms used in detecting diseases of a calamansi plant.

Through the use of a web tool, the overall performance of certain image recognition algorithms can be analyzed and a comparison can be made. The main purpose of this research is to address the undertaking of identifying the advantages and disadvantages, challenges, and areas for improvement in each of the selected image recognition algorithms used.

After the results were analyzed, the most promising algorithm was then utilized in the development of a mobile application that will feature common calamansi disease detection.

Specifically, this study aimed to:

1. utilize significant image recognition algorithms that will train, test, and validate common calamansi diseases;
2. analyze the overall performance of each algorithm using proper metrics;
3. determine the most appropriate image recognition algorithm for calamansi diseases; and,
4. develop a mobile application featuring the most promising algorithm for image detection.

The study analyzed and compared only three selected image recognition algorithms and did not include all available algorithms. After analysis and comparison, only the most promising algorithm or method was utilized to develop a mobile application. The app is operated only on an Android mobile phone with the recommended operating system.

The application can only predict or detect common diseases of the calamansi plant captured on the leaves and fruits and does not include diseases on roots and flowers or any other parts of the calamansi plant. Disease detection can be done through direct way by capturing images from the mobile phone through the installed application or through indirect way by uploading or transferring images captured from another device.

Data sets that were used for training, testing, and validation were gathered in calamansi farms of Oriental Mindoro, Philippines and its annotation was guided by experts in calamansi diseases to make sure that the disease classification was accurate.

Furthermore, training, testing, and validation of algorithms for analysis and comparison were done using the same sets of data. Through the use of web tools and different libraries, the algorithms are compared and analyzed using appropriate performance metrics.

LITERATURE REVIEW

According to Selvaraj, et al. (2019), innovative and rapid methods for the timely detection of pests and diseases will allow to monitor and develop control measures with greater efficiency. They utilized deep convolutional neural networks (DCNN) and transfer learning as it has freshly moved into the domain of just-in-time crop disease detection. Their research developed an AI-based banana disease and pest detection system using a DCNN and their results showed that the DCNN was a strong and easily deployable strategy for digital banana disease and pest detection. Using a pre-trained disease recognition model, they were able to achieve deep transfer learning (DTL) to produce a network that can make accurate predictions.

Recent advances in image processing techniques for automated leaf pest and disease recognition were also reviewed by Ngugi et al. (2021). They emphasized that fast and accurate plant disease detection is critical to growing agricultural productivity in a sustainable way. In this paper, they have offered a comprehensive review of recent research work done in plant disease recognition using Image Processing Techniques (IPTs). It can be seen in their results that deep learning techniques have outdated shallow classifiers trained using hand-crafted features. They also emphasized the importance of sufficient data that is available for training to achieve high accuracy in recognizing pests and diseases.

Chen et al. (2021) developed a smartphone-based application for detecting scale pests using AI-driven object detection models like Faster R-CNN, SSD, and YOLO v4, with YOLO v4 achieving the highest accuracy. The mobile app aids farmers in identifying pests and applying appropriate pesticides, helping to reduce crop losses.

A similar approach was deployed by Aldakheel et al (2024) wherein they explored the YOLOv4 algorithm for its effectiveness in detecting and categorizing plant leaf diseases. Leveraging the Plant Village Dataset, which contains over 50,000 images of healthy and diseased leaves from 14 plant species, the study enhances the dataset using techniques like histogram equalization and horizontal flipping to improve model robustness.

According to Buja et al (2021), innovations such as portable diagnostic systems, nanotechnologies, and IoT-based tools are transforming plant pathology by enabling early, fast, and cost-effective detection of diseases, even in challenging contexts like asymptomatic infections, ultimately revolutionizing preventive measures in agriculture.

On the other hand, using Euclidean distance is the approach conducted by Khanaa and Thooyamani (2015). In this paper, an overview of the efficient weed and pest detection system is presented and similarity distance measure is obtained using feature vectors for better performance to find the decision of leaf recognition. The system was trained with 100 images for both normal and diseased plant leaves. For testing 20 images in each kind of leaf like weed, normal tomato leaf, and diseased tomato leaf are tested. Overall accuracy reached up to 92% for three kinds of leaves.

Ashok, Jayachandran, Gomathi, & Jayaprakasan (2019) also introduced pest detection and pest identification systems by applying the color histogram and contour detection technique with image processing by SVM model. The pests can be identified using this method by extracting the features of the insect and getting out a layer of the insect for detection with the histogram-based graph. By using the validation algorithm, the process going to work so efficiently to boost up the process and provide an effective outcome and clear one.

Another approach called the color image segmentation algorithm was studied by Deng, et al. (2020) wherein they extracted the effective information of three main maize diseases and pests by taking maize plants as a unit, collecting experimental data as the original image, and segmenting the image. According to them by improving the apparent overlying drawback stuffs, the segmentation efficiency and accuracy are improved better. Moreover, the improved image segmentation algorithm attains a good spot segmentation effect in the static image of corn pests and diseases and has a high recognition.

Wang et al (2024) introduced a self-supervised learning approach for plant disease recognition, combining a masked autoencoder (MAE) and convolutional block attention module (CBAM) to reduce the dependence on large labeled datasets. The proposed model outperforms existing methods with high accuracy, recall, and F1 scores, achieving precise and efficient detection of 21 leaf diseases across five crops, demonstrating its potential for large-scale agricultural applications.

Deep learning-based features have been employed by Turkoglu and Hanbay (2019) to timely and accurately diagnose plant diseases. In this study, they used the different approaches of nine powerful architectures of deep neural networks for plant disease detection to assess the performance results. They also used support vector machine (SVM), extreme learning machine (ELM), and K-nearest neighbor (KNN) methods as classifiers and their results show that deep feature extraction and SVM/ELM classification produced better results than transfer learning.

The team of Kodors et al. (2020) also developed and implemented a project mobile application with a deep learning system for early identification and evaluation of apple and pear scab. Their research presented the comparison of deep learning architectures established for mobile devices (MobileNet and MobileNetV2) and used an open dataset ”Fruits-360" to classify the precision and speed of the neural networks. They found out that the model of MobileNetV2 showed the best results compared to Cohen's Kappa.

In addition, Kim et al (2023) developed an AI-based environmental control system to improve greenhouse sustainability by automatically acquiring and processing images of crop diseases and environmental data for classification and feedback using a Faster R-CNN model. The approach, which compensates for data imbalances through light-based image augmentation, achieved 94% accuracy in real conditions, demonstrating its potential to optimize pest control and reduce labor, pesticide use, and resource dependence.

Deep-learning models have been also applied in Venegas, et al. (2021) to automatically detect ladybird beetles. In this work, they employed a two-step automatic indicator for ladybird beetles in random setting images. They have used image processing modules to produce bounding boxes with probable ladybird beetles' locations within the image. To produce the final output, a deep convolutional neural network-based classifier selects only the bounding boxes with ladybird beetles.

Multiple color space features were also the basis of Yang et al. (2021) to automate greenhouse pest recognition. They have studied using image processing techniques to distinguish and count whiteflies and thrips on a sticky trap placed in a greenhouse setting. They have met several challenges such as the low resolution of the images combined with the small size of the target pests and the existence of other materials and markings in the image. Thus, the color and shape features of the pests in different color spaces were extracted and a collaborative decision trees algorithm was used to execute the recognition task.

The above-cited works prove that in today's challenge of changing climate and mankind's continuous demand for food, accurate and fast leaf disease detection is indeed an opportunity to sustain agricultural productivity. These also show that various algorithms of image processing technology and machine learning were also been proven effective in achieving a precise plant disease detection system.

METHODOLOGY

Selection of Algorithms and Performance Metrics

This study evaluated three widely used image recognition algorithms for detecting diseases in calamansi: YOLOv5, Faster R-CNN, and MobileNetSSDv2. The algorithms were selected based on their popularity and applicability to mobile-based real-time image recognition. The evaluation used standard performance metrics commonly employed in image recognition studies, including precision, recall, and mean average precision (mAP).

Data Collection

The dataset consisted of 2,990 images of calamansi leaves and fruits, representing both healthy and diseased conditions. These images were collected from farms in Alcate, Victoria, and Oriental Mindoro, using Android smartphones. The researcher personally gathered the images from the field to ensure the quality and accuracy of the data. Expert input was also provided by the Mindoro State University Calamansi Research Group to guide the correct classification of diseases.

Table 1. Number of Collected Calamansi Fruits and Leaves Data Sets

Data Set	Classes	Number of Images Collected
Calamansi Leaf Diseases (1,460 images)	Black Spot	123
	Canker	114
	Greening	539
	Healthy	407
	Leaf Miner	277
Calamansi Fruits (1,530 images)	Greening	388
	Healthy	516
	Scab	626
Total		2,990

Table 1 shows that Calamansi Fruits: Scab has the most number of images collected while Calamansi Leaves: Black Spot has the least.

Data Preparation

Once collected, the images were uploaded to Roboflow, a computer vision platform used for preprocessing and annotating the dataset. The key steps in data preparation were:

- Annotating/Labeling: Bounding boxes were drawn around diseased areas of the images. This annotation was conducted with guidance from calamansi disease experts to ensure correct classification.
- Preprocessing: After annotation, the images were preprocessed by splitting them into training (70%), validation (20%), and testing (10%) sets. Auto-orientation was applied to standardize the image layout, and resizing was performed to optimize the images for faster processing (set to 416x416 pixels).

Model Training and Evaluation

The three selected algorithms were trained on the preprocessed calamansi dataset using the Google Colaboratory platform with Python 3 and a synthetic GPU for hardware acceleration. Tensorboard was used to track the training process, including loss, precision, recall, and mAP scores.

Mobile Application Development

The best-performing algorithm, YOLOv5, was exported and deployed to a mobile application developed using Android Studio. The app allows users to detect calamansi diseases by either capturing new images or uploading existing ones for analysis. Testing of the application confirmed that the trained model could detect diseases with reasonable accuracy under real-world conditions.

RESULTS

Algorithm Performance Evaluation

The performance of YOLOv5, Faster R-CNN, and MobileNetSSDv2 was evaluated using the Calamansi dataset. Each model was trained and tested on the images of diseased and healthy calamansi leaves and fruits. The results are summarized based on precision, recall, and mean average precision (mAP).

YOLOv5 demonstrated the highest performance, achieving 96% precision, 96.2% recall, and 98.1% mAP. This model was able to accurately detect and classify calamansi diseases, including greening, scab, and canker. Its grid-based object detection strategy allowed for faster and more accurate recognition, especially in larger images.

Faster R-CNN performed moderately well but lagged behind YOLOv5, with precision values ranging from 25% to 35% and recall between 27% and 35%. Its deep convolutional network structure helped generate accurate region proposals but was slower in real-time detection tasks compared to YOLOv5.

MobileNetSSDv2, though optimized for mobile devices, had the lowest performance, with precision peaking at 11% and recall at 9.7%. While it trained faster than the other models due to its lightweight architecture, it struggled with the complexity of detecting diseases in higher-resolution images of calamansi leaves and fruits.

To summarize the results on the different metrics, the results are ranked accordingly. The higher the obtained values on Precision, Recall, and mAP metrics, the higher the ranking. Also, the faster the training time, the higher the ranking. Considering all metrics have the same weight, the average rank was calculated by averaging the obtained ranks on the different metrics. Below is the ranking of results:

Table 2. Ranking of Results for Calamansi Leaves Data Set

Image Recognition Algorithms	**Metrics**								**Average Rank**
	Precision	Rank	Recall	Rank	mAP	Rank	Time	Rank	
YOLOv5	0.96	1	0.962	1	0.981	1	1150	3	1.5
Faster R-CNN	0.2501	2	0.3507	2	0.4789	2	1065	2	2
MobileNetSSDv2	0.06053	3	0.09689	3	0.1125	3	269	1	2.5

Pre-App Deployment Testing

Once the models were trained, the top-performing model, YOLOv5, was deployed to a mobile application and tested under field conditions. The app achieved an accuracy rate of 77.5% when tested on 40 images captured directly from calamansi farms.

- Correct Classifications: 31 out of 40 images were classified correctly, demonstrating the model's effectiveness in recognizing common diseases such as greening and scab in both leaves and fruits.
- Misclassifications: The model encountered difficulties in classifying certain images where multiple diseases appeared simultaneously, or where lighting conditions affected the clarity of the image. This led to partial misclassifications in 5% of cases and incorrect detections in 7.5% of images.
- No Detection: The model failed to detect any disease in 10% of the images, likely due to poor image quality or objects being too small or clustered, which is a known limitation of YOLO-based models.

Figure 1. Some image results of field testing.

It can be seen in Figure 1 that the YOLOv5 model can successfully detect calamansi diseases. The figure above also shows the model can be able to detect multiple diseases in a single image.

DISCUSSION

The results suggest that YOLOv5 is the most suitable algorithm for calamansi disease detection due to its high precision and recall. Its ability to handle real-time detection makes it ideal for mobile applications aimed at supporting calamansi farmers. However, field testing revealed some challenges in real-world conditions, particularly in handling images with complex disease patterns or poor lighting.

The slightly lower performance in field tests highlights the need to improve the model's robustness in detecting small objects or diseases that appear in groups. Additionally, the dataset used was limited to a specific region (Oriental Mindoro), which may limit the model's applicability to other regions or disease variants.

This research highlights the transformative role of machine learning in boosting agricultural productivity by enabling precise and accessible disease detection. The mobile application developed provides a practical tool for farmers, combining accuracy with ease of use to help identify plant diseases directly in the field. By facilitating early and effective disease management, the app empowers farmers to reduce crop losses and optimize their farming practices. This innovation underscores the potential of integrating technology into agriculture for sustainable and efficient crop production.

CONCLUSIONS AND RECOMMENDATIONS

This study evaluated three image recognition algorithms for detecting common calamansi diseases, concluding that YOLOv5 offers the best performance in terms of precision, recall, and mAP. While it demonstrated strong accuracy in controlled settings, its field performance was slightly lower, indicating the need for further refinement. Nonetheless, the deployment of the YOLOv5 model in a mobile application demonstrates the potential for technological solutions to improve agricultural practices in the Philippines. Expanding the scope to include more diseases and optimizing the model for field conditions could further enhance its utility.

To further improve the outcomes of this study, it is recommended to acquire a larger dataset of calamansi images for training the model. A more extensive dataset will enhance the algorithm's ability to detect diseases accurately by providing it with diverse examples, thereby minimizing errors in real-world applications. Additionally, if resources and time allow, expanding the scope of this research to analyze other popular algorithms or incorporating additional classes of calamansi diseases and pests could significantly maximize the model's capability.

Moreover, addressing the challenges encountered with detecting small objects, especially those appearing in groups, is crucial for achieving better accuracy when utilizing the YOLOv5 model. It may be beneficial to explore techniques such as image augmentation or enhancing the resolution of input images to improve detection rates for these scenarios. Finally, deploying the trained model across various operating systems and devices, such as Windows and macOS, would broaden its usability and provide more farmers with access to this valuable tool, ultimately supporting the goal of enhancing calamansi production and disease management throughout the region.

PRACTICAL IMPLICATIONS

This research demonstrates the potential of machine learning for enhancing agricultural productivity. By providing an accessible and accurate disease detection tool, the mobile application can assist farmers in reducing crop losses and improving disease management practices.

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DECLARATIONS

Conflict of Interest

The researcher declares no conflict of interest in this study.

Informed Consent

Not applicable, as this study did not involve human subjects; all data were obtained from images of calamansi plants collected from local farms.

Ethics Approval

Not applicable, as the research did not involve human participants or animal subjects; only images of plant leaves and fruits were used in the study.

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Authors' Biography

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