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Deploying lightweight YOLO for Real-Time Sunflower Leaf Disease Detection and Severity Classification on Edge Devices

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***Abstract*— Sunflower, an important oilseed crop, is prone to numerous bacterial, viral, and fungal infections that can severely impact both yield and economic returns. Ensuring early and accurate identification of these diseases is essential to avoid large-scale crop damage and maintain productivity. To facilitate practical, on-field application, this study integrates a trained deep learning model onto the NVIDIA Jetson Nano, enabling real-time disease detection directly on a portable, low-power device. Conventional methods such as manual observation often lack reliability and efficiency, making automated detection a more effective alternative. This work focuses on utilizing object detection algorithms, specifically YOLOv8 and YOLOv11, for recognizing disease symptoms in sunflower leaves. The models were trained using a carefully compiled dataset that includes both healthy and diseased samples, enhanced with data augmentation and segmentation techniques to improve detection accuracy. Among the models, YOLOv11 showed stronger performance across key metrics such as precision, recall, and mean average precision. Deployed on Jetson Nano, the system classifies affected leaf regions into mild, moderate, and severe stages, allowing farmers to take timely preventive measures and reduce crop losses.**

***Keywords*— Disease detection, Jetson NANO, Precision agriculture, Deep learning, YOLO.**

I. INTRODUCTION

Sunflower (Helianthus annuus) is a vital oilseed crop cultivated globally, making a significant contribution to the agricultural economy, yet its production is often threatened by various bacterial, viral, and fungal diseases that impair plant growth and yield. Timely detection and accurate classification of these diseases are essential for effective management, as conventional diagnostic methods such as expert visual inspection are labor-intensive, subjective, and frequently unreliable [1].

Advances in deep learning and computer vision have spurred the adoption of automated plant disease detection using convolutional neural networks (CNNs), enabling rapid and precise diagnosis in precision agriculture [2]. Real-time object detection has been revolutionized by the YOLO (You Only Look Once) model family, known for delivering fast and accurate results [3], with YOLOv8 from Ultralytics offering enhanced robustness, efficiency, and detection accuracy [4] and the more recent YOLOv11 introducing improvements in computational efficiency, object localization, and feature extraction [5].

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Deep learning has shown promising outcomes in early plant disease detection, reducing dependence on conventional methods [6], while CNN-based approaches have proven effective for diseases in various crops such as rice, wheat, and tomatoes [7]. Nevertheless, accurate classification of sunflower leaf diseases remains challenging due to background noise in field images, varying climatic conditions, and symptom similarities across diseases [8], but advanced object detection models like YOLOv8 and YOLOv11 can overcome these obstacles through superior feature extraction [9] and by leveraging pre-trained weights with transfer learning, thereby minimizing the need for large labeled datasets [10]. Performance evaluation in this study will be based on metrics such as mean Average Precision (mAP), Intersection over Union (IoU), recall, and inference time [11], and the findings aim to guide farmers and agricultural experts in deploying efficient automated disease monitoring systems, ultimately supporting sustainable and productive agriculture through AI-driven solutions [12].

II. RELATED WORK

The integration of deep learning into plant disease detection has significantly enhanced early diagnosis, providing higher accuracy and efficiency than traditional manual inspection methods. laid the foundation for precision crop protection through advanced sensing technologies, while [13] implemented convolutional neural networks (CNNs) on large datasets, demonstrating their potential in disease identification. [14] introduced the YOLO (You Only Look Once) model for real-time detection, later improved in YOLOv8 by [15] and YOLOv11 by [16] with transformer-based modules for better feature representation and faster processing. [17] applied CNNs to classify diseases in multiple fruit crops, whereas [18] used deep models such as AlexNet and GoogleNet for multi-species classification. [19] focused on tomato leaf infections, while (Jiang et al., 2021) refined CNN models for apple disease detection. [20] developed approaches for potato tuber diagnosis, and applied Faster R-CNN for tomato plant disease recognition. [21] incorporated attention mechanisms into CNNs to improve classification accuracy, while [22] advanced CNN-based detection through complex feature extraction strategies. Lightweight architectures like MobileNet by [23] have been optimized for devices with limited computing resources. [24] emphasized evaluation metrics such as mAP and IoU, and [25] highlighted the influence of dataset quality and algorithm selection on deep learning performance in agriculture. [26] explored segmentation-based detection for cucumber diseases, whereas and [27] studied YOLO-based approaches for other crops worked on apple and bell pepper leaf classification, [28] proposed a YOLO model for mulberry leaf disease detection, [29] applied YOLOv4-tiny for real-time applications, and [30]improved YOLOv5 for vegetable disease detection. Transfer learning to enhance model generalization was employed by while, and [31] developed deep learning frameworks for crops like apples, bananas, and tomatoes. The shift toward hybrid CNN-transformer architectures and mobile-ready solutions signals a future where plant disease detection becomes more precise, faster, and accessible in real-time, promoting sustainable agriculture and healthier crops.

III. METHODOLOGY

This work proposes a solution leveraging advanced object identification models to meet the difficulty of identifying illnesses on the sunflower plant leaves. Specifically, we compare the performance of YOLOv11 and YOLOv8 to evaluate their effectiveness in plant disease detection by fully linked layers, which improves model accuracy. Convolutional and max-pooling layers work together to support hierarchical feature learning. Tasks involving object detection and image classification frequently employ this design which is shown in Fig. 1.

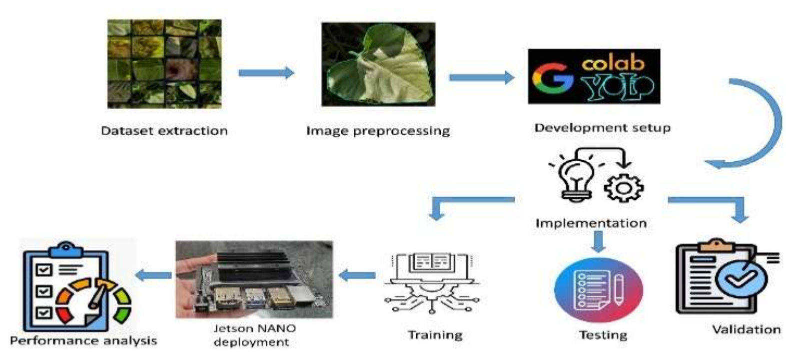
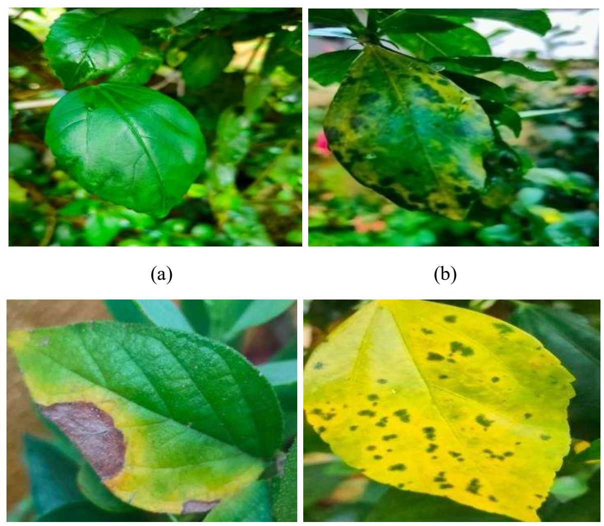


Fig.1. Bock diagram of the proposed work

A. Dataset

The sunflower leaf dataset utilized in this research was primarily obtained from the Roboflow repository, specifically curated for agricultural disease detection applications. It consists of a total of 432 annotated images, categorized into four major classes: disease-free, downy mildew, gray mold, and leaf scars. For training and evaluation, the dataset was divided into three subsets—70% for training (302 images), 20% for validation (86 images), and 10% for testing (44 images)—ensuring a balanced approach that supports reliable learning and model assessment. To further enhance the practical relevance of the study, additional images were collected directly from Talwandi, a rural area in the Chamarajanagar district of Karnataka, India. These locally sourced samples included both healthy and diseased leaves showing visible symptoms of infections like Leaf Spot, Downy Mildew, and Powdery Mildew. The collected images span a range of disease severities—from mild to severe—providing robust data for real-time classification tasks. A visual overview of the dataset categories and severity stages is presented in Fig. 2.



(a) (b) (c) (d)

Fig.2. Dataset for real-time detection (a) Healthy (b) Mild (c) Moderate (d) Severe

B. Preprocessing

To prepare images for training in a YOLO-based sunflower leaf disease detection system, a structured image processing approach is followed. The images are initially normalized and resized to match the expected input dimensions of the YOLO model. Although YOLO typically operates on raw images, certain preprocessing methods are applied beforehand to enhance visual clarity during the manual annotation phase. These techniques are not used as direct inputs to the model but serve as tools to improve annotation accuracy, especially when symptoms are subtle or partially visible. After this, common data augmentation methods—such as flipping, rotation, and brightness variation are applied to increase dataset diversity. Finally, annotated bounding boxes and encoded class labels are added to prepare the dataset for efficient training using the YOLO framework.

C. Object and Disease Detection

In the field of agriculture, ensuring plant health is essential for maximizing crop yield and reducing losses. To support this, our work applies advanced computer vision and image processing methods for detecting diseases in plant leaves. Specifically, we utilize deep learning models—YOLOv8 and the more recent YOLOv11—to automatically recognize and locate disease-affected areas in crop leaf images. These models use bounding box-based object detection to identify multiple diseases within a single image, helping farmers take faster and more informed actions to manage crop health effectively.image that contains multiple diseased leaves. Grids are created from the input image, with finer grids—like a 9x9 grid—being utilized in practical applications. Each grid cell is subjected to picture categorization and localization algorithms.

The purpose of this study is to compare the accuracy, precision, recall, and mAP of YOLOv11 and YOLOv8 in the detection of illnesses in sunflower plants. We evaluate both models' efficiency in detecting damaged leaves

by examining these parameters, guaranteeing accurate identification for better plant health monitoring and agricultural disease control.
Our model's efficacy is based on its accuracy. It shows how safe and portable our approach is for identifying both positive and negative values, as well as how closely our model has been reproducing the results in relation to the genuine values. Eq (1) is used to determine the accuracy of the suggested model.

$$\text{Accuracy} = \frac{TP+T}{TP+TN+FP+FN} \tag{1}$$

The total number of values that were successfully identified as being genuinely connected with a specific class by counting the occurrences of positive values that were correctly retrieved. The number of true positives divided by the sum of all successfully recognized values and classes is then used to calculate precision. Eq. (2) provides the following representation of this precision calculation.

$$precision = \frac{TP}{TP+FP} \times 100\% \tag{2}$$

The True Positive Rate (TPR), also known as recall, is a quantitative measure of the thoroughness of the result. It is computed by dividing the total number of true positive values by the sum of the true positive and false negative values. The true positive rate is the number of accurately detected values; good recall means that the data is recovered correctly and efficiently. Eq. (3) is used to calculate the recall.

$$recall = \frac{TP}{TP+FN} \times 100\% \tag{3}$$

The mean Average Precision (mAP) at an intersection over a Union (IoU) threshold of 0.5 is denoted by the metric mAP@0.5, while the average mAP computed over several IoU thresholds ranging from 0.5 to 0.95 is denoted by mAP@0.5:0.95. Eq (4) provides the calculation.

$$mAP = \frac{1}{n}\left(\sum_{k=1}^{k=n} A\,P_k\right) \tag{4}$$

The proposed sunflower leaf disease detection framework operates in real time using the Jetson Nano embedded platform. The workflow begins by capturing live images of sunflower leaves through a connected camera, after which several preprocessing techniques—including resizing, normalization, background elimination, and data augmentation—are applied to improve both image clarity and model reliability. Once processed, the images are analyzed using YOLOv8 or YOLOv11, which identify and localize disease-affected regions through bounding boxes and assign corresponding class labels with confidence scores. The system then categorizes the level of infection into mild, moderate, or severe, based on visual patterns extracted by the model. The results are displayed instantly on a connected output screen, allowing quick and informed decision-making in the field. Due to its lightweight design and offline functionality, this system is particularly well-suited for deployment in remote agricultural areas with limited network access, as depicted in Fig.3.

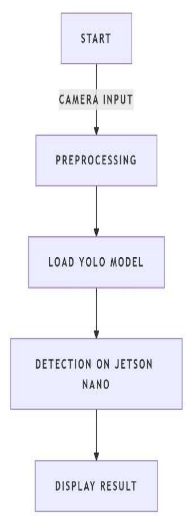


Fig. 3. Flowchart of real time leaf disease detection

IV. Novelty

The unique aspect of this work is the implementation of a real-time sunflower leaf disease detection system on the Jetson Nano 2 platform. While deep learning models such as YOLOv8 and YOLOv11 have been previously used in plant disease classification, their application has mostly been limited to offline analysis on high-performance computers. In this study, the trained model was successfully adapted for execution on a lightweight, low-power embedded device, making it suitable for direct use in agricultural environments. The system can accurately identify and classify leaf diseases into different severity levels—mild, moderate, and severe—in real time, without requiring internet connectivity or external computation. This approach improves practicality and accessibility, especially for farmers in remote areas. The ability to perform accurate detection directly on a portable device distinguishes this work from earlier methods and offers a step forward in developing field-ready solutions for crop health monitoring.

V. Results and Discussion

A comparison between the YOLOv8 and YOLOv11 models was conducted to evaluate their effectiveness in detecting sunflower leaf diseases. The results indicate that YOLOv11 delivers notable improvements across most performance metrics.

TABLE I: COMPARISON OF EVALUATION INDICATORS BETWEEN YOLOV11 AND YOLOV8

YOLO MODEL	EPOCHS	PRECISION (%)	RECALL (%)	F1-SCORE (%)	Map (%)
YOLO V11	60	95.4	99	97.16	93
YOLO V8	60	92.1	99	95.44	93.9

It achieves a precision of 95.4%, recall of 99%, and an F1-score of 97.16%, slightly surpassing YOLOv8, which records a precision of 92.1% and an F1-score of 95.44%. Although both models report similar mean Average Precision (mAP) values—93% for YOLOv8 and 93.9% for YOLOv11 this metric alone does not fully convey the model's practical detection reliability. mAP mainly averages precision over multiple thresholds, but it does not necessarily capture how effectively a model balances false positives and false negatives. In this regard, the higher recall and F1-score of YOLOv11 suggest that it can identify a greater number of diseased regions more accurately, with fewer missed cases. This advantage is clearly illustrated in the performance trends, as shown in Fig.4. and TABLE 1

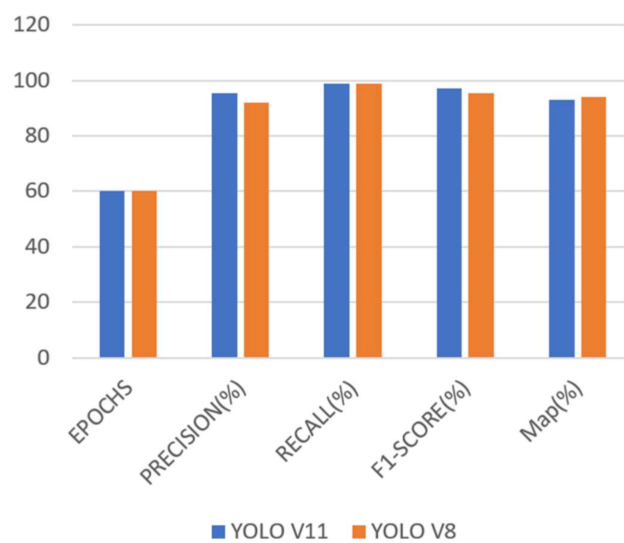


Fig.4. Plot comparing parameters and performance between yolov8 and yolov11.

The detection results produced by YOLOv8 show that diseased regions are generally identified, though minor inconsistencies can be seen in bounding box placement and classification confidence. These findings underline that, even with similar mAP scores, YOLOv11 delivers more consistent and accurate predictions, making it a more dependable choice for real-time agricultural crop health monitoring, as illustrated in Fig.5 & 6.

Fig.5. Sunflower leaf disease results using yolov8

Fig.6. Sunflower leaf disease detection results using yolo11

The strong performance of YOLOv11 is further validated through a series of evaluation plots. The precision-confidence curve reveals that the model sustains high precision across a broad range of confidence thresholds, demonstrating its reliability in producing correct predictions. The recall-confidence curve remains consistently high, reflecting its effectiveness in capturing the majority of true positive cases without overlooking actual infections. The F1-score curve highlights a stable and elevated balance between precision and recall, confirming the model's robustness and consistent performance.
The confusion matrix shows that most predictions align along the diagonal, indicating accurate classification of different disease categories with minimal errors. Lastly, the training loss curve displays a smooth and rapid decrease, suggesting efficient convergence and effective learning from the dataset. Collectively, these visual results affirm YOLOv11's high accuracy, stability, and learning efficiency for real-time plant disease detection, as illustrated in Fig.7–11.

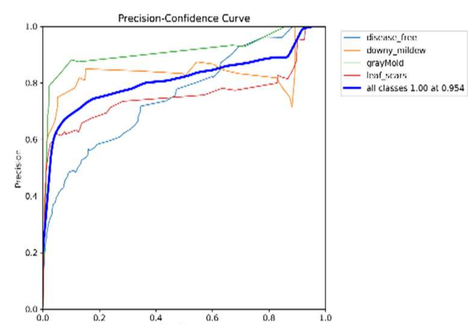


Fig.7. Precision confidence curve for yolov11

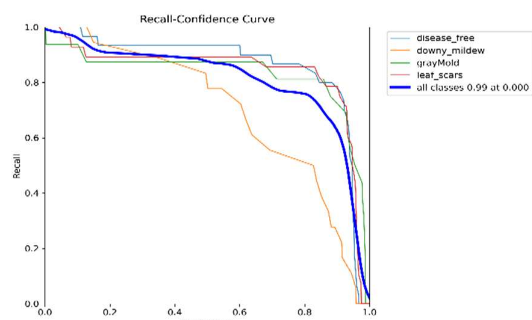


Fig.8. Recall confidence curve for yolov11

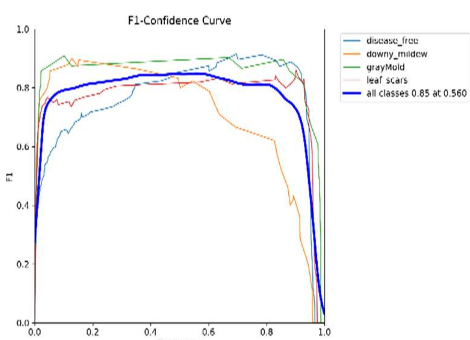


Fig.9. F-1 confidence curve for yolov11

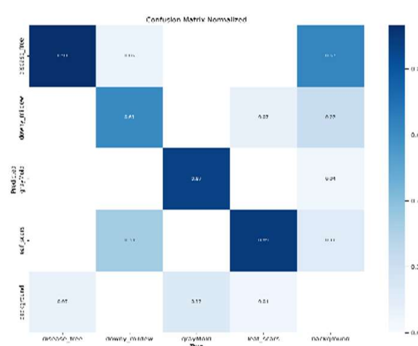


Fig.10. Confusion matrix for yolov11

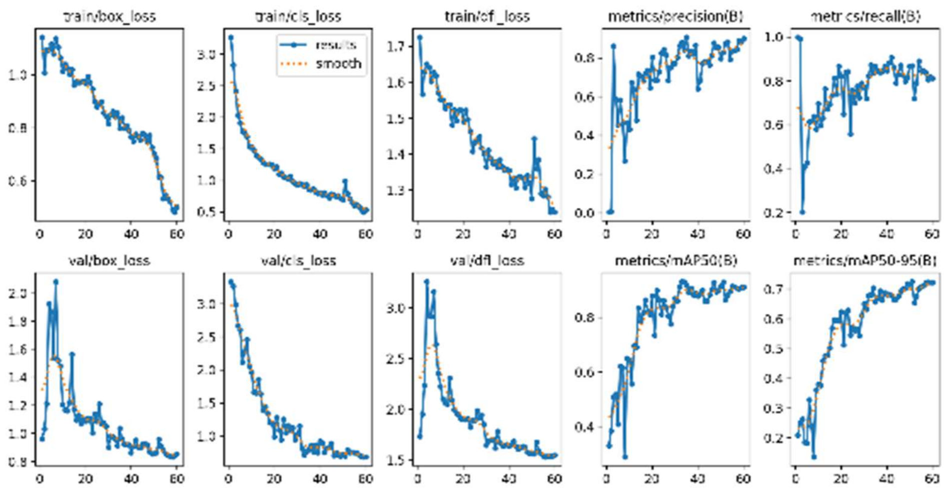


Fig.11. Loss curve for yolov11

The evaluation plots offer a detailed view of YOLOv8's performance in detecting sunflower leaf diseases. The precision-confidence curve indicates generally high precision, though with a slight dip at lower confidence levels, suggesting occasional false positives. The recall-confidence curve remains strong, confirming the model's ability to detect actual disease cases effectively. The F1-score trend shows minor fluctuations compared to YOLOv11, indicating a slightly less stable balance between precision and recall. The confusion matrix demonstrates mostly accurate classifications, with a few misclassifications among closely related disease categories, likely due to similar visual symptoms. The training loss curve shows steady learning progress, though the decline is slower than that of YOLOv11, implying that YOLOv8 may require more training epochs for optimal convergence. Overall, YOLOv8 performs well, but its marginally lower precision and slower convergence underscore YOLOv11's advantage in real-time, high-accuracy disease detection, as shown in Fig.12–16.

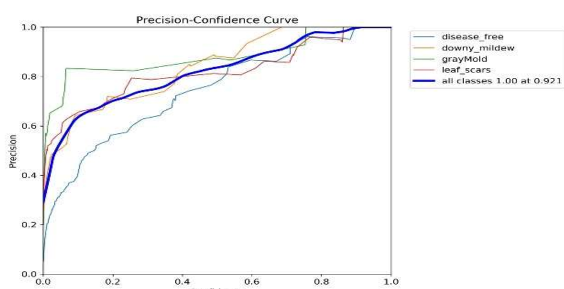


Fig.12. Precision confidence curve for yolov8

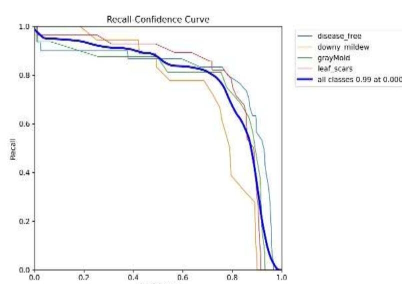


Fig.13. Recall confidence curve for yolov8

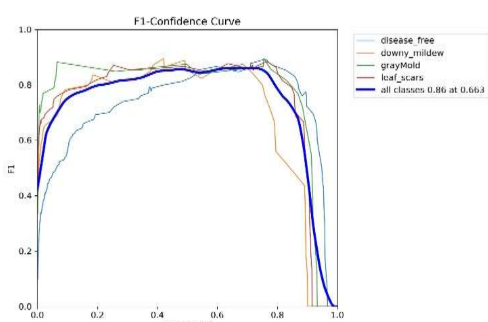


Fig.14. F-1 confidence curve for yolov8

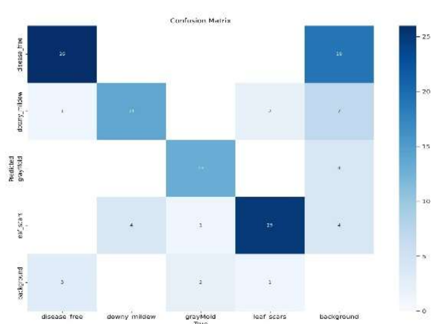


Fig.15. Confusion matrix for yolov8

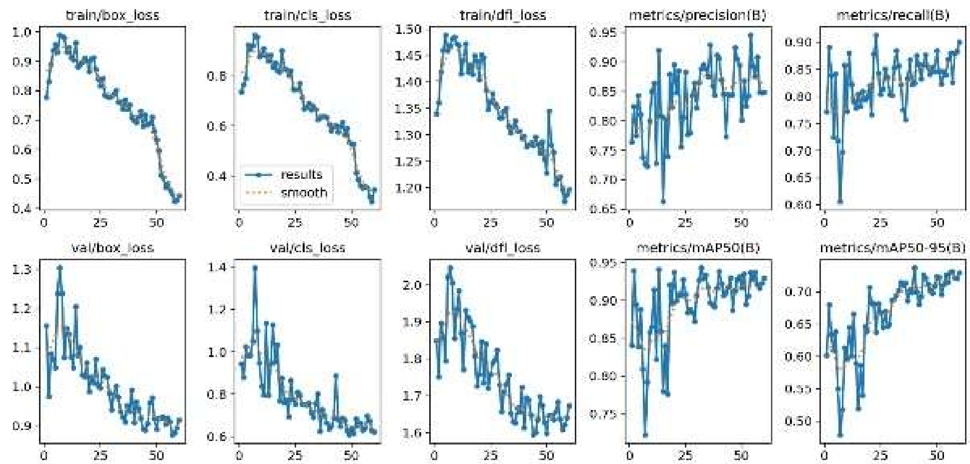


Fig.16. Loss curve for yolov8

In this experimental setup, real-time detection of sunflower leaf diseases was performed using the Jetson Nano. In this experimental setup, the jetsonnano was employed to perform real-time detection of sunflower leaf diseases. A live image of the leaf is captured through a connected camera and processed directly on the device. Based on its visual features, the system classifies the leaf into one of four categories: healthy (disease-free), mild infection, moderate infection, or severe infection. The output is displayed on a connected screen, enabling immediate identification in field conditions and making the solution practical for deployment in rural or low-connectivity environments.

Representative results demonstrate the system's classification capability: one example shows a leaf in the early stages of infection, labeled as mild with a confidence score of 0.91; another depicts a moderately infected leaf with visible symptoms, identified with a confidence score of 0.87; and a third example represents a healthy leaf, correctly classified as disease-free with a confidence of 0.90. These results confirm the model's ability to accurately distinguish between different severity levels of infection, enabling timely and informed agricultural decisions, as presented in Table II: and Fig.17–19.

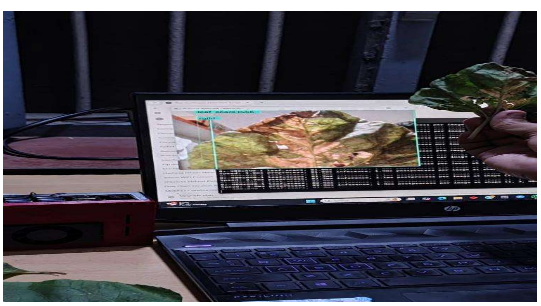


Fig.17. Mild infection

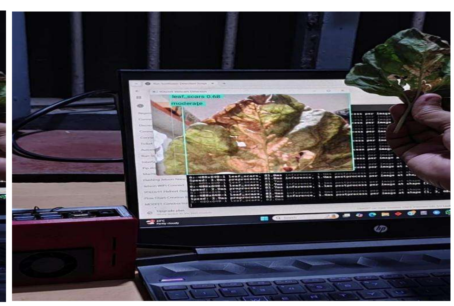


Fig.18. Moderate infection

Fig.19. Healthy leaf

TABLE II: INFERENCE RESULTS WITH SEVERITY CLASSIFICATION ON JETSON NANO PLATFORM

Fig. No.	Detected Class	Confidence Score	Severity Classification	Stage (Optional)	Inference Time (ms)
16	Leaf Scarf	0.91	Mild	Early	88
17	Leaf Scarf	0.87	Moderate	Mid	93
18	Leaf Scarf	0.94	Severe	Late	89
19	Healthy Leaf	0.90	-----	-----	91

VI. CONCLUSION AND FUTURE SCOPE

The results of this investigation demonstrate the efficiency of YOLOv8 and YOLOv11 for the identification of sunflower leaf disease, with YOLOv11 surpassing YOLOv8 in terms of precision (95.4% vs. 92.1%) while retaining a 99% recall. The findings show how deep learning may be used in precision agriculture to identify diseases early. Future studies should concentrate on optimizing lightweight models for real-time deployment, combining hybrid architectures for increased accuracy, and strengthening model robustness with larger datasets. Generalization across plant species can be further enhanced via domain adaptation and transfer learning. Improving AI-powered disease detection can help ensure food security, minimize crop losses, and support sustainable agriculture.

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