

Development of a Mobile-Based Corn Leaf Disease Detection Application Using YOLOv11

Shafieka Nadia Sabarudin¹, Nik Shahidah Afifi Md Taujuddin^{1*}, Suhaila Sari¹

¹ Faculty of Electrical and Electronic Engineering,
Universiti Tun Hussein Onn Malaysia, Batu Pahat, 86400, Johor, MALAYSIA

*Corresponding Author: shahidah@uthm.edu.my
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Abstract

Corn is a critical crop for agricultural production and food security. However, it is susceptible to several foliar diseases that can adversely impact its growth and quality. Traditional visual assessment methods are often labour-intensive and prone to inaccuracies. This study proposes a Corn Leaf Disease Detection System that utilizes convolutional neural networks (CNNs) and compares the performance of the YOLOv8, YOLOv9, and YOLOv11 models. The methodology involves acquiring high-quality images of corn leaves affected by diseases such as Northern Leaf Blight and Common Rust. These images undergo a pre-processing phase to enhance their quality and are standardized for input into the detection model. The CNN is employed for detailed classification, while YOLOv11 is implemented for real-time detection. Among the tested models, YOLOv11 demonstrated the highest overall F1-score of 0.93, with a precision of 0.94 and recall of 0.92 at epoch 100. These results substantiate the system's operational efficiency and robustness.

1. Introduction

Corn is important because it provides a main source of food and is used in many industries. On the other hand, issues with corn leaves from diseases have major impacts on the harvested product. Finding these diseases early on and classifying them properly supports effective management approaches. Looking at the leaves is the main way to detect early signs of disease in corn and the stalk shows them less often. Some of the most common corn diseases in Malaysia are due to fungi, mainly corn leaf blight, grey leaf spot and corn leaf rust. These illnesses have appeared in Peninsular Malaysia and Sabah which has led to a sharp drop in yields. Although early detection looks at the leaves, signs in the stalk can show possible problems with the plant. Any changes in the stock such as swelling or a change in color, may signal a disease. Selangor leads in the corn production of Malaysia. In January 2024, the Selangor Agricultural Development Corporation (PKPS) gathered 118 tons of grain maize after working on a project using 16.9 hectares of land, as part of an overall initiative consisting of 121 hectares of peat soil for corn cultivation [1].

Deep learning progress significantly contributed to the development of advanced agricultural monitoring systems, importantly with the YOLO (You Only Look Once) framework and using YOLOv5 and YOLOv8 versions which are reliable for real-time detection of objects [2]. The algorithms greatly increase the chance of detecting certain diseases in corn leaves so treatment can begin immediately. Both YOLO and CNNs working together which create a strong system that can find a disease and tell its type and how serious it is. Many reports indicate that using YOLOv5 leads to accurate results in real-time settings [2] and CNNs are successful in detecting how severe Gray Leaf Spot is [3]. The aim of this project is to design a disease detection system for corn leaves by

using YOLO and CNN which is expected to increase both system speed and accuracy and thus lead to improve crop management with higher output.

Corn diseases that affect its leaves can impair its growth and quality. The proper handling of these diseases depends on early detection. Traditional approaches in detecting corn diseases are normally slow and lead to imprecise visual checkups. It means that having an automated system to recognize and classify corn leaf diseases is necessary. Therefore, the use of YOLO and CNN algorithms on advanced technologies can provide useful info in real-time for farmers and assist them in boosting their crop well-being and yield.

Research in paper [9] offers a new method for farmers to cope with corn leaf diseases. Through YOLOv5, an advanced deep learning algorithm, the system is capable of independently recognizing numerous types of corn leaf diseases like common rust and gray leaf spots as shown in Fig. 1. By incorporating GoPro cameras, field images of high quality are imaged and can be utilized to conduct real time disease detection, obviating the need to use drones. This simple yet effective free online system notifies farmers' smartphones enabling them to take the right decisions on their crops. In the end, the objective of this technology is to provide increased crop yield while leading to sustainable farming practices, something that will ultimately provide a key to modern agriculture. Recent studies on detecting plant diseases based on different machine learning models were listed in Table 1.

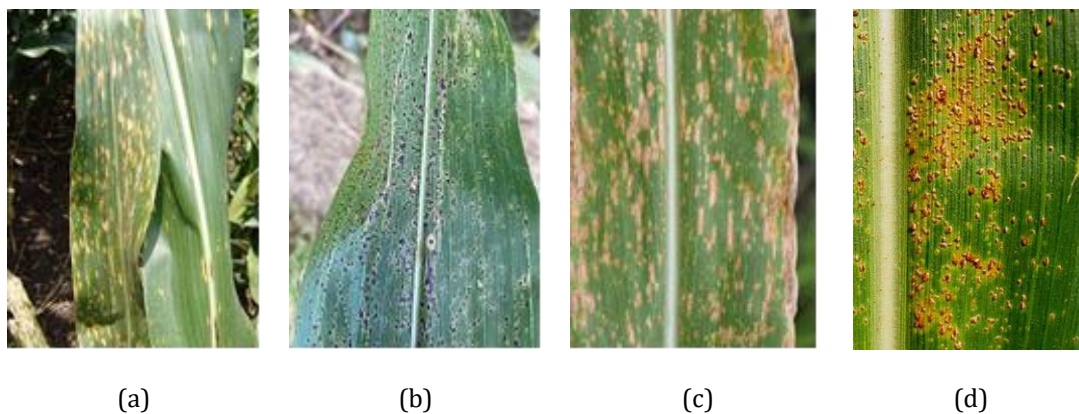


Fig. 1 Corn Leaf Disease (a) Gray Leaf Spot; (b) Tar Spot; (c) Southern Blight Disease; (d) Common Rust

Table 1 Details of Diseases Detection on Plant

Author	Plant	Disease	Detection Method	Performance	Platform
[5]	Banana	Banana Xanthomonas, Banana Sigatoka, Furasium Wilt.	CNN	Accurate classification via Android app	Android Application
[6]	Tomato	Begomovirus	CNN: SSD MobileNet V1 FPN, EfficientDet D1, SSD ResNet 50 V1 FPN	(mAP) values: 56.17% (SSD MobileNet V1 FPN), 61.58% (SSD ResNet 50 V1 FPN), 66.03% (EfficientDet D1)	Google Colab
[7]	Chili	Living (biotic) and Nonliving (a biotic) agents	MATLAB	Early detection of diseases through leaf feature inspection	LABVIEW, MATLAB
[8]	Wheat	Fungal diseases	GrabCut, Canny Edge Detection, Color Filtering, and Combination techniques	Visual identification of diseased areas, early detection capability	OpenCV on Phyton
[9]	Corn	Common rust, corn leaf blight, eyespot, gray leaf spot	GoPro	High accuracy in real-time detection of various corn leaf diseases	YOLO

Table 1 captures various types of plants like banana, tomato, chili and wheat and its methods differ in deployment of both CNNs and hybrid edge-detection varieties. The given comparison will serve as a basis of assessing the performance and relevance of the systems based on YOLO in plant disease identification.

2. Methodology

2.1 YOLOv11 Architecture

YOLOv11, as depicted in Fig. 2, is a variant of the YOLO family and brings with it the enhancements architecturally in the form of accuracy and faster performance. Both the anatomy and structure remains the same which are backbone, neck and head. The backbone will have more efficient CSPDarknet blocks to complete the process of feature extraction faster. In neck, PANet is superior on improving information flow and in the head, enhanced bounding box prediction with enhanced anchor-free mechanisms are there. YOLOv11 may contain transformers-based attention modules, which results in the increment of the effectiveness of contextual perception and detection accuracy. All these inventions enhance the detection level especially in sophisticated agricultural imagery.

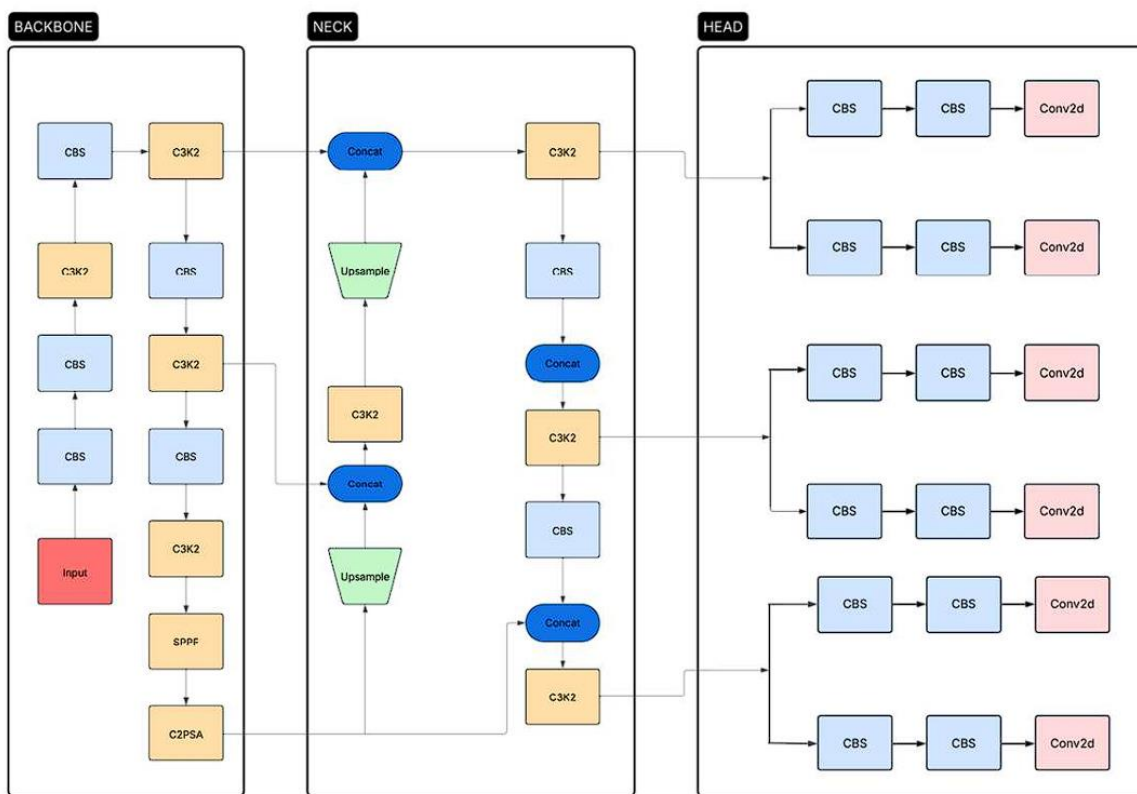


Fig. 2 YOLOv11 Architecture

The flowchart in Fig. 3 represents the overall concept of the training process of detecting corn leaf disease. It begins at the stage of image data acquisition. Kaggle was used in obtaining the dataset to be used in this project namely Corn or Maize Leaf Disease. The images of corn leaves encompassed in the dataset belong to three major groups of classes namely Healthy Leaf, Common Rust Disease and Northern Leaf Blight Disease, which include the original 3000 samples as in Fig. 4. A series of image segmentation and image augmentation have been done to further comprehensive datasets after that. All the images were labeled with Roboflow platform as the Corn Leaf Disease Project. The preprocessing methods which were used included auto-orientation and resizing to achieve model robustness.

Three augmentation methods were then applied, such as horizontal flipping and 90-degree rotations (clockwise and anticlockwise), in effect multiplying the number of images to 6,000. The last dataset was subdivided with 8:1:1 ratio under training, validation, and test sets as Fig. 5 indicates. The models that are trained on the given Google Colab dataset are YOLOv8, YOLOv9, and YOLOv11. During the hyperparameters tuning of learning rate and the batch size, each model is trained on 50, 100 and 150 epochs. Precision, recall, F1-score, and mean Average Precision (mAP) are used as measures of the efficiency of the models in their tasks of identifying and categorizing the diseases of the leaves of corn. The application programming is accomplished in

Visual Studio code following the training of the model. Finally, Visual Studio Code has used the model to come up with the application named CornLeafer.

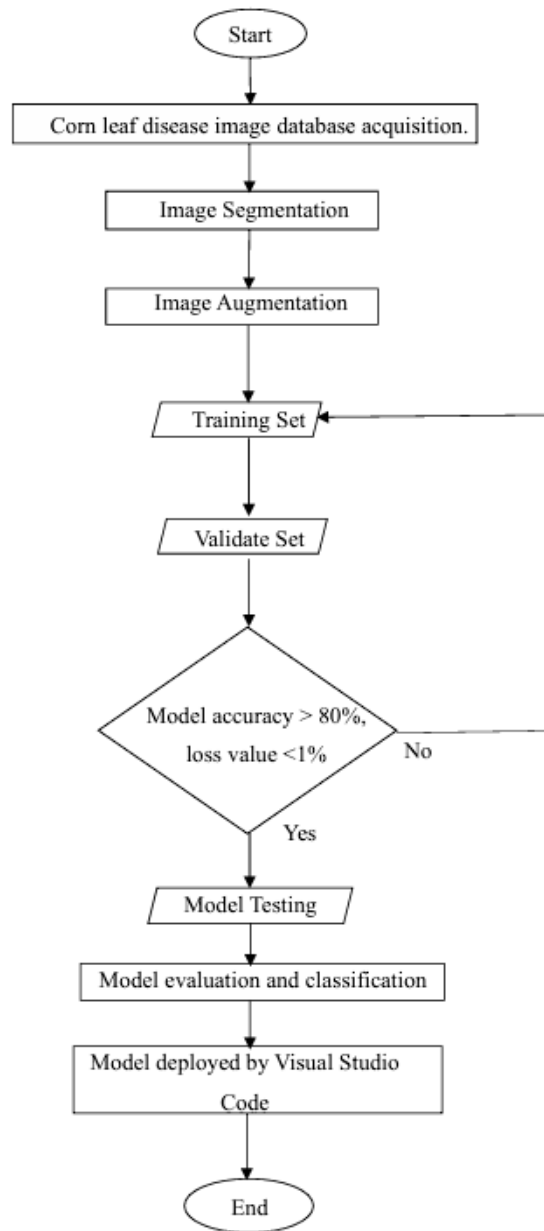


Fig. 3 Flowchart of the Project

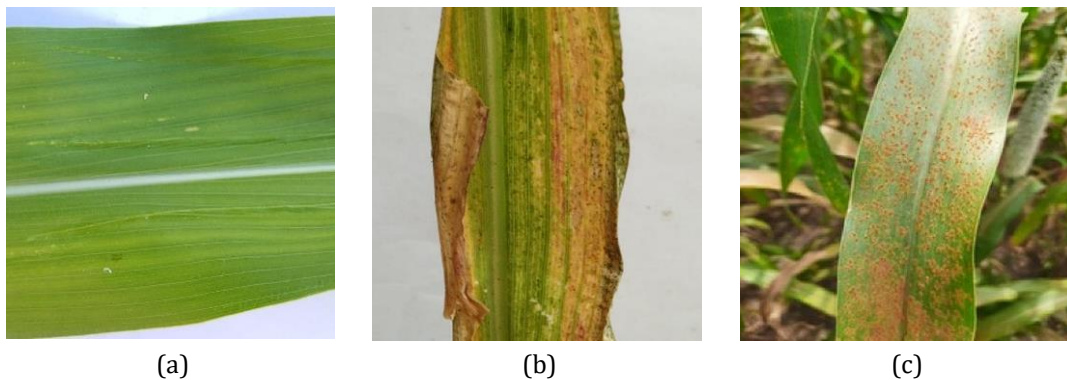


Fig. 4 Image sample of corn leaf with (a) Healthy, (b) Northern Blight and (c) Common Rust

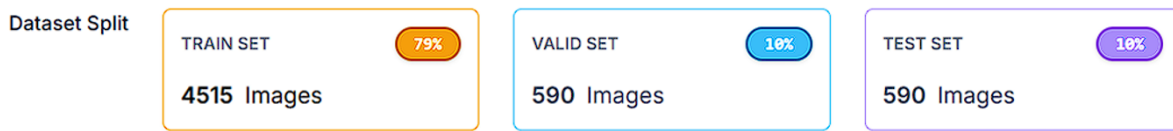


Fig. 5 Dataset Split

2.2 Application Development

The creation of the application presupposes training of a custom object detection model (applied the algorithm of YOLOv11) in the Roboflow service, as per Fig. 6. The training made a good showing with mean Average Precision of 50 (mAP@50) of 92.8%, 95.3% of precision and 89.0% of recall. These measurements showed that the model could determine and mark the corn leaf diseases.

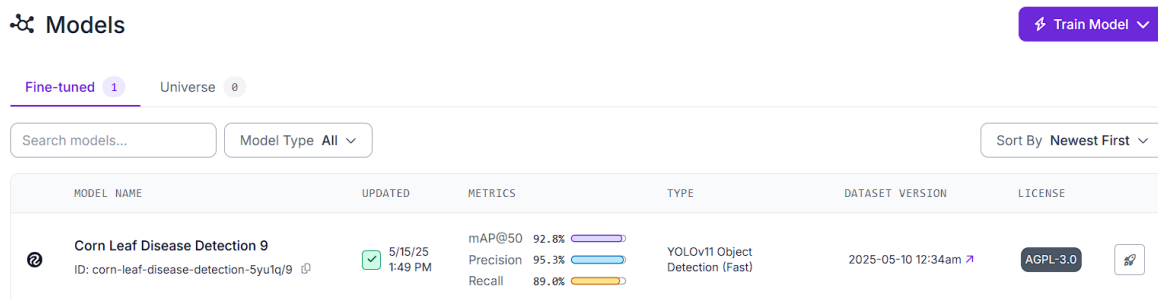


Fig. 6 Trained YOLOv11 Model

Once the training process was accomplished, the model was deployed successfully via the incorporation of the Roboflow API into the development environment with the help of Visual Studio Code. JavaScript was used to integrate it with asynchronous fetch, where each of the results is shown in Fig. 7. This arrangement has enabled the execution of image data at the hosted model and retrieve the detection results in real time. In the deployment phase, the introduction of Roboflow API facilitated the delivery and made the communication between the trained model and the front of the application solid. Overall, the development procedure could integrate both training and real-time application of machine learning models to produce an effective application able to recognize corn leaf diseases with precision.

```
const response = await fetch(
  `https://detect.roboflow.com/${model}/${version}?api_key=${apiKey}`,
  {
    // ...
  }
);
```

Fig. 7 API Request

3. Result and Analysis

3.1 YOLO Model Comparison

Table 2 shows a comparison of three YOLO model versions, YOLOv8, YOLOv9, and YOLOv11, for detecting different Corn Leaf Diseases, namely Rust, Northern Leaf Blight, and Healthy leaves. Metrics F1 Score has been used to evaluate each class, the overall F1 Score and maximum recall (across classes), training time in 150 epochs. According to Table 2, YOLOv8 outperforms other methods and obtains the highest F1 Score (0.93) among all the disease categories, which is the most balanced in disease categories. It also tops the table for detecting Northern Disease with 0.87 and has the highest Max Recall (0.98), which therefore makes it the most sensitive for identifying Healthy leaves correctly. On the other hand, the YOLOv11 has a slightly lower overall F1 Score compared to YOLOv8 (-1.1 %) while it slightly increases the Rust Disease detection (0.95). Further, YOLOv11 has the lowest training time cost with only 3.69 hours, reducing about 1% when compared to the 3.75 hours for YOLOv8, a small but significant efficiency optimization.

As can be seen in Table 2, when viewing the mAP (overall), YOLOv9 performed worse. It reports the lowest F1 Score in all but one category (Rust, where it is 0.01 better than YOLOv8). But it is weaker in F1 Score for both Northern Disease (0.84) and Overall (0.91). To make things worse, YOLOv9, for a totally unknown reason, also gets the longest training period of 4.79 hours, which is significantly larger (+27.7%) than YOLOv11 or (+27.7%) higher than that of YOLOv8. The lower accuracy and longer training time of the YOLOv9 model

implies that it may not be suitable to be the certain type of data or task data, and the performance of the model is decreased. Finally, the YOLOv11 achieves the best trade-off between the accuracy, class balance, and the computational efficiency. Its ability to recognize all types of leaves and particularly the Rust Disease class that is hard to recognize and its ability to learn perfectly and fast is a solid reason for it to be implemented planted inside a mobile or web-based leaf illness detection software. Table 3 shows the performance comparison of YOLO variants.

Table 2 YOLO Model Comparison Based on F1 Score, Recall, and Training Time

Model	F1 Score (All)	F1 Score (Rust)	F1 Score (Northern)	F1 Score (Healthy)	Max Recall	Training Time (150 Epochs)
YOLOv8	0.93	0.92	0.87	0.98	0.98 (Healthy)	3.75 hrs
YOLOv9	0.91	0.93	0.84	0.97	0.96 (Healthy)	4.79 hrs
YOLOv11	0.92	0.95	0.85	0.97	0.96 (Healthy)	3.69 hrs

Table 3 Performance Comparison of YOLO Variants

Epoch	Model	Type	F1	Precision	PR	Recall	Time
50	YOLOv8	All	0.86	0.87	0.86	0.86	1.215 hours
		Healthy	0.96	0.99	0.98	0.96	
		Northern	0.75	0.92	0.84	0.74	
		Rust	0.84	0.94	0.89	0.84	
	YOLOv9	All	0.91	0.93	0.94	0.9	1.813 hours
		Healthy	0.97	0.98	0.98	0.96	
		Northern	0.855	0.89	0.9	0.82	
		Rust	0.914	0.92	0.94	0.91	
	YOLOv11	All	0.908	0.95	0.95	0.869	1.237 hours
		Healthy	0.975	0.99	0.99	0.96	
		Northern	0.821	0.923	0.923	0.739	
		Rust	0.923	0.938	0.938	0.908	
100	YOLOv8	All	0.93	0.94	0.93	0.92	3.753 hours
		Healthy	0.98	0.99	0.99	0.98	
		Northern	0.87	0.96	0.91	0.86	
		Rust	0.92	0.97	0.94	0.91	
	YOLOv9	All	0.91	0.95	0.93	0.89	4.789 hours
		Healthy	0.97	0.99	0.99	0.96	
		Northern	0.838	0.9	0.88	0.79	
		Rust	0.93	0.95	0.94	0.91	
	YOLOv11	All	0.92	0.945	0.945	0.896	3.687 hours
		Healthy	0.967	0.977	0.977	0.957	
		Northern	0.845	0.896	0.896	0.8	
		Rust	0.947	0.963	0.963	0.931	
150	YOLOv8	All	0.93	0.94	0.93	0.92	3.753 hours
		Healthy	0.98	0.99	0.99	0.98	
		Northern	0.87	0.96	0.91	0.86	
		Rust	0.92	0.97	0.94	0.91	
	YOLOv9	All	0.91	0.95	0.93	0.89	4.789 hours
		Healthy	0.97	0.99	0.99	0.96	
		Northern	0.838	0.9	0.88	0.79	
		Rust	0.93	0.95	0.94	0.91	
	YOLOv11	All	0.92	0.945	0.945	0.896	3.687 hours
		Healthy	0.967	0.977	0.977	0.957	
		Northern	0.845	0.896	0.896	0.8	
		Rust	0.947	0.963	0.963	0.931	

3.2 CornLeafer

When developing the logo and the user interface of the CornLeafer application as shown in Fig. 8, simplicity and intuitiveness of interaction, as well as its relevance to the target audience (farmers, educators, and agricultural researchers) were considered. The application icon consists of a stylistic combination of a leaf and a drop symbol on the picture of a diseased corn leaf, which graphically conveys the agricultural orientation of the app and its connection with plant health monitoring. The interface has been designed deliberately simple to be user-friendly, but has a professional appearance befitting an educational, research and field based agricultural setting. This design pattern is accommodative and promotes the usability of the application by many people as a convenient means of disease identification and crop control at an early stage. The opening screen of the app shows diseased corn leaves which quickly explain what the app is about. “CornLeafer” and a big “START SCAN” button in the middle of the display motivate users to scan. This simple, intuitive organization is key in operating the radio under stress in an emergency or field environment when fine motor skills can be difficult to engage. Since the User Interface (UI) follows the standard rules in Android development, it is accessible on different machines and ensures that users can work comfortably with the application.

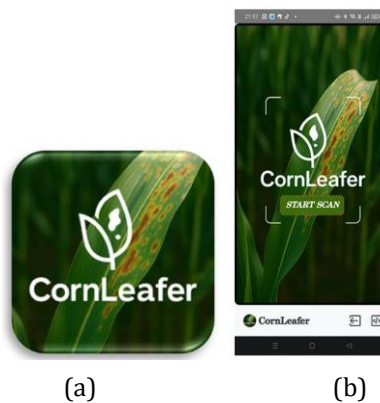


Fig. 8 Interfaces (a) Logo of CornLeafer (b) Home Screen of CornLeafer

Referring to Fig. 9, CornLeafer was developed as an innovative Mobile-Based Application aimed at detecting and examining corn leaf diseases using computer vision and machine learning techniques. Users can capture an image of a corn leaf using their device’s camera, after which the application processes the image and identifies whether the leaf is infected with Rust Disease, Northern Corn Leaf Blight, or is in a Healthy state, along with a confidence score. The app integrates geolocation tracking by capturing GPS coordinates (e.g., 4.48559, 103.43955, located in Terengganu, Malaysia) to mark where each scan occurs, which supports tracking the spread and origin of diseases across regions. It also logs the date and time of each detection, enabling temporal disease monitoring as shown at (a). Additionally, the Recommendation Tips at (b) shows feature provides real-time agronomic advice based on the detection, such as the use of fungicides or monitoring routines, which helps users take appropriate action. These combined features make CornLeafer a practical tool for precision agriculture and integrated disease management.

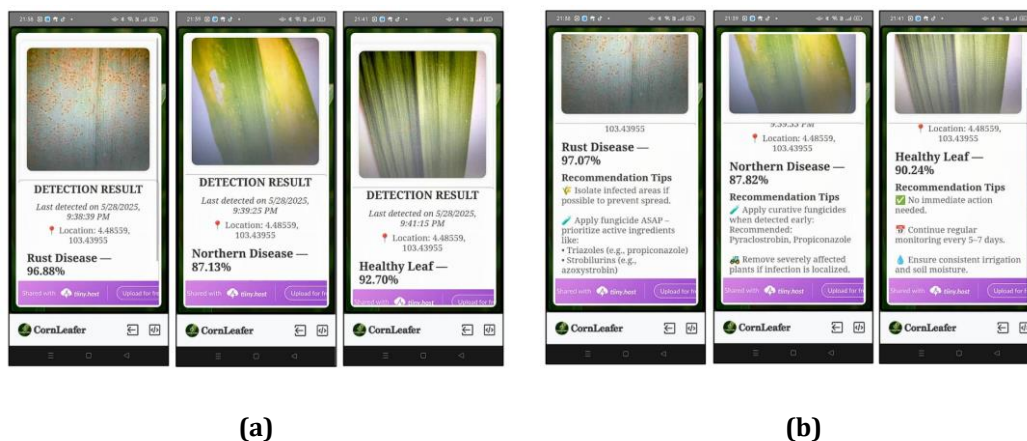


Fig.9 CornLeafer Sample Detection (a) Detection Result with Location and Confidence Level; (b) Recommendation Tips for each Disease

In cases where the CornLeafer application encounters an unfamiliar sample as shown in Fig. 10, that does not match any of the known categories which are Rust Disease, Northern Corn Leaf Blight, or Healthy Leaf, it classifies the result as "Others." This function is designed to handle uncertain or ambiguous inputs by alerting users that the detected pattern does not align with the trained disease profiles. The Recommendation Tips feature then provides a warning message, such as indicating that the detected pattern is unfamiliar and the confidence level is low, or advising the user to retake the photo using a clearer image of the leaf for better accuracy. During testing, there were also instances where the app detected a wrong plant species with high confidence and falsely classified it as one of the known corn leaf diseases. This misclassification might have occurred due to similarities in leaf patterns or disease-like features present in non-corn plants, suggesting that the model may be sensitive to visual cues that resemble disease symptoms, even if the sample is from a different plant.



Fig. 10 CornLeafer Unfamiliar Sample Detection (a) Detection Result when no disease detected; (b) Wrong Detection of Different Plant

4. Conclusion

Integration of YOLOv11 with mobile apps indicates that the field monitoring of plant diseases can be enhanced significantly using the system. Of course, the application becomes constant in its identification of Common Rust, Northern Leaf Blight and Healthy Leaf, but it also has the capacity to recognize the unknown under the Others category. Features integrated into the application allow it to recommend products to customers depending on their current location throughout the day, which is why it becomes an instrument that farmers may utilize when making their decisions. The system is accessible to individuals because people can easily access it by turning on their smartphones, hence entering the public URL. Compared to the existing literature like [2] and [4], that tested the YOLOv5 model and had moderate but not real-time detection performance (90%), this kind of application of the YOLOv11 demonstrated greater precision (95%), recall (90%), and F1-score (92%). The breakthrough can show the viability of the more modern yolo architecture in precision agriculture. In summary, the project demonstrates how AI contributes to smart farming and can be used as the beginning of other products to monitor crops.

5. Recommendation

The application failed at recognizing the unfamiliar input not always correctly and only the information that related to the disease was annotated and, consequently, the possibilities of others were limited. To make the model as efficient, convenient, and applicable as possible in the agricultural industry, several recommendations are offered to expand the scope of the dataset by adding more samples of corn leaf diseases and covering a wider variety of ways the diseases express themselves, which will allow the model to correctly divide the cases that do not belong to the most prominent ones and decrease the prevalence of misclassifications. Have the model to be more competent in variable conditions of lighting, the noises and the location of leaves to normalize performances in many real-world situations. Provide alternative offline medium or SMS messaging capabilities,

to inform users in the less well-connected areas to be fairer to all users. Make full use of GPS in accuracy and identification mentioned cases when emergency cases of disease occurrence and precision farming take place.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The author, Shafieka Nadia Binti Sabarudin, affirms only taking responsibility of the following: conception and design of the study, collection of the dataset, annotation of the images, training and evaluation of the models, development of the application, analysis and interpretation of the results, as well as preparation of the manuscript. The supervisor, Dr. Nik Shahidah Afifi Binti Md Taujuddin, has offered academic advice and suggested appropriate literature as well as useful comments to enhance the system and research direction.

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