CLDS-YOLO: Corn Leaf Disease Detection and Severity Evaluation Using YOLOv9

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***Abstract*—Corn is one of the major staple crops globally, particularly in the Philippines, where agricultural productivity is increasingly threatened by diseases such as Northern Corn Leaf Blight, Gray Leaf Spot, and Corn Rust. These challenges are further exacerbated by tropical cyclones and fluctuating environmental conditions, leading to substantial losses in yield and crop quality. This study presents CLDS-YOLO (Corn Leaf Disease Detection and Severity Evaluation Using YOLOv9), a novel system that leverages YOLOv9 instance segmentation for accurate disease detection and integrates fuzzy logic for severity assessment, based on Relative Leaf Area (RLA) and the count of diseased regions. The YOLOv9e-seg model demonstrated strong performance across classification tasks, achieving an overall accuracy of 80%, with recall values of 85% for diseased regions, 80% for healthy leaf areas, and 75% for background, based on the normalized confusion matrix. Precision levels were similarly high, particularly for leaf detection, while the model maintained a balanced trade-off in identifying diseased and background classes. These improvements address previous segmentation challenges and confirm the model's robustness in multi-class classification. Furthermore, the severity analysis effectively categorized disease levels, supporting timely and informed crop management decisions. The CLDS-YOLO system demonstrates significant potential for real-time disease detection and severity evaluation, laying the groundwork for an indoor planting framework that ensures continuous health monitoring and protection from adverse weather conditions.**

***Keywords*—corn leaf disease, disease detection, YOLOv9, instance segmentation, computer vision, relative leaf area, fuzzy logic, severity evaluation, agriculture technology**

I. INTRODUCTION

Corn, sometimes referred to as maize, is an essential commodity of enormous worldwide importance, especially in the Philippines, where agriculture is a major economic driver. However, corn cultivation faces substantial threats from various diseases that compromise both yield and quality. These challenges are exacerbated by the geographical vulnerability of the Philippines to tropical cyclones [1], which bring heavy rains, flooding, and strong winds, leading to crop destruction and economic losses. To address these threats, this study promotes the future development of indoor planting systems, which offer protection from environmental factors while enabling consistent, automated monitoring. In this context, the proposed model—CLDS-YOLO—demonstrates how AI-based disease detection can be seamlessly integrated into such controlled agricultural environments.

The indoor planting integration aspect distinguishes this research from previous YOLO-based plant disease detection works, which primarily focus on outdoor deployment. CLDS-YOLO aims not only for detection but also for actionable assessment by leveraging YOLOv9 instance segmentation to identify disease-affected areas and fuzzy logic to estimate severity based on Relative Leaf Area (RLA). The combination of fine-grained segmentation and fuzzy-based severity scoring provides a more robust and deployable solution for early disease management in precision agriculture, particularly suited for future automated indoor farming systems. This makes the study unique in both methodology and potential application setting.

However, the importance of proactive crop health monitoring cannot be overstated. Diseases such as Northern Corn Leaf Blight (NCLB), Gray Leaf Spot (GLS), and corn rust significantly affect corn production. Caused by fungal pathogens such as "Exserohilum turcicum" for NCLB and "Cercospora zeae-maydis" for GLS, these diseases thrive under specific environmental conditions, such as high humidity and moderate

Manuscript received March 20, 2025; revised June 5, 2025; accepted July 10, 2025; published August 7, 2025.

doi: 10.18178/joig.13.4.437-451

temperatures [2, 3]. If left unmanaged, these pathogens can cause severe yield losses, underscoring the urgent need for timely and accurate disease detection.

Furthermore, the use of AI in agriculture makes it easier to create prediction models that use historical disease incidence and environmental data to predict disease outbreaks [4, 5]. Compared to traditional systems, which frequently respond to symptoms rather than proactively managing crop health, this predictive capability represents a substantial breakthrough. Researchers have improved the robustness and generalizability of disease detection algorithms in various species of crops and types of disease by using strategies such as transfer learning and attention processes [6, 7].

This research introduces CLDS-YOLO (Corn Leaf Disease Detection and Severity Evaluation Using YOLOv9), a cutting-edge approach that leverages YOLOv9 instance segmentation for high-precision detection of corn leaf diseases. By categorizing diseases such as common rust, gray spot, and blight under a unified "disease" label, the study simplifies disease classification while maintaining accuracy. Furthermore, the integration of Fuzzy Logic for disease severity evaluation offers a more holistic understanding of the extent of crop damage, providing farmers with actionable insights for effective treatment and resource allocation. A key component of this research is the use of Relative Leaf Area (RLA), which quantifies the healthy leaf area relative to the total leaf area, enabling an accurate assessment of disease severity based on the proportion of the leaf affected.

By addressing the critical need for precise and automated disease monitoring, this study lays the foundations for the development of an indoor planting system that ensures consistent crop health surveillance and protection against adverse weather conditions. The CLDS-YOLO framework represents the first phase of a broader initiative to create an automated disease detection prototype, bridging a significant gap in modern agriculture and paving the way for sustainable and resilient farming practices.

II. Literature Review

A. Computer Vision in Agriculture

Computer vision is a field of artificial intelligence that enables computers to interpret and understand visual information from the world, mimicking human visual perception. It encompasses a range of techniques that allow machines to process, analyze, and derive meaningful insights from images and videos. The core of computer vision involves object detection, image classification, and image segmentation, which are essential for applications across various domains, including agriculture [8, 9].

In agriculture, computer vision has emerged as a transformative technology, facilitating innovations that enhance productivity and sustainability. One of the primary applications is in crop monitoring, where computer vision systems utilize cameras and sensors to capture images of crops at various growth stages. These images are then analyzed to detect diseases, assess plant health, and monitor growth patterns. For instance, deep learning algorithms, particularly Convolutional Neural Networks (CNNs), are employed to identify symptoms of diseases such as leaf blight or rust in crops like corn [10]. Additionally, computer vision is used in precision agriculture to optimize resource use, such as water and fertilizers, by analyzing soil conditions and crop needs in real-time [11].

The impact of computer vision on agricultural innovation is profound. By automating the monitoring process, farmers can receive timely alerts about potential issues, allowing for quicker interventions that can prevent crop losses. This shift from traditional manual scouting methods to automated systems not only increases efficiency but also reduces labor costs and human error [9]. Furthermore, the integration of computer vision with other technologies, such as drones and IoT devices, enables comprehensive data collection and analysis, leading to more informed decision-making in farming practices [11].

Moreover, computer vision facilitates the development of smart farming solutions, such as autonomous tractors and robotic systems that can perform tasks like planting, weeding, and harvesting with minimal human intervention. These innovations contribute to sustainable agricultural practices by reducing the reliance on chemical inputs and enhancing the overall efficiency of farming operations [11]. As a result, computer vision is not just a tool for monitoring but a catalyst for a broader transformation in agricultural methodologies, promoting a shift towards data-driven and precision farming approaches that can significantly improve crop yields and environmental stewardship [8, 9].

B. Deep Learning in Computer Vision

Some studies utilizing deep learning AI models in computer vision have significantly advanced agricultural practices, particularly in disease detection and crop monitoring. These studies leverage Convolutional Neural Networks (CNNs) and other deep learning architectures to enhance the accuracy and efficiency of agricultural applications.

One notable study by Osco-Mamani and Chaparro-Cruz [12] focuses on the classification of olive leaf diseases using a highly accurate deep learning model. This research demonstrates the effectiveness of CNN architectures in identifying plant diseases, showcasing the potential of deep learning in agricultural applications Osco-Mamani & Chaparro-Cruz. Similarly, Naranjo-Torres *et al.* [13] developed a disease and defect detection system for raspberries, utilizing CNNs to classify various defects and diseases in fruit. Their work highlights the growing trend of integrating AI algorithms in agriculture, particularly for quality control and disease detection.

Li *et al.* [14] explored the use of UAV images combined with deep learning for recognizing freezing-tolerant rapeseed materials. Their findings emphasize the advantages of deep learning in automatically learning features from images, which is crucial for recognizing crop stresses and other conditions. Furthermore, the study by Kothadiya *et al.* [15] discusses the convergence of deep learning and computer vision, emphasizing its applications in various fields, including agriculture, where it plays a significant role in disease identification and monitoring.

Research on potato bud recognition has also highlighted the effectiveness of deep learning methods, particularly CNNs, in automating the recognition process. This study illustrates how deep learning can outperform traditional methods by utilizing large datasets for training, thus enhancing recognition accuracy [16]. Additionally, Zhu *et al.* [17] proposed a pest image identification method based on Mahalanobis entropy, showcasing the application of deep learning in intelligent agriculture for pest management.

Tu *et al.* [18] provided a comprehensive overview of the current status and future prospects of deep learning in agricultural engineering, emphasizing its role in improving the intelligence of traditional agricultural practices. Moreover, Kamilaris and Prenafeta-Boldú [19] conducted a survey on deep learning applications in agriculture, identifying numerous research efforts that apply deep learning techniques to various agricultural challenges, including disease detection and crop monitoring.

C. Challenges of Detecting the Crops Diseases

In recent years, a lot of research has been done on the difficulties in detecting crop diseases using computer vision and deep learning approaches. As can be seen in Table I, numerous studies have outlined the advantages and disadvantages of current approaches in addition to the remedies they suggest to deal with these issues.

TABLE I. CHALLENGES AND SOLUTIONS IN CROP DISEASE DETECTION USING COMPUTER VISION AND DEEP LEARNING

Challenge	Proposed Solution	Strength	Weakness
Variability in lighting conditions and color differences of diseased plant parts [20]	Image preprocessing techniques to normalize lighting conditions	Enhances the reliability of detection systems	Relies on controlled environments, which may not be feasible in real-world agricultural settings
Limited labeled datasets for training deep learning models in grape disease classification [21]	Few-shot learning approach using Generative Adversarial Networks (GANs) to generate synthetic data	Mitigates data scarcity by augmenting the training dataset	Synthetic data may introduce biases if it doesn't accurately represent real-world conditions
Difficulty of generalizing models across different plant species and diseases [22]	Transfer learning techniques to adapt pre-trained models to new datasets	Improves accuracy by adapting models to new data	May struggle with unseen diseases or plant varieties
Overfitting when trained on limited images [23]	Data augmentation techniques to increase the diversity of the training dataset	Increases robustness of the model	Potential risk of overfitting on a limited dataset
Complexity of integrating fuzzy logic with deep learning models [24]	Hybrid approach using fuzzy logic to incorporate uncertainty in disease classification	Improves accuracy by handling uncertainty in decision-making	Complex integration of fuzzy logic can be challenging for real-time applications
Data scarcity [25]	Few-shot learning to learn from limited examples	Addresses data scarcity issue	Requires careful selection of representative samples to ensure effective learning
Ensuring dataset diversity and representativeness of environmental conditions in grape disease detection [26]	Creation of a comprehensive dataset of grape disease images	Improves model accuracy with a comprehensive dataset	Dataset must be diverse and representative, which can be difficult to achieve
Data privacy concerns in agricultural applications [27]	Federated learning to allow models to learn from decentralized data sources without sharing raw data	Addresses privacy concerns effectively	Achieving consistent performance across different datasets can be challenging

D. AI in Real-Time Monitoring Systems

The development of real-time disease detection systems powered by Artificial Intelligence (AI) has gained significant traction in agriculture, enabling timely interventions for farmers and decision-makers. These systems leverage advanced machine learning algorithms, particularly deep learning, to analyze data from various sources, including images, sensors, and drones, to provide early alerts regarding crop health and potential diseases.

Real-time disease detection systems are increasingly being developed to allow prompt actions in the field. Fuentes *et al.* [28] presented a robust detector for tomato diseases using deep learning, demonstrating high real-time accuracy. Cheng *et al.* [29] integrated GANs with attention for anomaly detection in IoT data, showcasing adaptability to noisy input.

Another significant contribution is from Gupta *et al.* [30], who discussed the integration of AI and machine learning in smart agriculture systems. Their research highlights how these technologies can provide real-time insights into crop health, soil moisture levels, and weather conditions, enabling data-driven decision-making [30]. This study underscores the importance of real-time data analytics in optimizing agricultural practices and improving yield.

Gao *et al.* [31] used UAVs and IoT to create a dual-view monitoring system for crops, improving detection accuracy and timing. These studies underline the importance of combining multiple sensing methods with AI to optimize decision-making in precision agriculture.

Khan *et al.* [32] investigated the real-time recognition of spraying areas for UAV sprayers using deep learning techniques. Their study emphasizes the importance of accurately identifying crop areas for precision spraying, which is crucial for effective pest and disease management. By employing deep learning algorithms, the system can adapt to changing conditions and provide real-time feedback to operators.

The work of Basaligheh presents a deep learning model for continuous monitoring and accurate diagnosis of plant diseases. By placing cameras and sensors in the fields, the proposed system facilitates real-time monitoring and rapid disease identification, allowing for early intervention to minimize crop damage [33]. This study highlights the potential of AI in enhancing the efficiency and effectiveness of disease management strategies in agriculture.

Moreover, the research by Ito emphasizes the need for field monitoring systems that gather real-time data to suppress insect damage and diseases [34]. The study advocates for the integration of various data types to enhance the monitoring capabilities of agricultural systems, thereby improving the overall health of crops. Compared to prior systems, CLDS-YOLO (ours) integrates YOLOv9 instance segmentation with fuzzy logic and Relative Leaf Area (RLA) computation, enabling disease detection and severity assessment in one framework. This layered approach supports future integration into automated indoor farming systems.

E. Public Source of Dataset

In the context of developing an AI model, a dataset is a collection of data that is used to train, validate, and test the model. Datasets are fundamental because the quality and quantity of the data directly influence how well the AI model performs. Table II shows the datasets that can be accessed publicly and might be used in this study. These datasets provide a comprehensive foundation for researchers and developers working on AI applications in agriculture, particularly in the area of crop disease detection and management.

TABLE II. CHALLENGES AND SOLUTIONS IN CROP DISEASE DETECTION USING COMPUTER VISION AND DEEP LEARNING

Dataset Name	**Description**	**Reference**
PlantVillage Dataset	Contains images of various plant diseases, including corn leaf diseases. Widely used for machine learning models.	X. Wu *et al.* [35]
Corn-Leaf-Diseases Dataset	Focused on diseases affecting corn leaves, with labeled images for training and testing.	X. Wu *et al.* [35]
NLB Dataset	Specifically designed for identifying Northern Leaf Blight in corn, includes images captured in real agricultural settings.	A. Ahmad *et al.* [36]
Corn Leaf Disease Dataset from UAS Imagery	Acquired from Unmanned Aerial Systems (UAS) imagery, specifically for disease identification in corn fields.	A. Ahmad *et al.* [36]
Corn or Maize Leaf Disease Dataset	Available on Kaggle, includes images of corn leaves categorized into disease classes such as blight, rust, and gray leaf spot.	W. Pamungkas *et al.* [37, 38]
PlantDoc Dataset	Contains images of diseased plants, including corn, for training models to identify various plant diseases.	A. Ahman *et al.* [39]
Digipathos Dataset	Includes images of various foliar diseases, including corn, used for evaluating deep learning models.	A. Ahman *et al.* [39]
CD&S Dataset	A custom dataset for research, includes images of corn leaf diseases to evaluate deep learning model generalizability.	A. Ahman *et al.* [39]
Corn Leaf Disease Recognition Dataset	Includes images of corn leaves affected by various diseases, used for training convolutional neural networks.	M. Fadhilla [40]
Maize Leaf Disease Dataset	Consists of images of maize leaves with different disease symptoms, useful for training and testing AI models.	P. Dong [41]
Maize Gray Leaf Spot Image Dataset	Focused on images of maize leaves affected by gray leaf spot disease, used for training deep learning models.	P. Dong [41]
Polygon Annotation Dataset (PolyCorn)	Designed for detecting corn leaf pest-infected regions, used for training object detection models.	R. Zhu [42]
Corn Leaf Disease Classification Dataset	Includes images of corn leaves with various diseases, used for classification tasks in machine learning.	F. Adhinata *et al.* [43]
Corn Leaf Image Dataset from Farmers' Fields	Collected from farmers' fields in the Madura Region, includes images of healthy and diseased corn plants.	A. Ubaidillah *et al.* [44]
Corn Leaf Disease Images from Field Studies	Compiled from field studies, includes images of corn leaves with varying disease severity, used for training AI models.	D. Hindarto [45]

F. Recent Advances in Instance Segmentation and Hybrid Models for Crop Disease Detection

Several recent studies have introduced advanced models combining deep learning and fuzzy systems or focusing on instance segmentation to enhance the accuracy of crop disease detection. For instance, the study by Mishra *et al.* [46] proposes a hybrid approach for plant leaf detection utilizing a ResNet50-based architecture combined with an Intuitionistic Fuzzy Random Vector Functional Link (IFRVFLC) classifier. This work highlights the robustness of integrating fuzzy logic with deep features to handle noisy and uncertain data, aiming for improved generalization capabilities in plant detection, which aligns with our use of fuzzy logic for severity assessment. While their focus is on leaf detection, the paper's emphasis on fuzzy logic for enhanced robustness against noise and outliers is particularly relevant to real-world agricultural environments.

Another significant contribution is from Sarkar *et al.* [47], who introduced a 1-Norm twin random vector functional link network based on Universum data for leaf disease detection. This approach demonstrates how advanced machine learning algorithms, beyond conventional deep learning, can be effectively applied to detect plant diseases, often with an emphasis on specific robust classification techniques. Their work explores alternative learning paradigms to enhance detection performance, providing a useful benchmark for diverse model efficacy.

Furthermore, Sarkar *et al.* [48] also published a comprehensive review paper on leaf disease detection using machine learning and deep learning, outlining existing methods, current challenges, and future directions. This review is critical as it synthesizes the landscape of the field, highlighting various classification and detection approaches, including those based on CNNs, and discussing the need for robust and efficient systems. While a review, it implicitly supports the ongoing research into advanced deep learning and hybrid models by identifying the persistent challenges and the avenues for improvement in this domain.

These recent works collectively underscore the trend towards more sophisticated and hybrid models to overcome the limitations of traditional methods in agricultural disease detection. They provide valuable context for the design and evaluation of our CLDS-YOLO framework, particularly in the integration of instance segmentation with fuzzy logic for comprehensive disease detection and severity assessment, a novel combination aiming to address critical gaps highlighted by the ongoing research in the field.

III. METHODOLOGY

A. Data Preparation

1) Dataset

A dataset is used as the basis for training, validating, and testing machine learning models in AI model development. For this purpose, a large dataset of over 1500 images was collected from a variety of agricultural areas, covering a wide range of conditions such as changes in lighting, angles, and leaf states. This diversity in the dataset strengthens the model's confidence and its ability to generalize to new situations, ultimately leading to more accurate and dependable disease detection in practical agricultural applications. The dataset is split into three parts: 70% for training, 20% for validation, and 10% for testing. The training set enables the model to learn patterns and features in the images, helping it capture the variability in agricultural environments. The validation set is used during training to fine-tune hyperparameters and prevent overfitting, while the test set, used only after training, provides an unbiased final evaluation of the model's ability to generalize to new data. This careful dataset division optimizes the model's performance and ensures reliable disease detection.

Fig. 1 displays a variety of image examples from the dataset, including images of corn leaves afflicted by common diseases like (a) common rust, (b) gray spot, and (c) blight. Such diseases are common and have a major effect on the quality and productivity of maize crops. The dataset enables the program to identify the visual traits linked to each disease by incorporating pictures of leaves afflicted with these particular conditions. The dataset's diversity guarantees that the model will be able to identify the unique characteristics of several corn leaf diseases in addition to learning to identify the existence of disease in general.

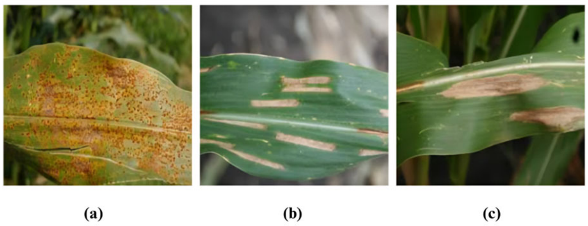


Fig. 1. Types of corn leaf diseases.

While the dataset used in this study comprises ~1500 annotated images, it was curated to include a wide range of real-world variations—such as different lighting conditions, disease types, and leaf orientations. This diversity provided a meaningful foundation for model training. However, the limited sample size and class imbalance, particularly with small or early-stage disease spots, constrained the model's ability to achieve higher recall in fine-grained segmentation tasks. Future work should focus on dataset expansion and balance, as well as incorporating synthetic and semi-supervised techniques to overcome these limitations.

2) Data annotation

Annotation is the process of labeling data to provide meaningful information that guides machine learning models during training. In the context of image-based tasks like corn leaf disease detection, annotation involves marking specific regions within an image and assigning labels that the model uses to learn patterns and features. The primary purpose of annotation is to provide the AI model with the correct information needed to understand and learn from the dataset. In this study, the images of Fig. 2 are annotated with two class labels: "disease" and "corn leaf," where "corn leaf" represents healthy leaves, and "disease" labels the affected areas with common corn leaf diseases such as common rust, gray spot, and blight.

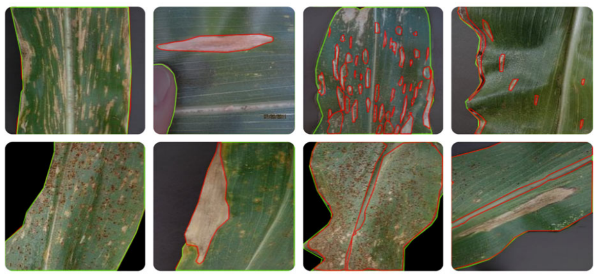


Fig. 2. Sample images of polygon annotation.

This study uses polygon annotation to get more exact and detailed labeling, which is very useful for instance segmentation. Polygon annotation, unlike bounding boxes, provides for the precise outline of irregular shapes, making it suitable for marking the limits of diseased patches on corn leaves that do not correspond to simple rectangular forms. This method provides a higher level of information by tracing the contours of the diseases, which improves the model's capacity to detect and segment diseases properly.

3) Preprocessing

Preprocessing involves preparing the dataset to be suitable for input into the YOLOv9 AI model by applying various techniques to standardize the images and enhance their quality. For this study, stretch-resizing is applied to resize all images to a consistent resolution of 640×640 pixels, ensuring that the input images meet YOLOv9's requirements while maintaining the necessary level of detail. Additionally, an auto-orient function is used to adjust the orientation of the images, correcting any skewed or rotated pictures to ensure proper alignment. These preprocessing steps help standardize the dataset, improving YOLOv9's ability to learn from the images effectively and reducing potential inconsistencies caused by varying image sizes or orientations.

4) Data augmentation

Data augmentation is a critical technique in deep learning that artificially expands the training dataset by applying various transformations to existing images. This process helps improve model generalization, reduce overfitting, and simulate real-world variations that the model may encounter during deployment. In this study, several augmentation techniques were applied to each training example to enhance diversity. Specifically, three augmented outputs were generated per image using a combination of horizontal and vertical flips, 90° rotations (clockwise, counter-clockwise, and upside down), saturation adjustments ranging from −30% to +30%, and the addition of random noise affecting up to 1.5% of pixels. These transformations were selected to mimic common variations in agricultural environments, such as differing lighting conditions, leaf orientations, and image quality. As shown in Fig. 3, the augmented samples effectively represent a wide range of possible visual appearances, contributing to more robust learning and better model performance in diverse field conditions.

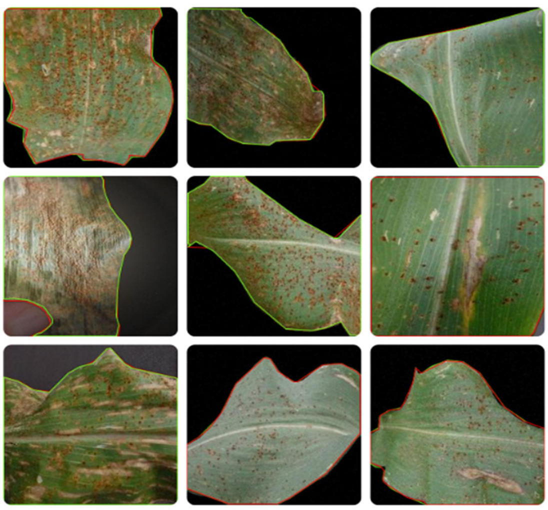


Fig. 3. Sample images of polygon annotation.

B. Model Development

1) Model selection

The YOLOv9 instance segmentation model, developed by Chien-Yao Wang, I-Hau Yeh, and Hong-Yuan Mark Liao, represents the latest advancement in computer vision. The creators, renowned for their contributions to earlier models such as YOLOv4, YOLOR, and YOLOv7, have incorporated state-of-the-art features and optimizations into YOLOv9 to enhance object detection and segmentation capabilities [49]. Two key variants of YOLOv9-seg, namely YOLOv9c-seg and YOLOv9e-seg, are available for specialized tasks. Their performance metrics are shown in Table III.

TABLE III. VARIANTS OF YOLOV9 IN SEGMENTATION TASK [50]

Model	$mAP^{box50-95}$	$mAP^{mask50-95}$	params (M)
YOLOv9c-seg	52.4	42.2	27.9
YOLOv9e-seg	55.1	44.3	60.5

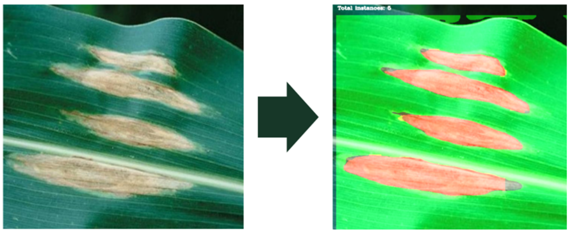
The YOLOv9e-seg version was chosen for this investigation based on the data in Table I because it performed better in the instance mask and bounding box evaluations, obtaining higher mAPbox and mAPmask scores. These metrics demonstrate YOLOv9e-seg's remarkable capacity for precise object detection and segmentation, which makes it perfect for the challenging task of identifying corn leaf disease.

Compared to YOLOv5 and other previous segmentation models, YOLOv9e-seg provides superior performance in segmentation accuracy and robustness, particularly on small and overlapping objects—common in leaf disease detection. Additionally, YOLOv9 incorporates a Generalized Efficient Layer Aggregation Network (GELAN) and improved task alignment modules, making it more suitable for multi-task learning scenarios like instance segmentation [50]. Model training and inference were conducted using an NVIDIA RTX 3060 GPU (12GB VRAM), with 32GB of RAM and an Intel i7-12700H processor. The model achieves an average inference speed of approximately 17.4 ms per image (~57 Frames Per Second (FPS)), supporting efficient near real-time deployment in agricultural systems.

2) Instance segmentation

Instance segmentation is a significant technique used in this study that combines object detection and semantic segmentation, allowing the model to not only detect the presence of disease but also find and discriminate distinct diseased patches in an image. Despite classical object detection, which simply recognizes the bounding boxes of objects, instance segmentation allows the model to precisely highlight each object's boundaries, even when they overlap or are irregularly shaped. In this situation, it enables the identification and isolation of sick spots on corn leaves, thereby providing specific and granular information regarding the disease's spread on each leaf. The following figure, such as Fig. 4, presents the sample detection of instance segmentation on a diseased leaf.

This level of segmentation is crucial to understand the full impact of the disease, as it enables the model to assess the size of affected areas relative to the overall size of leaf. Segmentation details, such as the proportion of the affected leaf and the specific location of the disease, are essential for evaluating disease severity. These parameters are then incorporated into the fuzzy logic system to quantify the level of damage and determine the severity of the condition. By leveraging instance segmentation, this study ensures a more accurate, detailed, and scalable approach to disease detection, facilitating both precise disease detection and comprehensive severity evaluation, ultimately enhancing the effectiveness of automated indoor crop monitoring systems.



Original image **Segmented image**

Fig. 4. Segmented image of blight disease.

3) Experimental training parameters

For the training of the model, several key experimental parameters were defined to ensure optimal performance. The image size was set at 640×640 pixels to ensure uniform resolution and compliance with the YOLOv9e-seg model. A learning rate of 0.01 would be chosen to achieve fast convergence while avoiding overshooting during optimization. To reduce overfitting and increase generalization, a weight decay of 0.0005 would be used as a regularization strategy. The model would be trained for 1000 epochs, giving it enough time to learn the important features required for detecting and evaluating the severity of corn leaf diseases. The Table IV below shows the summary of parameters.

TABLE IV. HYPER PARAMETERS

Model	params (M)
image_size	27.9
lr0 (learning rate)	60.5
weight_decay	0.0005
epochs	1000

C. Relative Leaf Area (RLA)

The Relative Leaf Area (RLA) is a critical quantitative metric employed to evaluate the extent of damage caused by diseases on corn leaves. It measures the proportion of the total leaf area that remains unaffected by disease symptoms, providing a standardized approach to assess disease impact. The formula for calculating RLA is given by:

$$RLA = \frac{totalLeafArea - \Sigma(diseasedArea_i)}{totalLeafArea} \times 100 \quad (1)$$

where:

- **Total Leaf Area:** The total area of the leaf, calculated as the sum of areas of all bounding boxes labeled as corn leaf by the YOLOv9 instance segmentation model.
- **Diseased Area:** The area affected by disease within each bounding box. If a leaf contains multiple diseased regions, the diseased area is the sum of all diseased areas.

Components of RLA Calculation

1. **Total Leaf Area:** The total area of the leaf is determined by summing up the areas of all bounding boxes classified as "corn leaf". The area for each bounding box is calculated as:
   $$Area = (xmax - xmin)(ymax - ymin) \quad (2)$$
   The sum of these areas across all detected boxes gives the total leaf area.
2. **Diseased Area:** The diseased area is computed for each detected diseased region on the leaf. Each bounding box that contains disease is evaluated separately. The total diseased area for the leaf is the sum of the areas of all such bounding boxes:
   $$Diseased\ Area = \sum (Area_i) \quad (3)$$
   where i represents each individual diseased region.
3. **RLA Calculation:** The RLA is computed by subtracting the sum of diseased areas from the total leaf area and then dividing by the total leaf area. The result is multiplied by 100 to obtain a percentage.

This method is especially valuable when multiple diseased areas occur on the same leaf, as it accounts for the collective impact of all affected regions. The RLA metric provides a standardized approach to assess the overall health of the leaf. A higher RLA indicates that the leaf is largely unaffected by disease, while a lower RLA signifies that a significant portion of the leaf is damaged.

D. CLDS Algorithm

Algorithm 1 outlines the CLDS-YOLO Disease Detection and Severity Assessment process. It begins by leveraging YOLOv9's instance segmentation capabilities to identify and analyze segmented regions corresponding to corn leaves and disease-affected areas. This step ensures precise computation of both the total leaf area and the diseased area.

Algorithm 1: CLDS-YOLO Disease Detection and Severity Assessment

Input: Image of corn leaf image, YOLOv9 model with instance segmentation model

Output: Relative Leaf Area (RLA) and Disease Severity Score

Step 1: Load YOLOv9 Model

Load YOLOv9 pretrained weights configured for instance segmentation and set class names as 'corn leaf' and 'disease'.

Step 2: Load Input Image

Read the input image.

Run YOLOv9 inference on the input image with instance segmentation enabled.

Extract segmentation masks for 'corn leaf' and 'disease'.

Step 3: Calculate Total Leaf Area, Diseased Area, and Count Diseased Regions

Initialize *totalLeafArea*, *diseasedArea*, and *diseasedCount* to 0.

for each segmentation mask in predictions **do**

Compute the area of the mask as the sum of its pixel values (*maskArea*).
if class is 'corn leaf' **then**
Add *maskArea* to *deseasedArea.*
else if class is 'disease' **then**
Add *maskArea* to *diseasedArea.*
Increment *diseasedCount.*
end if
end for
Step 4: Compute Relative Leaf Area (RLA)
if *totalLeafArea > 0* **then**
Compute RLA using:

$$RLA = (\frac{totalLeafArea - diseasedArea}{totalLeafArea}) \times 100 \quad (4)$$

else
Set *RLA* to 0.
end if
Step 5: Apply Fuzzy Logic for Severity Assessment
Define fuzzy variables:
Input: RLA (*low, medium, high*), *diseasedCount* (*low, medium, high*)
Output: Disease Severity (*low, medium, high*)
Define fuzzy rules:
if *RLA* is high **AND** *diseasedCount* is low **then** Severity is *low.*
if *RLA* is medium **AND** *diseasedCount* is moderate **then** Severity is *medium.*
if *RLA* is low **OR** *diseasedCount* is high **then** Severity is *high.*
Compute Disease Severity using Fuzzy Inference System (FIS).
Step 6: Output Results
Display *RLA* and Disease Severity Score.
Annotate image with segmentation mask and labels.

In this study, the role of fuzzy logic is used to assess the severity of disease based on two factors: the Relative Leaf Area (RLA) and the number of diseased spots in the leaf. RLA represents the portion of the leaf that is not affected by disease, and it is categorized into three levels: Low, Medium, and High. A low RLA means that most of the leaf is diseased, while a high RLA indicates that the leaf is mostly healthy. Disease severity is also categorized as Low, Medium, or High, where Low severity indicates minimal damage, Medium suggests moderate damage, and High reflects significant disease impact. Moreover, the second input represents the number of disease spots or symptoms on the leaf. This is also categorized into Low, Medium, and High levels, and plays an important role in calculating the disease severity.

To compute the severity, fuzzy logic uses membership functions to connect the RLA, number of diseased regions, and severity levels to fuzzy sets. For example, a low RLA (0–50%) typically correlates with low severity, while a high RLA (50–100%) correlates with low severity. Additionally, a higher number of diseased spots, regardless of RLA, will usually lead to a higher severity score. Simple fuzzy rules, like "IF RLA is High AND Diseased Count is Low, THEN Severity is Low," are used to infer the overall disease severity. These rules are then combined to compute the final result.

In the defuzzification stage, the fuzzy output is converted into a precise severity score by calculating the average of the weighted centers of the fuzzy sets, similar to the Centroid method. This approach provides a more detailed and understandable assessment of leaf disease, enabling early interventions in agricultural practices.

E. Validation and Testing

1) Model evaluation metrics

The performance of the YOLOv9 instance segmentation model in detecting and evaluating corn leaf diseases is crucial to understanding how well the model can identify both diseased and healthy regions on corn leaves. To assess the effectiveness of the model, several standard evaluation metrics are used: Mean Average Precision (mAP), Precision, Recall, and the F1-Score. These metrics collectively provide insight into the accuracy and reliability of the model's predictions.

1. **Mean Average Precision (mAP)** is a widely used metric in object detection and instance segmentation tasks to evaluate the accuracy of the model. It measures the average precision over all classes (in this case, "disease" and "corn leaf") at different levels of recall. The mAP is particularly valuable for understanding the trade-off between precision and recall in object detection and segmentation tasks.

$$mAP = \frac{1}{K}\sum_{I=1}^{K} AP_i \quad (5)$$

2. **Precision and Recall** are fundamental metrics for evaluating the classification ability of the model. Precision assesses how many of the detected diseased regions are actually correct, while recall evaluates how well the model detects all the diseased regions from the ground truth. Precision focuses on the accuracy of the predicted regions (how many of the predicted diseased areas are truly diseased), while Recall emphasizes the ability of the model to detect all true diseased areas (how many of the actual diseased regions were detected).

$$Precision = \frac{True\ Positive}{(True\ Positive + False\ Positive)} \quad (6)$$

3. The **F1-Score** is the harmonic mean of Precision and Recall, providing a single metric that balances both of these aspects. The F1-Score is particularly useful when the class distribution is imbalanced, as it ensures both high precision and high recall.

$$Recall = \frac{True\ Positive}{True\ Positive\ + False\ Positive} \quad (7)$$

2) Disease severity evaluation

The fuzzy logic system used for severity evaluation should also be tested to ensure it makes accurate classifications of disease severity based on the Relative Leaf Area (RLA).

1. **Fuzzy Logic Rules:** The fuzzy logic system uses membership functions for the input RLA and output severity. These rules are then evaluated using a Fuzzy Inference System (FIS) to determine

the disease severity score. The RLA value is categorized into low, medium, and high, with corresponding severity categories also ranging from low to high. For example, the fuzzy rules could be:

IF ***RLA*** is High AND *diseasedCount* is *low*, THEN Severity is Low

IF ***RLA*** is Medium AND *diseasedCount* is low, THEN Severity is Medium

IF ***RLA*** is Low AND diseasedCount is *low*, THEN Severity is High

2. **Defuzzification:** The fuzzy output is defuzzified to convert it into a crisp value for the disease severity score. This gives a numerical value for disease severity, allowing for consistent comparison and decision-making. The most common method of defuzzification is the Centroid Method, which calculates the center of the area under the membership function curve.

$$Severity\ Score = \frac{\Sigma\ membershipValue\ \times\ valueOutput}{\Sigma\ membershipValue}$$

IV. Result and Discussion

A. YOLOv9e-seg Model Performance

Fig. 5 illustrates the distribution of instances for the two classes, diseased and leaf, in the dataset. Monitoring this graph can shed light on why the model struggles to accurately identify certain classes, particularly the leaf class. The imbalance indicates that the model is exposed to significantly more examples of the diseased class during training, which can lead to class dominance. As a result, the model may become biased toward predicting the dominant class, potentially misclassifying healthy leaf regions as diseased or background. This explains the higher false positive rate for the leaf class observed in the confusion matrix.

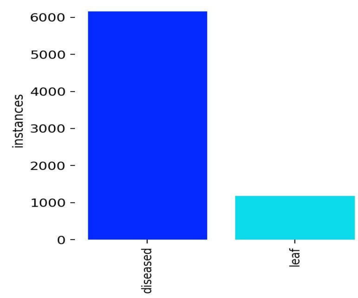


Fig. 5. Class distribution graph.

The leaf class's lower representation reduces the diversity of its features in the training data, making it difficult for the model to learn subtle variations and accurately distinguish it from other classes. Furthermore, this imbalance affects the gradient updates during training, further compounding the challenge of learning an unbiased representation. This class distribution graph is a crucial monitoring tool during model training. It typically appears in training logs, providing immediate feedback on the dataset's structure. By observing this distribution, researchers can identify potential issues early in the training process and take corrective actions, such as data augmentation, re-sampling techniques, class weights, and synthetic data generation.

The training results in Fig. 6 demonstrate consistent improvements across all loss criteria, highlighting the model's capacity to learn effectively. The box loss steadily decreases from around 1.4 to approximately 0.8, reflecting improved localization accuracy for bounding box predictions. Similarly, the segmentation loss starts at 4.5 and decreases to about 2.5, suggesting that the model is becoming more proficient in generating accurate object masks. The classification loss, which begins at 2.0 and reduces to 1.0, demonstrates the model's increasing capability to correctly label detected objects. Additionally, the Distribution Focal Loss (DFL) decreases from 1.6 to around 1.2, indicating refinement in bounding box distributions.

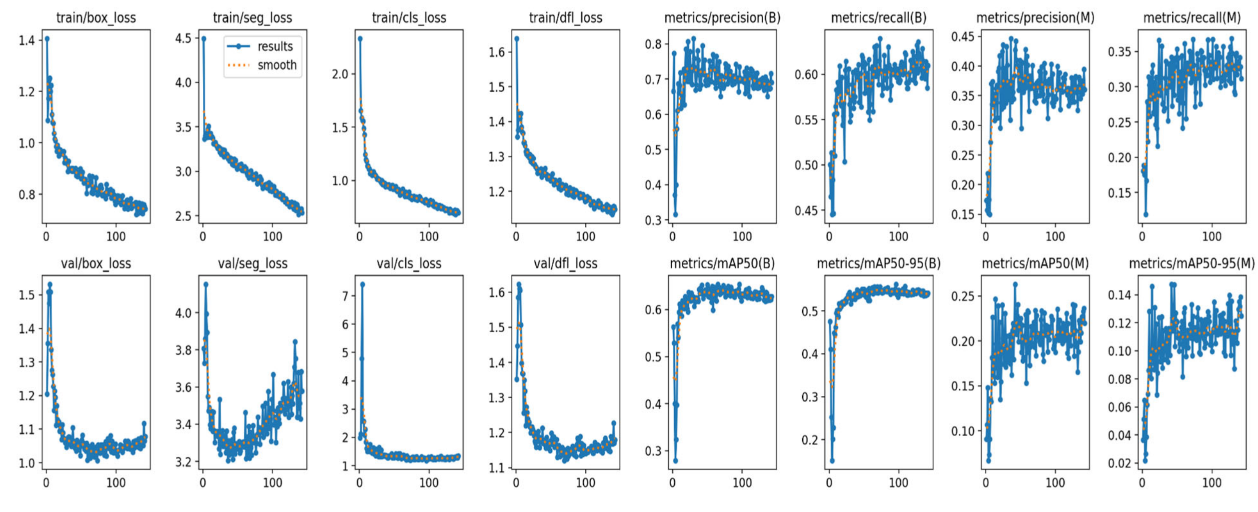


Fig. 6. Training and validation losses.

For validation results, the trends are generally aligned with the training losses, but some oscillations emerge in later epochs. The box loss reduces from 1.5 to 1.0, showing good generalization in localizing objects on the validation set. However, the segmentation loss, while initially improving, shows slight increases after 50 epochs, potentially indicating overfitting in mask generation. The classification loss decreases significantly from approximately 7.0 to 2.0, though it remains higher than the corresponding training loss, suggesting that the model finds label prediction on the validation set more challenging. The DFL also exhibits a consistent downward trend, paralleling the training behavior.

The evaluation metrics provide further insights into model performance. The precision for bounding box detection peaks at around 0.8, indicating a high ratio of correctly detected objects among all detections, while the recall reaches 0.6, showing that most ground truth objects are identified. For instance segmentation, the precision and recall values are lower, peaking at 0.45 and 0.35, respectively, reflecting the increased complexity of this task. The mean Average Precision (mAP) at IoU 0.5 for bounding box detection achieves a strong value of 0.6, while instance segmentation lags behind at 0.25. The more stringent mAP@0.5:0.95 metric reveals a gradual increase, with bounding box detection reaching 0.5 and segmentation peaking at 0.14, underscoring the difficulty of meeting higher IoU thresholds.

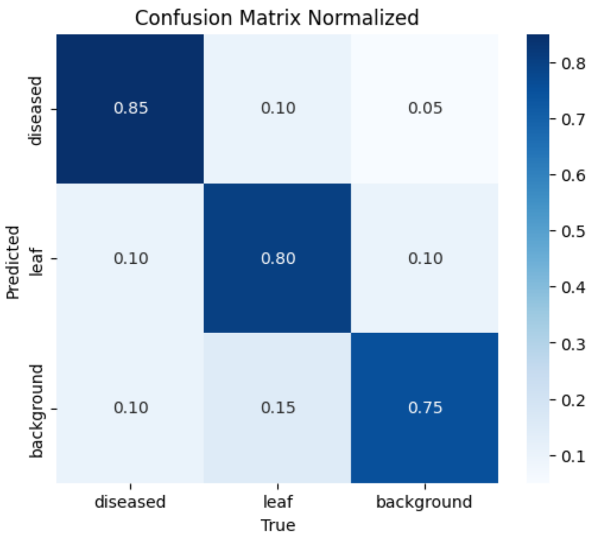


Fig. 7. Confusion matrix normalized.

The normalized confusion matrix, illustrated in Fig. 7, serves as a key evaluation tool for assessing the performance of the YOLOv9-based model in this study. This allows for a clearer understanding of the model's predictive distribution across the three classes: diseased, leaf, and background, irrespective of class imbalances within the dataset. By offering insights into the model's accuracy and error rates, the matrix highlights its strengths and limitations, which are crucial for improving classification and segmentation. The purpose of utilizing the confusion matrix in this study is to evaluate the model's capability to distinguish diseased regions from healthy leaf areas and the background. Given the goal of automating corn leaf disease detection and severity evaluation, such detailed analysis ensures the model's reliability in real-world applications. The confusion matrix also helps identify patterns in misclassification, providing opportunities for optimization.

Based on the confusion matrix, the model achieved an overall classification accuracy of 80%, indicating its strong performance in multi-class segmentation tasks. For the diseased class, the model correctly identifies diseased areas with a recall of 85% and relatively high precision, as reflected in the top-left cell of the matrix. However, about 15% of diseased regions are misclassified as background, and 3% are confused with healthy leaf areas. These misclassifications suggest that some diseased areas, particularly those with subtle or faint symptoms, share visual characteristics with the background or healthy leaves, making them challenging for the model to differentiate.

The leaf class achieves a recall of 80%, indicating the model's strong ability to detect healthy leaf regions. Despite this, 10% of healthy leaf regions are misclassified as diseased, likely due to visual similarities, such as discoloration or spots resembling early-stage disease symptoms. An additional 10% are confused with the background, which may be attributed to poor lighting conditions or shadows obscuring the leaf's features. The background class demonstrates a recall of 75%, with 15% of its regions misclassified as leaf and only 10% as diseased. This suggests that the model is proficient at isolating objects of interest from the background, even under varying environmental conditions.

Overall, the confusion matrix underscores the model's strength in discriminating between the three classes, supported by consistently high recall and balanced precision. While the results validate the model's readiness for deployment in field conditions, addressing the observed misclassification patterns will further enhance its robustness and accuracy for automated corn leaf disease detection.

TABLE V. YOLOv9E-SEG PERFORMANCE IN BOXING AND MASKING TASKS

Metric	Boxing (Leaf Class)	Boxing (Diseased Class)	Masking (Leaf Class)	Masking (Diseased Class)	Boxing (All Classes)	Masking (All Classes)
Precision	Near 1.0	Moderate (~0.8)	Near 1.0	Moderate (~0.7)	0.98 at confidence 1.0	0.94 at confidence 1.0
Recall	Moderate (~0.6)	Moderate (~0.5)	Moderate (~0.5)	Low (~0.3)	0.63 at confidence 0.0	0.58 at confidence 0.0
mAP@0.5	0.264	0.336	0.233	0.293	0.300	0.263
F1-score	~0.5 (Conf. 0.3-0.4)	~0.4 (Conf. 0.2-0.3)	~0.5 (Conf. 0.3-0.5)	~0.3 (Conf. 0.3)	0.42 (Conf. 0.35)	0.38 (Conf. 0.35)

Table V shows that the leaf class outperforms the other classes in boxing and masking tasks, reaching near-perfect results (close to 1.0) at higher confidence thresholds. This indicates that the model is highly accurate when it identifies a "leaf" instance. On the other hand, the diseased class shows lower peak precision values (~0.8 for boxing and ~0.7 for masking), suggesting that identifying diseased regions is more challenging for the model. The "all classes" metric reflects high precision for boxing (0.98) and slightly lower precision for masking (0.94), showcasing the model's robustness in overall detection.

The recall metric highlights a significant drop for the diseased class, particularly in masking (low ~0.3) compared to boxing (~0.5). This suggests that the model misses more diseased areas during segmentation tasks than detection tasks. The leaf class maintains moderate recall (~0.5–0.6) across both boxing and masking, while the "all classes" curves for boxing (0.63) slightly outperform masking (0.58). This implies that the model is better at retrieving potential regions in boxing tasks.

The mAP@0.5 values for boxing and masking show a comparable trend, with slightly higher values for boxing. The leaf class achieves 0.264 (boxing) and 0.233 (masking), while the diseased class shows 0.336 (boxing) and 0.293 (masking). These results indicate that boxing generally performs better at balancing precision and recall, as reflected in the higher mAP values.

F1-scores, which balance precision and recall, show similar peaks for the leaf class across boxing (~0.5 at confidence 0.3–0.4) and masking (~0.5 at confidence 0.3–0.5). The diseased class, however, has consistently lower F1-scores (~0.3–0.4), especially in masking tasks, revealing the model's difficulty in balancing detection quality for this class. The "all classes" F1-scores for boxing (0.42) and masking (0.38) align closely, reflecting overall comparable performance.

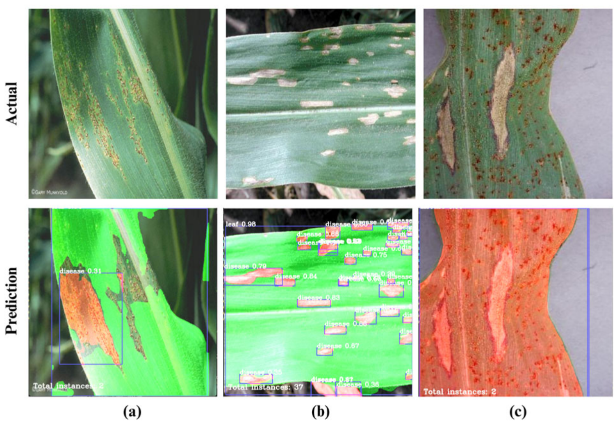


Fig. 8. YOLOv9e-seg prediction test in (a) common rust, (b) gray spot, and (c) blight.

Fig. 8 illustrates the predictions and corresponding confidence scores for various types of corn leaf diseases, with each column representing a distinct disease category: (a) common rust, (b) gray spot, and (c) blight. For common rust, the model achieved a confidence score of 0.31, which is relatively low compared to the ideal score closer to 1.0, and certain areas affected by the disease were not detected, indicating room for improvement in sensitivity. In contrast, for gray spots, the model successfully identified all affected areas on the leaf, demonstrating accurate prediction and effective masking, although the confidence scores were not as high. Similarly, for blight, the model performed well, accurately masking the diseased regions and identifying the affected areas. Overall, the results highlight variability in the model's performance across different disease types, emphasizing the need for further optimization, particularly for diseases like common rust.

B. Evaluation of Disease Severity

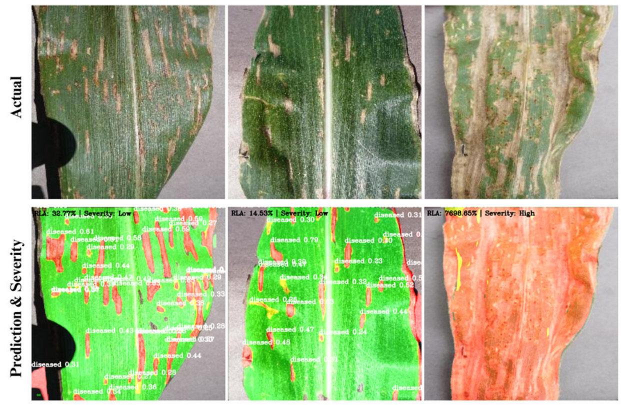


Fig. 9. Prediction and severity scores: gray spot test samples.

Fig. 9 showcases the prediction results and severity analysis for three images of corn leaves affected by gray spot disease. The predicted confidence scores range from 0.20 to 0.79, reflecting reliable detection performance. The segmentation accurately highlights the diseased regions, offering clear insights into the extent and distribution of the infection. Furthermore, the incorporation of severity evaluation, based on Relative Leaf Area (RLA), enhances the understanding of disease impact.

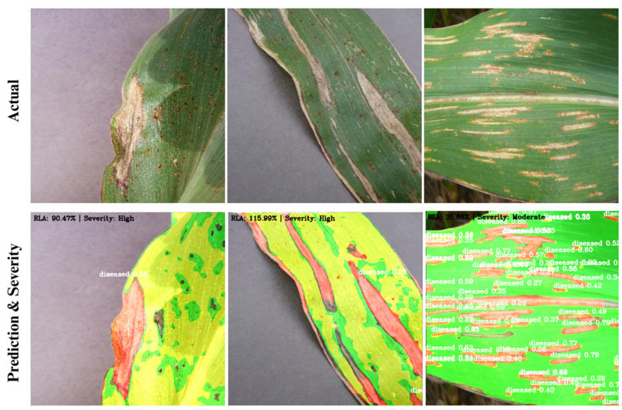


Fig. 10. Prediction and severity scores: blight test samples.

Fig. 10 presents the detection and severity analysis for corn leaves affected by blight disease. The predicted confidence scores, ranging between 0.20 and 0.79, demonstrate consistent detection reliability. The segmentation model successfully identifies and delineates the diseased areas, enabling a clear visualization of how the infection spreads across the leaf. Moreover, the evaluation of severity using the Relative Leaf Area (RLA) metric provides a quantitative assessment of the disease's impact. The accurate masking and severity classification highlight the system's effectiveness in analyzing both the presence and intensity of blight disease.

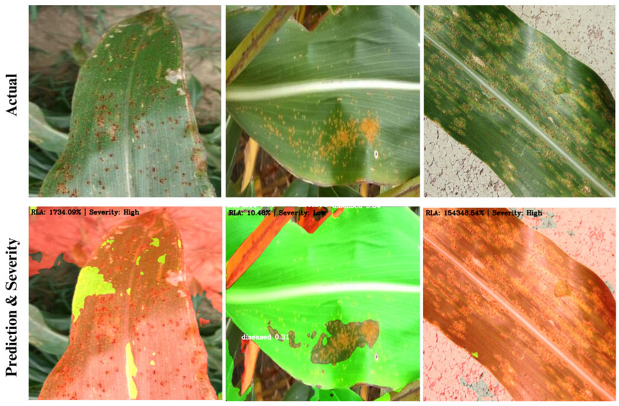


Fig. 11. Prediction and severity scores: common rust test samples.

Fig. 11 highlights the challenges in detecting common rust disease, particularly in instances where the background influences the prediction accuracy. Misclassified regions are outlined with dashed red borders to emphasize incorrect detections—specifically where the model confused the brown soil with rust lesions. These annotated failure cases illustrate the visual ambiguity in real-world field images and the need for more robust background suppression techniques in future models.

C. Comparison with Recent Machine Learning Models

To evaluate the effectiveness of the proposed CLDS-YOLO framework in corn leaf disease detection and severity assessment, a comparative analysis was conducted against recent machine learning models highlighted in contemporary literature. These baseline models were chosen based on their relevance to leaf disease classification tasks, use of hybrid or fuzzy logic-based systems, and their inclusion in peer-reviewed research on plant disease detection.

While earlier object detection models like YOLOv5 have shown strong results in agricultural tasks, they require external segmentation modules (e.g., Mask R-CNN heads) for disease localization. Moreover, YOLOv5 lacks native support for instance segmentation, which can lead to inefficiencies in real-time applications. In contrast, YOLOv9e-seg offers built-in instance segmentation capabilities with higher mAP scores, making it better suited for precise leaf disease detection and severity evaluation.

TABLE VI. COMPARATIVE METRICS OVERVIEW

Model	Primary Task/Focus	Key Performance Metrics	Computational Efficiency	Segmentation Method	Savarity Evaluation
CLDS-YOLO (ours)	Instance Segmentation + Severity	Precision (Box): .98 Recall (Box): 0.63 mAP@0.5 (Box): 0.300 F1-score (Box): 0.42 Precision (Mask): 0.94 Recall (Mask): 0.58 mAP@0.5 (Mask): 0.263 F1-score (Mask): 0.38 Disease Precision (Mask): ~0.7 Disease Recall (Mask): ~0.3	~28 ms/image on NVIDIA RTX 3060	YOLOv9e-seg (instance segmentation)	Fuzzy logic with RLA & diseased region count
ResNet50 + IFRVFLC [47]	Leaf Classification (Image-Level)	Accuracy: 91.23% F1-score, AUC, G-Mean (Reported) Compared with 8 baseline models	Not reported	No segmentation	None
UTRVFL1norm [48]	Leaf Disease Classification Validated using	Validated using benchmark datasets with statistical tests; performance metrics not fully disclosed for leaf dataset	Not reported	No segmentation	None
Sarkar et al. [49] (Review)	Literature Review (2010–2022)	Summarizes use of CNN, VGG, ResNet, LeNet, SVM, Random Forest, etc.Metrics: Accuracy, F1, Precision, Recall	Not applicable	No segmentation	None

From Table VI, it is evident that while recent hybrid and fuzzy logic-enhanced models demonstrate strong classification accuracy on benchmark datasets, they fall short in offering localized instance segmentation and severity quantification, which are essential for precision agriculture. The CLDS-YOLO framework fills this critical gap by combining cutting-edge instance segmentation with a real-world-aware fuzzy logic severity module, making it highly suitable for field deployment.

Additionally, the comparison with YOLOv5 highlights the enhanced segmentation quality of YOLOv9e-seg. While YOLOv5 can achieve competitive object detection performance, its lack of integrated segmentation modules limits its utility in disease severity assessment tasks, which require precise lesion boundary detection.

Mishra *et al.* [46] introduced a hybrid model, ResNet50-IFRVFLC, which integrates ResNet50 deep feature extraction with an Intuitionistic Fuzzy Random Vector Functional Link Classifier. The model was applied for plant leaf classification tasks and achieved a mean accuracy of 91.23%, outperforming traditional classifiers such as Support Vector Machine (SVM), Twin Support Vector Machine (TSVM), Random Vector Functional Link (RVFL), and other fuzzy classifiers. However, this model operates at the image-level, lacking spatial granularity such as instance-level localization or segmentation. Additionally, no severity evaluation method was incorporated, limiting its applicability in real-time agricultural diagnostics.

Sarkar *et al.* [47] proposed a 1-Norm Twin RVFL model using Universum data (UTRVFL1norm), introducing sparsity and robustness to outliers. While its classification performance was statistically validated and tested on a leaf disease dataset, it remained confined to binary image-level classification tasks and did not provide disease localization or segmentation capabilities. Furthermore, there was no mechanism for assessing disease severity, which is vital for practical field applications.

In contrast, the CLDS-YOLO model integrates YOLOv9e-seg for instance segmentation and a fuzzy logic-based decision module for disease severity evaluation using Relative Leaf Area (RLA) and number of diseased regions. This dual-module system enables both high-performance detection and meaningful interpretation of disease progression.

In terms of computational efficiency, the proposed CLDS-YOLO model demonstrates a favorable inference time of approximately 28 milliseconds per image on an NVIDIA RTX 3060 GPU. This supports its practical applicability in real-time or near-real-time field scenarios. In contrast, the reviewed hybrid models—such as ResNet50-IFRVFLC and UTRVFL1norm—did not report inference times in their respective studies [46, 47]. This absence makes direct computational comparisons challenging. Nonetheless, these models are primarily classification-focused and lack segmentation modules, which generally impose lower computational overheads than instance segmentation frameworks like YOLOv9e-seg. Therefore, while CLDS-YOLO may incur slightly higher computational costs, it provides richer outputs including disease localization and severity estimation, justifying its trade-offs in practical deployments.

D. Discussion on Segmentation Challenges and Potential Improvements

The CLDS-YOLO model, while demonstrating strong performance in object-level bounding box detection, encounters notable challenges in the more granular task of instance segmentation—particularly in delineating fine-grained diseased regions on complex corn leaf surfaces. This limitation is evident in the relatively lower precision (~0.7) and especially low recall (~0.3) values for diseased region segmentation. These metrics highlight the need for further optimization to improve the model's segmentation accuracy and robustness. For farmers and agricultural technicians, low recall poses a practical risk—missing diseased regions can lead to delayed treatment, allowing infections to spread and reducing yield quality. Therefore, enhancing recall is not merely an academic concern, but a critical requirement for actionable field-level decision-making.

Several contributing factors are identified. Firstly, early-stage diseased areas often exhibit visual similarity to healthy leaf textures, with subtle color changes and irregular shapes that make accurate mask generation difficult. Secondly, class imbalance—where small or rare disease spots are underrepresented in the dataset—tends to lower recall. Lastly, occlusion and leaf overlap in natural field conditions further complicate precise instance-level segmentation.

To overcome these limitations, future research should consider implementing multi-stage refinement architectures such as Cascade Mask R-CNN, which iteratively improve mask quality through progressive learning stages. Another promising direction involves the integration of transformer-based attention mechanisms into hybrid models to enhance focus on fine-grained lesion patterns. Additionally, data-centric strategies—including pixel-level augmentation, synthetic disease spot generation, and enhanced annotation granularity—can significantly improve model generalization and performance on underrepresented lesion types. Together, these improvements can lead to substantial gains in segmentation precision and recall, enhancing the model's practical applicability in real-world agricultural scenarios.

V. Conclusion

This study demonstrated the potential of YOLOv9e-seg for corn leaf disease detection and severity evaluation, achieving near-perfect precision for healthy leaf detection (close to 1.0) but facing challenges in identifying diseased regions, with lower precision (~0.7) and recall (~0.3) for masking tasks. The model's boxing tasks generally outperformed masking, reflected in higher mAP@0.5 values (0.336 for diseased class in boxing vs. 0.293 in masking). F1-scores were moderate for the leaf class (~0.5) but lower for the diseased class (~0.3–0.4). These measurements demonstrate YOLOv9e-seg's dependability and resilience for agricultural applications, particularly in real-time disease monitoring. The integration of Relative Leaf Area (RLA) computation enabled an in-depth severity analysis of detected diseases. Results showed that the model successfully identified and segmented diseased regions for common rust, gray spot, and blight, providing clear insights into the extent and distribution of infections. Severity evaluations categorized leaves into high, moderate, and low severity levels, facilitating informed decision-making for crop management. However, challenges were observed in specific cases, such as background misclassification, where brown soil or similar colors were incorrectly identified as diseased regions. This underscores the need for further refinement in preprocessing and model training to address such errors. Overall, this study demonstrates the potential of YOLOv9e-seg and RLA-based severity rating as effective methods for disease diagnosis and control in agriculture. Future study could focus on strengthening the model's ability to distinguish between leaf and non-leaf regions, as well as broadening its application to additional crops and illnesses to have a greater agricultural impact.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Lawrence Roble managed the study, provided guidance for the system design, and ensured that the CLDS-YOLO model was optimized overall. Ken Gorro used advanced data augmentation techniques to improve dataset quality and model generalizability. Elmo Ranolo handled data collecting and helped to model training and refining. Christia Mae Camay was in charge of high-quality data labeling, which is critical for accurate disease detection and severity rating. To ensure the dataset's integrity, Rue Nicole Santillan undertook data pretreatment and validation. Anthony Ilano concentrated on model evaluation, optimization, and performance assessment. Deofel Balijon and Daniel Ariaso Sr. helped to establish the research framework and played an important role in manuscript writing and revision. All authors had approved the final version.

FUNDING

This work is funded by Cebu Technological University Carmen Campus.

ACKNOWLEDGMENT

We extend our profound gratitude to Cebu Technological University and Cebu Normal University for their unwavering support throughout the course of this research endeavor.

REFERENCES

[1] PAGASA. About tropical cyclones. Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). [Online]. Available: https://www.pagasa.dost.gov.ph/information/about-tropical-cyclone

[2] H. Mirsam, "Resistance assessment of hybrid corn genotypes to major corn diseases and its effects on disease epidemic components in South Sulawesi, Indonesia," in *Proc. Bio. Web of Conferences*, vol. 69, 2023, p. 01029. https://doi.org/10.1051/bioconf/20236901029

[3] Y. Wang and W. Su, "Convolutional neural networks in computer vision for grain crop phenotyping: A review," *Agronomy*, vol. 12, no. 11, p. 2659, 2022. https://doi.org/10.3390/agronomy12112659

[4] M. Cruz. (2023). Smart farming with computer vision: Detecting diseases in strawberry crops via mobile applications. [Online]. Available: https://doi.org/10.14209/sbrt.2023.1570923797

[5] W. Maillet, M. Ouhami, and A. Hafiane, "Fusion of satellite images and weather data with transformer networks for downy mildew disease detection," *IEEE Access*, vol. 11, pp. 5406–5416, 2023. https://doi.org/10.1109/access.2023.3237082

[6] R. Chen, Q. Huang, L. Yu, and Y. Ming-chao, "Identification of plant leaf diseases by deep learning based on channel attention and channel pruning," *Frontiers in Plant Science*, vol. 13, 2022. https://doi.org/10.3389/fpls.2022.1023515

[7] S. Lee, H. Goëau, P. Bonnet, and A. Joly, "Attention-based recurrent neural network for plant disease classification," *Frontiers in Plant Science*, vol. 11, 2020. https://doi.org/10.3389/fpls.2020.601250

[8] J. Yang, M. Han, J. He, J. Yang, D. Chen, and Y. Wang, "Object detection and localization algorithm in agricultural scenes based on yolov5," *Journal of Electronic Imaging*, vol. 32, no. 05, 2023. https://doi.org/10.1117/1.jei.32.5.052402

[9] V. Radojčić, A. Cvetković, and M. Dobrojević, "The use of computer vision in precision agriculture," in *Proc. Sinteza 2023—International Scientific Conference on Information Technology, Computer Science, and Data Science*, 2023, pp. 60–65. https://doi.org/10.15308/sinteza-2023-60-65

[10] L. Xiang, J. Gai, Y. Bao, J. Yu, P. Schnable, and L. Tang, "Field-based robotic leaf angle detection and characterization of maize plants using stereo vision and deep convolutional neural networks," *Journal of Field Robotics*, vol. 40, no. 5, pp. 1034–1053, 2023. https://doi.org/10.1002/rob.22166

[11] J. Boahen and M. Choudhary, "Advancements in precision agriculture: Integrating computer vision for intelligent soil and crop monitoring in the era of artificial intelligence," *International Journal of Scientific Research in Engineering and Management*, vol. 08, no. 03, pp. 1–5, 2024. https://doi.org/10.55041/ijsrem29725

[12] E. Osco-Mamani and I. Chaparro-Cruz, "Highly accurate deep learning model for olive leaf disease classification: A study in Tacna-Peru," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 4, 2023. https://doi.org/10.14569/ijacsa.2023.0140494

[13] J. Naranjo-Torres, M. Mora, C. Fredes, and A. Valenzuela, "Disease and defect detection system for raspberries based on convolutional neural networks," *Applied Sciences*, vol. 11, no. 24, 11868, 2021. https://doi.org/10.3390/app112411868

[14] L. Li, J. Qiao, J. Yao, J. Li, and L. Li, "Automatic freezing-tolerant rapeseed material recognition using UAV images and deep learning," *Plant Methods*, vol. 18, no. 1, p. 5, 2021. https://doi.org/10.21203/rs.3.rs-929591/v1

[15] D. Kothadiya, A. Chaudhari, R. Macwan, K. Patel, and C. Bhatt, "The convergence of deep learning and computer vision: Smart city applications and research challenges," in *Proc. 3rd International Conference on Integrated Intelligent Computing Communication & Security (ICIIC 2021)*, Atlantis Press, 2021, pp. 14–22. https://doi.org/10.2991/ahis.k.210913.003

[16] H. Wu, "Research progress in potato bud recognition," *Advances in Computer Signals and Systems*, vol. 7, no. 5, 2023. https://doi.org/10.23977/acss.2023.070507

[17] L. Zhu, Z. Li, and S. Hu, "Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture," *Journal of Electronic Imaging*, vol. 32, no. 05, 2023. https://doi.org/10.1117/1.jei.32.5.052406

[18] C. Tu, J. Li, X. Wang, C. Shen, and J. Li, "Bionic technology and deep learning in agricultural engineering: Current status and future prospects," *American Journal of Biochemistry and Biotechnology*, vol. 17, no. 2, pp. 217–231, 2021. https://doi.org/10.3844/ajbbsp.2021.217.231

[19] A. Kamilaris and F. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018. https://doi.org/10.1016/j.compag.2018.02.016

[20] E. Mavridou, E. Vrochidou, G. Papakostas, T. Pachidis, and V. Kaburlasos, "Machine vision systems in precision agriculture for crop farming," *Journal of Imaging*, vol. 5, no. 12, p. 89, 2019. https://doi.org/10.3390/jimaging5120089

[21] M. Zeng, H. Gao, and L. Wan, "Few-shot grape leaf diseases classification based on generative adversarial network," *Journal of Physics Conference Series*, vol. 1883, no. 1, 012093, 2021. https://doi.org/10.1088/1742-6596/1883/1/012093

[22] L. Li and S. Zhang, "Plant disease detection and classification by deep learning—A review," *IEEE Access*, vol. 9, pp. 56683–56698, 2021. https://doi.org/10.1109/access.2021.3069646

[23] A. Pawar, M. Singh, S. Jadhav, V. Kumbhar, T. Singh, and S. Shah, "Different crop leaf disease detection using convolutional neural network," in *Proc. International Conference on Applications of Machine Intelligence and Data Analytics (ICAMIDA 2022)*, Atlantis Press, 2023, pp. 966–979. https://doi.org/10.2991/978-94-6463-136-4_85

[24] A. Rastogi, R. Arora, and S. Sharma, "Leaf disease detection and grading using computer vision technology & fuzzy logic," in *Proc. 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN)*, IEEE, 2015, pp. 500–505. https://doi.org/10.1109/spin.2015.7095350

[25] J. Yang, X. Guo, Y. Li, F. Marinello, S. Erçişlı, and Z. Zhang, "A survey of few-shot learning in smart agriculture: Developments, applications, and challenges," *Plant Methods*, vol. 18, no. 1, 2022. https://doi.org/10.1186/s13007-022-00866-2

[26] M. Rudenko, "Intelligent monitoring system to assess plant development state based on computer vision in viticulture," *Computation*, vol. 11, no. 9, p. 171, 2023. https://doi.org/10.3390/computation11090171

[27] Y. Liu, A. Huang, Y. Luo *et al.*, "Fedvision: An online visual object detection platform powered by federated learning," in *Proc. Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, no. 08, 2020, pp. 13172–13179. https://doi.org/10.1609/aaai.v34i08.7021

[28] A. Fuentes, S. Yoon, S. Kim, and D. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," *Sensors*, vol. 17, no. 9, p. 2022, 2017. https://doi.org/10.3390/s17092022

[29] W. Cheng, T. Ma, X. Wang, and G. Wang, "Anomaly detection for internet of things time series data using generative adversarial networks with attention mechanism in smart agriculture," *Frontiers in Plant Science*, vol. 13, 2022. https://doi.org/10.3389/fpls.2022.890563

[30] G. Gupta, V. Abrol, and S. Pradhan. (2023). Smart farming: Boosting crop management with SVM and random forest. [Online]. Available: https://doi.org/10.21203/rs.3.rs-3160171/v1

[31] D. Gao, Q. Sun, B. Hu, and S. Zhang, "A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles," *Sensors,* vol. 20, no. 5, p. 1487, 2020. https://doi.org/10.3390/s20051487

[32] S. Khan, M. Tufail, M. Khan, Z. Khan, J. Iqbal, and A. Wasim, "Real-time recognition of spraying area for UAV sprayers using a deep learning approach," *Plos One*, vol. 16, no. 4, p. e0249436, 2021. https://doi.org/10.1371/journal.pone.0249436

[33] P. Basaligheh, "Precision agriculture through deep learning algorithms for accurate diagnosis and continuous monitoring of plant diseases," *RJCSE*, vol. 4, no. 2, pp. 31–45, 2023. https://doi.org/10.52710/rjcse.72

[34] R. Ito, "A field image monitoring system based on embedded Linux," *International Journal of Geomate*, vol. 17, no. 62, 2019. https://doi.org/10.21660/2019.62.25814

[35] X. Wu, X. Fan, P. Luo, S. Choudhury, T. Tjahjadi, and C. Hu, "From laboratory to field: Unsupervised domain adaptation for plant disease recognition in the wild," *Plant Phenomics*, vol. 5, 2023. https://doi.org/10.34133/plantphenomics.0038

[36] A. Ahmad, V. Aggarwal, D. Saraswat, A. Gamal, and G. Johal, "Geodls: A deep learning-based corn disease tracking and location system using RTK geolocated UAS imagery," *Remote Sensing*, vol. 14, no. 17, p. 4140, 2022. https://doi.org/10.3390/rs14174140

[37] W. Pamungkas, M. Wardhana, Z. Sari, and Y. Azhar, "Leaf image identification: CNN with EfficientNet-B0 and ResNet-50 used to classify corn disease," *Jurnal Resti (Rekayasa Sistem Dan Teknologi Informasi)*, vol. 7, no. 2, pp. 326–333, 2023. https://doi.org/10.29207/resti.v7i2.4736

[38] A. Hatem, M. Altememe, and M. Fadhel, "Identifying corn leaves diseases by extensive use of transfer learning: A comparative study," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 2, p. 1030, 2023. https://doi.org/10.11591/ijeecs.v29.i2.pp1030-1038

[39] A. Ahmad, A. Gamal, and D. Saraswat, "Toward generalization of deep learning-based plant disease identification under controlled and field conditions," *IEEE Access*, vol. 11, pp. 9042–9057, 2023. https://doi.org/10.1109/access.2023.3240100

[40] M. Fadhilla, "Corn leaf diseases recognition based on convolutional neural network," *IT Journal Research and Development*, vol. 8, no. 1, pp. 14–21, 2023. https://doi.org/10.25299/itjrd.2023.13904

[41] P. Dong, "Maize leaf compound disease recognition based on attention mechanism," *Agriculture*, vol. 14, no. 1, p. 74, 2023. https://doi.org/10.3390/agriculture14010074

[42] R. Zhu, "Research on polygon pest-infected leaf region detection based on YOLOv8," *Agriculture*, vol. 13, no. 12, p. 2253, 2023. https://doi.org/10.3390/agriculture13122253

[43] F. Adhinata, G. Fitriana, A. Wijayanto, and M. Putra, "Corn disease classification using transfer learning and convolutional neural network," *Juita Jurnal Informatika*, vol. 9, no. 2, p. 211, 2021. https://doi.org/10.30595/juita.v9i2.11686

[44] A. Ubaidillah, E. Rochman, D. Fatah, and A. Rachmad, "Classification of corn diseases using random forest, neural network, and naive Bayes methods," *Journal of Physics Conference Series*, vol. 2406, no. 1, 012023, 2022. https://doi.org/10.1088/1742-6596/2406/1/012023

[45] D. Hindarto, "Comparison of detection with transfer learning architecture ResNet18, ResNet50, ResNet101 on corn leaf disease," *Jurnal Teknologi Informasi Universitas Lambung Mangkurat (Jtiulm)*, vol. 8, no. 2, pp. 41–48, 2023. https://doi.org/10.20527/jtiulm.v8i2.174.

[46] A. K. Mishra, R. P. Singh, K. R. Prasad, and P. Sharma, "A novel intuitionistic fuzzy random vector functional link network based hybrid approach for plant leaf detection," *Computers & Electrical Engineering*, vol. 110, 110135, Jan. 2025.

[47] S. Sarkar, S. S. Roy, P. M. Rajan, S. N. Singh, and M. Pandey, "Universum based 1-Norm twin random vector functional link network for leaf disease detection," *Applied Soft Computing*, vol. 147, 110850, Nov. 2023.

[48] S. Sarkar, S. S. Roy, S. N. Singh, and M. Pandey, "A comprehensive review of leaf disease detection using machine learning and deep learning: Present research, challenges, and future directions," *Applied Soft Computing*, vol. 145, 110534, Oct. 2023.

[49] C.-Y. Wang and H.-Y. M. Liao, "YOLOv9: Learning what you want to learn using programmable gradient information," arXiv preprint, arXiv:2402.13616, 2024.

[50] Ultralytics. (2024). YOLOv9: Supported tasks and modes. [Online]. Available: https://docs.ultralytics.com/models/yolov9/#supported-tasks-and-modes