APPLICATION OF ARTIFICIAL INTELLIGENCE FOR CASSAVA LEAF DISEASE RECOGNITION USING YOLOV8 AND EFFICIENTNET-V2

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ABSTRACT

In Vietnam, cassava is the major industrial crop with 511.000 hectares in area, 10.4 million tons of yield in 2023 and reaches the 5th highest productivity in the world. However, pests, especially the mosaic disease, and soil degeneration have posed great challenges. This research is presented in order to focus on improving a pest identification system in cassava leaves by artificial intelligence, using YOLOv8 to detect leaves and EfficientNet-V2 to classify the 5 common diseases: leaf mosaic, leaf spot, leaf scorch, tuber rot and wellness. The process includes collecting, labelling more than 10,000 images, training on Google Colab, associating with GPU, testing and evaluating. The system reaches 75% accuracy in detecting cassava leaves, supporting farmers to manage crops effectively. This study provides automated solutions, decreasing productivity losses, promoting sustainable cassava production and extending to other crops. The research not only contributes to automating agriculture but also paves the way for the development of pest identification systems in other crops.

Keywords: *Pest identification, cassava leaves, YOLOv8, EfficientNet-V2, intelligent agriculture.*

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1. INTRODUCTION

In the modern context of agriculture, applying information technology and artificial intelligence (AI) has become an inevitable outlook in order to enhance production efficiency, optimize crop management and save costs. The cassava (Manihot esculenta Crantz), an important type of industrial and food crop in many developing countries, has played an essential role in food security and economic development. In Vietnam, cassava is one of the key agricultural products, with about 511.000 hectares of cultivation area in 2023, 10,4 million tons of yield, 20 tons/ hectares of average productivity, which makes Vietnam become the 5th highest productivity of cassava in the world. Cassava not only meets the demand of national consumption, but it also becomes important export goods, contributing significantly into crop export turnover. However, the cassava production sector has been facing many serious challenges, especially problems relating to pests, among them, the Cassava Mosaic Disease (CMD) has caused great damage. According to the statistics, in 2023, the total area of domestic infected cassava is 83.734 hectares, among them, 20.956 hectares are seriously infected, despite decreasing by more than 30% compared to 2021 thanks to several intervention measures such as using resistant varieties on about 5.500 hectares in Quang Ngai, Binh Thuan, Gia Lai, Dak Lak, Tay Ninh and Đong Nai. Moreover, the soil degeneration state, resulting from long-term monoculture and lack of effective pest management solutions, continues to reduce productivity and quality of the crops.

Traditional pest detecting measures are mostly based on experiences of farmers or agricultural experts, which often spend a lot of time, effort and lose accuracy, especially in the condition where the cultivation area is large and diseases spread widely. To solve the issue, this research suggests developing a pest identification system in cassava leaves by artificial intelligence, using the deep learning model YOLOv8 to identify cassava leaves within images and EfficientNet-V2 to classify the 5 common diseases: leaf mosaic, leaf spot, leaf scorch, tuber rot and wellness. This system arises with a view to provide an automated solution, allowing to discover and categorize pests quickly and precisely, supporting farmers to make timely decisions to supervise crops. This study demonstrates detailedly the procedure of building the system, including collecting and labelling data with more than 10.000 images, training models in Google Colab using GPU, testing manually and integrating API to implement practical application.

This study proposes a two-stage pipeline (YOLOv8 → EfficientNet-V2) fine-tuned on Vietnamese field data, enabling effective detection and classification of cassava leaf diseases under natural lighting conditions. Unlike previous lab-based studies, the system was tested in real-field environments, achieving 80% accuracy, demonstrating its practical applicability and potential for smart agriculture deployment. The main contribution lies in the integration of advanced models, localized training process, and real-world evaluation, aiming toward AI solutions for Vietnamese agriculture, which is suitable with the "Scheme for Sustainable Development of the Cassava Industry to 2030, with a Vision to 2050", approved by the Ministry of Agriculture and Rural Development.

2. RELATED WORKS

In order to develop pest identification system in cassava leaves by artificial intelligence, in this research the authors have inherited and referred to outstanding architecture about deep learning application and computer vision in agriculture.

2.1. Researches applying deep learning to identifying pests in crops

Brahimi and colleagues in the research named "Deep Learning for Tomato Diseases: Classification and Symptoms Visualization" in 2017 [1] have pointed out that CNN models, namely FAlexNet and GoogleNet can classify diseases in crops, particularly tomatoes with outstanding accuracy compared to traditional methods, paving the way for the potential of applying deep learning in agriculture.

Le Quang Thao and colleagues in the article named "Pest Early Detection in Greenhouse Using Machine Learning" [18] have presented a pest early identification system in the greenhouse by convolutional neutral network (CNN). The model applies transfer learning to detect diseases in crops with more than 90% accuracy.

Nguyen Cao Tri and colleagues in the article named "A novel approach based on deep learning techniques and UAVs to yield assessment of paddy fields" [17] have introduced the smart system of pest early identification in the greenhouse by convolutional neutral network (CNN). The model uses transfer learning from a pre pre-training network to increase detecting accuracy. The result reaches more than 90%.

2.2. Researches discovering pests in cassava

Amanda Ramchanran and colleagues in the 2019 research [19] have pointed out a mobile app using the CNN model that can classify Cassava Mosaic Disease (CMD) and the disease caused by cassava leaf bacteria in Tanzania with 80% accuracy, but there is one limit which is the users have to choose image segmentation manually.

Owomugisha and colleagues in the research [15] have pointed out that the combination of spectral imaging data and machine learning model can early detect the CMD in cassava, reaching 85% sensitivity, but requires dedicated equipment.

G. Sambasivam and colleagues in the research "A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks" [2] have displayed a machine learning application to detect and classify cassava disease by convolutional neutral network (CNN), using dataset including 10.000 images with serious class imbalance. The authors have applied techniques such as class weights, SMOTE and focal loss to improve accurate classification, especially the classes which have few data. The model result reaches more than 93% accuracy.

Scientific articles about deep learning application in detecting crop disease, as those belonging to Brahimi et al. [1] and Sambasivam & Opiyo [2] both show great potential of convolutional neutral network (CNN) in agriculture. However, both also exist definite drawbacks, for instance the training data is collected in standard condition, lack of field testing, only using leaf images without integrating with environmental data, and the feasibility of them hasn't been evaluated completely.

When compared to Vietnam's agricultural reality, these models, despite their high application potential, still need significant adjustment. National farmers mostly cultivate with traditional methods, and have few conditions to use modern equipment to collect standard image data as in the research. Simultaneously, complicated environmental conditions in Vietnam such as weak lightness, diverse crops and local strains of disease also require the model to be retrained in domestic data. Thereby, in this article, we, as the authors, have recommended a study closing to Vietnam's condition. All of these will be detailed in the following section.

3. METHODOLOGY

Cassava - Manioc is one of the major food crops in Vietnam's agriculture. Vietnam is the country reaching the 5th highest productivity in the world.

According to the Department of Crop Production (The Ministry of Agriculture and Rural Development), cassava (the manioc) is one of the crops named in the national major crops list, contributing essentially in developing agricultural as well as rural economics, and enhancing farmer's lives.

From that perspective, the cassava is thoroughly concerned and protected against disease. Now there are over 40 cities and provinces growing cassava around the country, focusing in 5 key regions, including the Northern midlands and mountainous region, the North Central region, the South Central coast, the Central Highlands and the South East region, with total area is fluctuating from 520.000 to 550.000 hectares, 19-20 tons/ hectares of productivity, yield reaches more than 10 million tons of raw products.

With the importance above, similarly continuing researching and improving cassava varieties, the issue of discovering diseases in cassava's leaves quickly and promptly has cost a lot of effort and material resources.

Commonly, to solve this issue, the farmers often use traditional methods, which is collaborating with those who are long-experienced, and the agricultural experts have to test the disease status of cassava, and with such a great scale like that, it requires a significant potential of time, effort and knowledge. Furthermore, other subjective factors also decrease the accuracy of predicting pests.

In this section, the authors have described the method of developing a pest identification system in cassava leaves by artificial intelligence, integrating the YOLOv8 model to identify cassava leaves and EfficientNet-V2 to classify diseases.

The researching process includes collecting, processing data, training models, evaluating productivity and carrying out practical applications.

This model is suitably designed for cassava manufacturing conditions in Vietnam, in which there are 511.000 hectares of cultivation area and 83.734 hectares affected by pests in 2023, with a view to providing tools to support farmers to manage disease effectively and motivating sustainable agricultural improvements.

3.1. Overall process

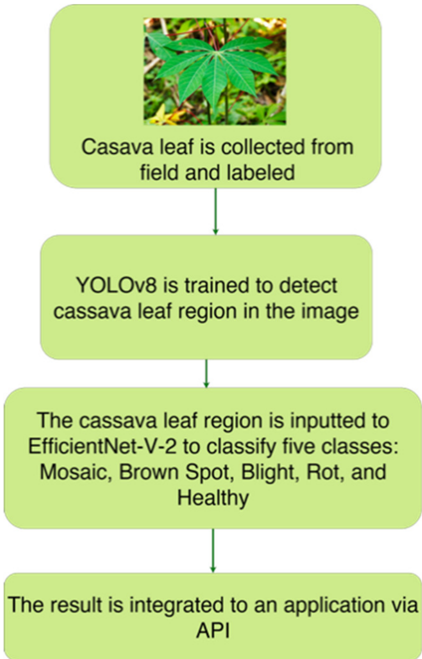

Figure 1. Schematic Representation of the Model Operation

The proposed system is designed as a sequential pipeline, as depicted in Figure 1.

Initially, cassava leaf images are acquired from both publicly available repositories (i.e., Kaggle) and field surveys, followed by annotation and pre-processing. Subsequently, the YOLOv8 model is trained to detect and localize cassava leaves within the collected images. The extracted leaf regions are then processed by the EfficientNet-V2 network to perform classification into five representative categories: cassava mosaic disease, leaf spot, blight, root rot, and healthy condition. Finally, the entire framework is deployed into a mobile application through a RESTful API, enabling real-time disease classification and the provision of immediate pest management recommendations. The overall pipeline has been optimized to ensure robustness against diverse illumination conditions and varying camera viewpoints typically encountered in field environments.

3.2. Model conceptualization

In the development of a cassava leaf disease recognition system, two state-of-the-art deep learning models namely YOLOv8 and EfficientNet-V2 are employed, leveraging the advanced capabilities of computer vision to address detection and classification tasks. These models were selected based on their high performance, robustness in handling field-acquired data, and suitability for the cassava production context in Vietnam. The following section provides an overview of the models, their respective roles within the system, and the rationale behind their selection.

3.2.1. YOLOv8

YOLOv8, developed by Ultralytics, is a variant within the You Only Look Once (YOLO) object detection framework and is widely recognized as a state-of-the-art solution for real-time object detection. Its architecture comprises three primary components: backbone, neck, and head. The backbone employs CSPDarknet53, a convolutional neural network with Cross Stage Partial connections, enabling efficient feature extraction with reduced computational cost. The neck utilizes the Path Aggregation Network (PANet) to integrate features across multiple layers, thereby enhancing detection performance for objects of varying scales. The head adopts an anchor-free prediction mechanism, eliminating fixed anchor boxes and incorporating composite loss functions (Binary Cross-Entropy and Complete IoU Loss) to jointly optimize accuracy and inference speed. Additional enhancements, such as mosaic data augmentation and dynamic scaling, further strengthen the model's capability to process complex field imagery, including cassava leaf images collected from Vietnamese provinces and Kaggle repositories.

For the cassava leaf detection task, YOLOv8 is fine-tuned to accurately localize cassava leaf regions within field-acquired images, where variations in illumination and camera perspectives are prevalent. The training process is dedicated to optimizing the model with meticulously annotated cassava leaf data, thereby enhancing its robustness against challenging scenarios, including partial occlusion of leaves and the presence of early disease symptoms. As a result, YOLOv8 provides a solid foundation for integration with classification models such as EfficientNet-V2 in the proposed cassava leaf disease recognition system.

3.2.2. EfficientNet-V2

EfficientNet-V2 is a convolutional neural network (CNN) architecture optimized to achieve high performance in image classification while substantially reducing computational complexity compared to traditional models. Building upon the original EfficientNet framework, it employs a compound scaling strategy to jointly balance network depth, width, and resolution, while incorporating Fused-MBConv blocks to accelerate both training and inference. In general image classxification tasks, EfficientNet-V2 has demonstrated state-of-the-art accuracy on large-scale datasets such as ImageNet, with significantly improved resource efficiency.

For the cassava leaf classification task, EfficientNet-V2 is fine-tuned to recognize five common categories-cassava (mosaic disease, bacterial blight, brown leaf spot, root rot, and healthy condition) once the leaf regions have been localized by a detection model such as YOLOv8. The training process leverages meticulously annotated cassava leaf data together with data augmentation techniques tailored to field conditions in Vietnam, thereby enabling the model to achieve high accuracy in identifying disease symptoms and effectively supporting sustainable agricultural management.

3.3. Cassava leaf disease detection model using YOLOv8 and EfficientNet-V2

3.3.1. Introduction to the Proposed Model

In this study, we propose an advanced hybrid model for cassava leaf disease recognition that effectively integrates two convolutional neural network architectures: YOLOv8 and EfficientNet-V2. YOLOv8, built upon CSPDarknet and adopting an anchor-free detection paradigm, is employed to accurately localize cassava leaf regions in field-acquired imagery, ensuring both high processing speed and robust reliability under varying illumination conditions and camera perspectives. Subsequently, EfficientNet-V2, which incorporates compound scaling across network depth, width, and resolution along with Fused-MBConv blocks, undertakes the task of classifying five prevalent disease categories (cassava mosaic disease, leaf spot, blight, root rot, and healthy condition) while optimizing performance and reducing computational cost. The training process is conducted on a carefully annotated cassava leaf dataset, augmented with data augmentation strategies tailored to field conditions in Vietnam, thereby enhancing accuracy in detecting disease symptoms. The findings of this research are expected to provide a valuable tool that assists farmers in effective pest and disease management, ultimately contributing to the sustainable development of the agricultural sector.

3.3.2. Data Collection and Pre-processing

a) In this research, we using the dataset consists of 10,886 cassava leaf images, aggregated from two principal sources: Kaggle and field images collected in Vietnam. All data were carefully annotated following the guidelines of experts from the Vietnam Plant Protection Institute to ensure the accuracy of each disease category.

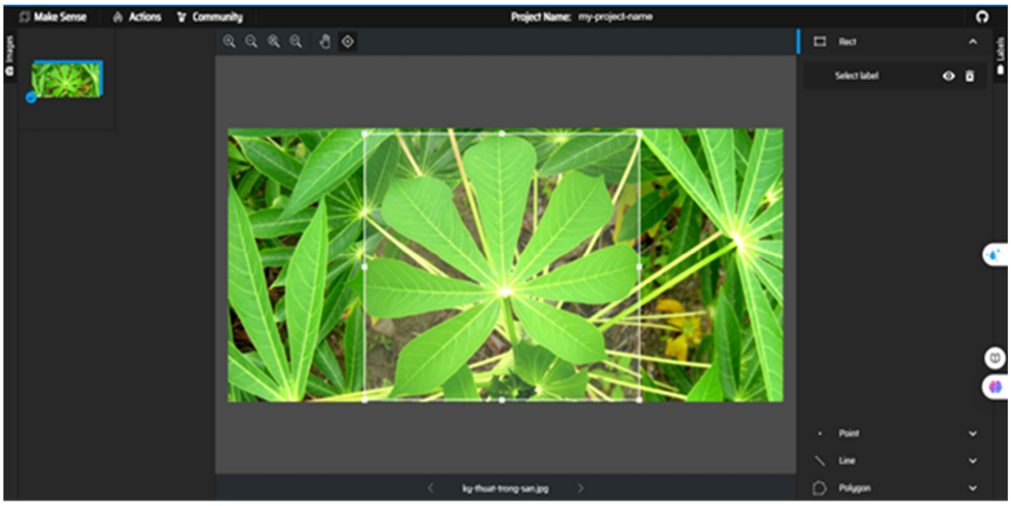

Figure 2. Data Annotation Process

Public source from Kaggle: A portion of the dataset was obtained from publicly available repositories on the Kaggle platform, such as the "Cassava Leaf Disease Classification" competition (https://www.kaggle.com/competitions/cassava-leaf-disease-classification), which contains cassava leaf images exhibiting common diseases including cassava mosaic disease (CMD), leaf spot, and blight. The data were filtered to ensure consistency with disease conditions observed in Vietnam, contributing approximately 4,000 images (36.7% of the dataset).

Field-collected data in Vietnam: The remaining 6,886 images (63.3% of the dataset) were collected from cassava plantations located in Quang Ngai, Gia Lai, Dak Lak, Tay Ninh, and Dong Nai provinces during the 2022 - 2023 period. Images were captured using smartphones (Samsung Galaxy, iPhone) and digital cameras (Canon EOS, Nikon D) under natural lighting conditions, with resolutions ranging from 1080×1920 to 4000×3000 pixels. The image acquisition process was conducted under the guidance of experts from the Plant Protection Institute of Vietnam to ensure accurate representation of cassava health conditions, including cassava mosaic disease, leaf spot, blight, root rot, and healthy status.

The diseases were identified based on the following characteristics:

- Cassava Mosaic Disease (CMD): Characterized by mosaic yellow-green patterns on the leaves and leaf margin deformation, caused by viruses transmitted by insect vectors.
- Cassava Bacterial Blight: Brown or black spots (1 - 5mm), Xanthomonas bacteria.
- Cassava Brown Leaf Spot: Dry, necrotic brown lesions on the leaves, caused by Cercospora fungi.
- Cassava Root Rot: Yellowing leaves with wilting symptoms progressing from the base, caused by Fusarium or Phytophthora fungi.
- Healthy condition: Uniformly green leaves without any visible symptoms of disease.

Table 1. Statistics of cassava leaf disease dataset

Disease Label	No of images	Percentage (%)	Source (Kaggle / Field)
Mosaic Disease	2.178	20.0	720 / 1.458
Leaf Spot	2.156	19.8	810 / 1.346
Bacterial Blight	2.162	19.9	720 / 1.442
Root Rot	2.118	19.4	580 / 1.538
Healthy	2.272	20.9	1.170 / 1.102
Total	**10.886**	**100%**	**4.000 / 6.886**

The dataset was divided into 70% for training (≈7,620 images), 20% for validation (≈2,177 images), and 10% for testing (≈1,089 images).

Each disease class accounts for approximately equal proportions (~20%, around 2,177 images per class). The images were collected at different times of the day (morning, noon, and afternoon) to capture diverse lighting conditions.

b) Data labeling

The images were manually annotated using the LabelImg tool to support two tasks:

Cassava leaf detection (YOLOv8): Each image was labeled with bounding boxes indicating the location and size of cassava leaves. In total, 10,886 leaf regions were annotated, with an average of 1 - 3 leaves per image.

Disease classification (EfficientNet-V2): Each annotated leaf region was assigned one of five disease types or the healthy condition. All annotations were validated by domain experts to ensure accuracy.

Although the class distribution is relatively balanced (~20%), the authors applied a Focal Loss mechanism combined with class weighting to mitigate the influence of classes with fewer field samples, such as "tuber rot."

The data obtained from Kaggle already contained labels, but these were re-examined to align with the disease standards relevant to Vietnam. The field-collected data were annotated from scratch, involving the research team with cross-validation procedures to minimize errors. Annotations were stored in YOLO format (.txt) for the detection task and in CSV format for the classification task.

Figure 3. Results of the Cassava Leaf Disease Recognition System

Table 2. Effect of confidence threshold on model performance

Threshold	Accuracy	False Rate	Overall
30%	90%	46%	79,5%
35%	89%	54%	80%
40%	83%	67%	79,75%
50%	77%	78%	77,5%
60%	66%	85%	70,75%
70%	49%	89%	59,8%

The preprocessing workflow is illustrated in Figure 4, this process ensures that the data are consistently processed, balanced, and representative of real agricultural conditions in Vietnam.

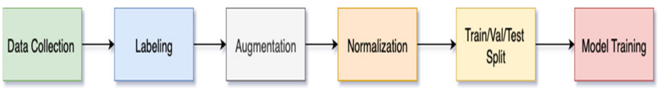

Figure 4. Pipeline process data

c) Data Pre-processing and Augmentation

In this study, data pre-processing and augmentation techniques were employed to improve the generalization capability of the models. Specifically, image normalization in terms of both size and pixel values was applied. The images were resized to 640×640 pixels for YOLOv8 and 224×224 pixels for EfficientNet-V2, while maintaining the aspect ratio through padding. In addition, pixel values were normalized to the range [0, 1].

Regarding data augmentation, several techniques were incorporated and applied directly during the training process, with all transformations performed randomly to ensure the model was exposed to diverse variations of the same samples.

Table 3. Data augmentation techniques used in training

Technique	Applied Parameters	Purpose
Rotation	±15°	Enhance recognition capability for rotated leaves
Horizontal/ Vertical Flip	Probability 0.5	Increase image orientation diversity
Brightness	±20%	Simulate various lighting conditions
Random Crop	80 - 100% of image area	Mimic partially occluded leaves
Gaussian Noise	σ = 0.01 - 0.02	Simulate real-world image noise
Color Jitter	±10% Hue / Saturation	Reduce the influence of natural light variation
CLAHE (Contrast Limited Adaptive Histogram Equalization)	Clip limit 2.0	Enhance contrast in low-light regions

By consensus, the authors partitioned the dataset as follows: 70% for training (7,620 images), 20% for testing (2,177 images), and 10% for validation (1,089 images). Experimental results on the training set showed that applying augmentation and Focal Loss improved the average Accuracy by 3.8% and the F1-Score by 4.1% compared to the imbalanced training setup, with a notable improvement in the "tuber rot" class (Accuracy increased from 71% to 75%).

3.3.3. Model Training

The training process of the proposed system is designed in two main stages: cassava leaf detection using YOLOv8 and disease classification using EfficientNet-V2.

An overview of the training procedure is presented as follows.

a) Cassava Leaf Detection with YOLOv8

In this study, YOLOv8 was selected due to its superior capability in real-time object detection. The model leverages a CSPDarknet53 backbone combined with a Path Aggregation Network (PANet) to optimize feature extraction and prediction. Training was conducted on the Google Colab Pro platform, utilizing an NVIDIA Tesla T4 GPU with 16 GB VRAM, and implemented with the Ultralytics framework. The hyperparameters were configured as follows: an input image size of 640×640 pixels, 100 training epochs, an initial learning rate of 0.001 decayed according to a cosine scheduler, and a batch size of 16. The optimization process employed stochastic gradient descent (SGD) with a momentum of 0.9. The loss function comprised three components: Binary Cross-Entropy for classification, Complete IoU Loss for localization, and Confidence Loss for reliability assessment. Model initialization was performed using pretrained weights from YOLOv8n (nano). Early stopping was applied when the mAP@0.5 metric did not improve after 10 consecutive epochs. The model's performance was evaluated using mAP@0.5 and mAP@0.5:0.95 metrics, reflecting overall detection accuracy under varying conditions.

b) Disease Classification with EfficientNet-V2

In this study, the EfficientNet-V2-S model was selected owing to its optimized architecture with Fused-MBConv blocks, which provide an effective balance between accuracy and computational efficiency. The cassava leaf regions extracted by YOLOv8 were resized to 224×224 pixels and used as inputs. Training was conducted on the Google Colab Pro platform, with the following hyperparameter settings: 50 epochs, an initial learning rate of 0.0001 decayed exponentially, a batch size of 32, and the Adam optimizer with $\beta 1 = 0.9$ and $\beta 2 = 0.999$. The loss function employed was Categorical Cross-Entropy to optimize the classification task. To mitigate overfitting, several regularization techniques were implemented, including Dropout with a rate of 0.3, L2 regularization with a coefficient of 0.01, and data augmentation strategies as described in Section 3.3.2. Model initialization utilized pretrained weights from the ImageNet dataset, which were subsequently fine-tuned on the cassava-specific dataset. The model's performance was evaluated using Accuracy, Precision, Recall, and F1-Score, ensuring comprehensive and reliable assessment of cassava leaf disease classification.

The training hyperparameters were selected through a systematic grid search to achieve a balance between convergence speed and model stability. The initial learning rate was set to 0.001 after experiments within the range [0.0005 - 0.005], showing the fastest and most stable convergence, and was gradually decreased using a cosine annealing schedule to prevent overfitting. The batch size was set to 16 for YOLOv8 and 32 for EfficientNet-V2 to optimize GPU memory usage and maintain stable gradients. The momentum was set to 0.9 to preserve update inertia and reduce oscillations in the loss landscape. Regarding the optimization algorithms, YOLOv8 employed SGD with a momentum of 0.9 to ensure stable gradient control and mitigate overfitting, while EfficientNet-V2 utilized the Adam optimizer with a learning rate of 0.0001 to achieve faster convergence in the multi-class classification task.

3.3.4. Testing and Evaluation

In this study, the proposed models were evaluated on a validation set consisting of 1,089 images and an additional 200 field images collected in Tay Ninh province in October 2023. Performance metrics were assessed as follows: for YOLOv8, mAP@0.5 and mAP@0.5:0.95 were measured, while for EfficientNet-V2, Accuracy, Precision, Recall, and F1-Score were employed. The average processing time was also recorded on both an NVIDIA Tesla T4 GPU and an Intel Core i7 CPU. The detailed results are presented in Table 1. YOLOv8 achieved an mAP@0.5 of 75% and an mAP@0.5:0.95 of 52%. EfficientNet-V2 recorded an Accuracy of 80%, with a Precision of 78%, Recall of 79%, and F1-Score of 78%. Performance across specific classes showed higher scores for cassava mosaic disease and the healthy condition (85%), whereas root rot was relatively lower at 72%. In terms of computational efficiency, the models required an average of 0.5 seconds per image on the GPU and 2 seconds on the CPU. Nevertheless, several common errors were observed, including misdetections under low-light conditions (10%) and confusion between leaf spot and brown leaf spot. These findings highlight the necessity for further refinements in future work.

4. EXPERIMENTS AND RESULTS

4.1. Training evaluation

During the analysis of YOLOv8 training performance, a clear convergence trend was observed based on the loss and performance metrics, as illustrated in the training curves. Specifically, the bounding box loss on the training set decreased from 0.09 to below 0.04, the object loss declined from 0.0080 to approximately 0.0032, while the classification loss remained close to zero, reflecting effective optimization during the learning process. Similarly, on the validation set, the bounding box loss decreased from 0.06 to below 0.03, the object loss from 0.0044 to 0.0032, and the classification loss remained stable near zero, indicating strong generalization capability without clear evidence of overfitting. In terms of performance evaluation, the model achieved a precision of 0.75, a recall of 0.70, an mAP@0.5 of 0.80, and an mAP@0.5:0.95 of 0.40, demonstrating reliable object detection capability under real-world conditions. The smoothed curves across 50 epochs confirmed the consistency and stability of the training process, providing a robust scientific basis for deploying the model in effective cassava leaf detection.

4.2. Experimental comparison results

Following the stable convergence of YOLOv8, as discussed in the training evaluation above, experimental

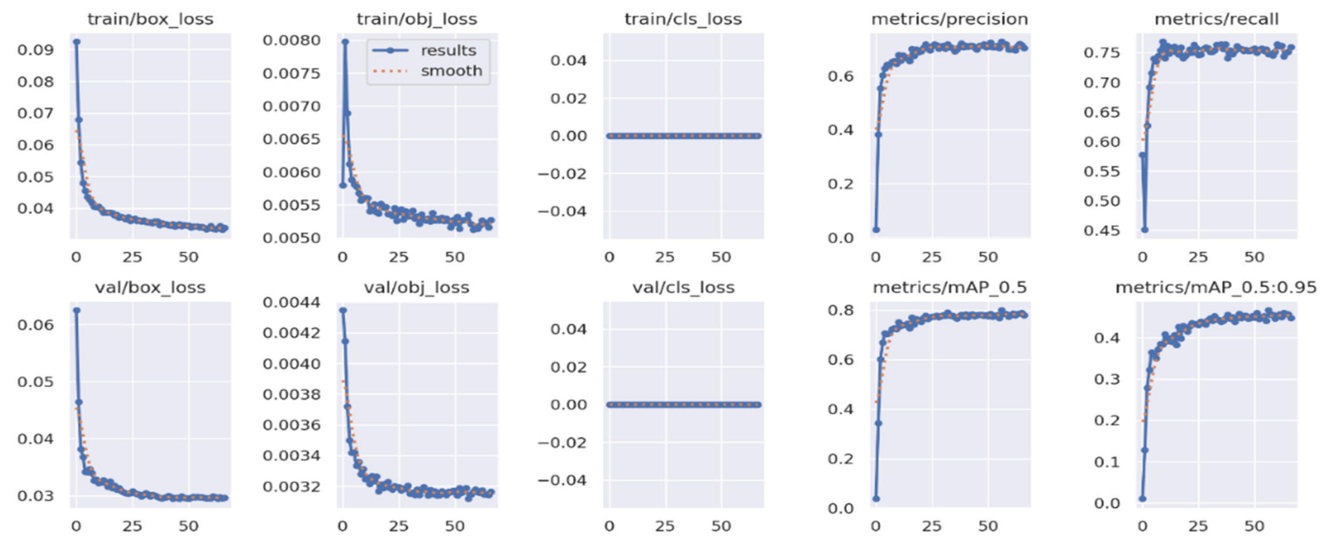

Figure 5. Overall visualization of the YOLOv8 training process

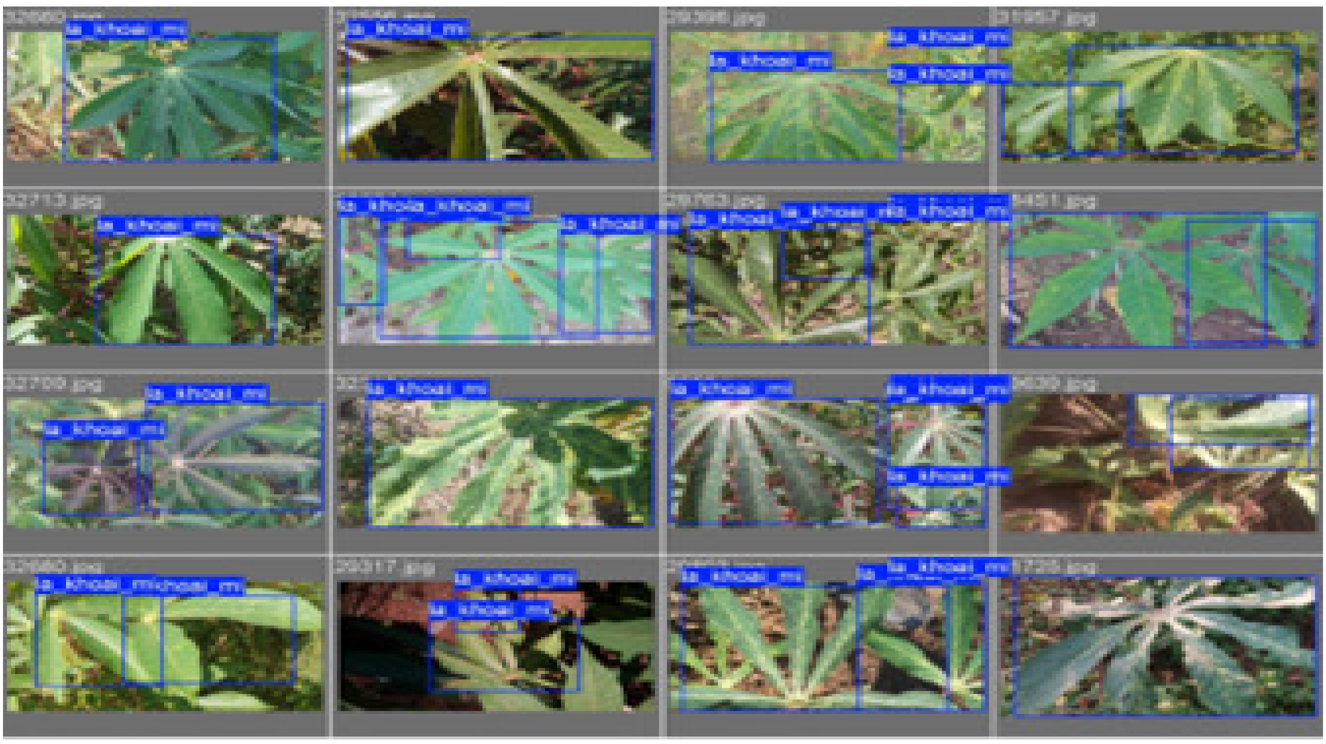

Figure 6. Train results

performance was assessed on a dataset comprising 1,089 images and 200 field images collected in Tay Ninh (October 2023) under varying confidence thresholds, as presented in Table 1. The results indicate that at a 30% threshold, accuracy reached 90% but with a false confirmation rate of 46%, whereas a 40% threshold yielded 83% accuracy with the false confirmation rate reduced to 33%. The overall metric peaked at 80% with a threshold of 35%, but gradually declined to 59.8% when the threshold increased to 70%. This analysis suggests that a threshold range of 30 - 40% provides the optimal trade-off between accuracy and coverage, making it suitable for practical applications in cassava leaf disease management.

4.3. Comparison with other studies

To further validate the effectiveness of the proposed approach, we compare its performance with several widely used models in recent studies, as shown in Table 4.

Table 4. Comparison with other studies

Model	Dataset	Accuracy	F1-Score
ResNet50	Cassava Leaf Disease	76%	75%
MobileNetV2	Cassava Leaf Disease	78%	76%
EfficientNet-V2 (our)	Cassava + Việt Nam	**80%**	**78%**

Although the model does not outperform others in terms of absolute accuracy, it maintains a balanced trade-off between processing speed and practical deployability in real-world agricultural conditions in Vietnam.

In near future, we want to push their performance can be further improved through technical optimization and dataset expansion.

Firstly, the authors plan to fine-tune the EfficientNet-V2-M variant, which provides higher feature representation capacity, combined with DropBlock regularization to reduce overfitting on complex real-field data.

Secondly, the dataset will be expanded with at least 1,000 additional field images collected from other provinces such as Gia Lai, Dak Lak, and Dong Nai, increasing environmental diversity in lighting, soil background, and disease expression.

Advanced data augmentation techniques including ColorJitter (brightness, contrast, and hue adjustment) and CLAHE (Contrast Limited Adaptive Histogram Equalization) will also be applied to enhance model robustness under varying illumination conditions.

To improve real-world applicability, the model will be optimized for mobile deployment using TensorRT and ONNX quantization, significantly reducing inference time and model size, thus enabling direct usage on smartphones by farmers.

5. CONCLUSION

This study has presented a comprehensive approach to the development and evaluation of a cassava leaf disease recognition system through the integration of two advanced artificial intelligence models: YOLOv8 and EfficientNet-V2. The workflow, encompassing data collection and processing, model training, and real-world testing on a dataset of 1,089 images and 200 field images collected in Tay Ninh (October 2023), was carefully executed to ensure scientific reliability. The YOLOv8 training results demonstrated effective leaf region detection with mAP@0.5 of 75% and mAP@0.5:0.95 of 52%, while EfficientNet-V2 achieved an overall accuracy of 80%, with particularly strong performance in cassava mosaic disease and healthy condition classification (85%) as well as root rot (72%). Confidence threshold analysis ranging from 30% to 70% revealed that the optimal range of 30 - 40% achieved the highest overall metric (80%), reflecting a balanced trade-off between accuracy and coverage. The training process was optimized on Google Colab Pro with appropriate hyperparameters and techniques such as data augmentation and early stopping, ensuring model convergence without overfitting. Although the system has demonstrated significant potential in supporting farmers with pest and disease management, certain limitations remain-such as misclassification between leaf spot and brown leaf spot under low-light conditions- which require further improvements. These findings not only confirm the feasibility of the proposed solution but also open promising directions for future research, including dataset expansion, confidence threshold refinement, and extension to other crops, with the ultimate goal of enhancing agricultural efficiency and sustainability in Vietnam.

The authors recognize that the initial success of this model represents an important step forward; however, its practical effectiveness can be further enhanced by integrating real-time data from mobile devices and in-field sensors. In future work, the authors plan to expand the field dataset nationwide and implement model optimization using TensorRT for deployment on mobile devices. In addition, we believe that collaboration with agricultural experts and local farmers will help optimize the system, ensuring high applicability across diverse cassava production contexts in Vietnam. Ultimately, we expect that this research will serve as a foundation for larger-scale projects aimed at developing intelligent systems to support agriculture at the national level.

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