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Yolov8-Based Automated Leaf Curl Disease Detection and Localization for Smart Agriculture

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***Abstract*- Leaf curl disease is one of the significant viral infections of the crops with great economic significance, like tomato and chilli that cause serious abatement of the yield and substantial financial losses to farmers[1], [2], [3]. The timely intervention [1], [3] depends on the early and correct detection of the disease to avoid mass destruction of crops and timely intervention. The traditional disease detection techniques are very subjective that involves manual visual inspection which is labor-intensive and cannot be applied to large farms. The latest developments in the field of deep learning and computer vision have offered effective substitutions to automated plant disease detection. This paper proposes a real-time leaf curl disease detection system with the use of the YOLOv8 object detection model[10]. The system is trained using annotated images of normal leaves and infected leaves in order to detect and locate areas of disease in leaf surfaces. YOLOv8 is chosen because of its high detection rates, rapid inference rate, and low-weight platform acceptable to be used in precision agriculture systems. Experimental test is high in terms of precision, recall and general detection accuracy in different lighting and background conditions. The suggested solution can improve the detection of diseases at an early stage, minimize the reliance on manual surveillance, and facilitate the intelligent farming solutions on a large scale.**

***Keywords*-- Leaf Curl Disease, YOLOv8, Deep Learning, Object Detection, Precision Agriculture, Computer Vision.**

I. INTRODUCTION

Food security and sustainable use of the economy, especially in developing countries where agricultural output is a direct determinant of livelihoods is a key arena of agriculture. Nevertheless, plant diseases still remain as a major problem to agricultural production and quality. [3], [4] One of these infections is the leaf curl disease which is one of the most devastating viral infections in crops like tomato, chilli and other solanaceous plants.

The disease is usually characterized by such symptoms as the curling of leaves, their yellowing, coagulation of veins and a shortage of growth, which eventually causes the loss of photosynthetic activity and decreases the level of yield significantly.

Timely diagnosis of the leaf curl disease is therefore important in minimizing the destruction of crops and achieving timely management of the disease[6], [7].

The latest development on artificial intelligence, in general, the deep learning and computer-vision industries in particular, has profoundly altered the agricultural moving monitoring. The convolutional neural networks (CNNs) have shown excellent results in the image-based computer-based classification [6], [7] of plant diseases. But most systems currently in existence are only image-level classifying ones that determine whether a leaf is healthy or diseased but not localize the location of the infected area. To obtain useful applications in agriculture, particularly in precision farming, detecting the presence of disease is only a part of the problem; it is necessary to identify and localize, with accuracy, the area of disease on the leaf surface.

More appropriate solution to this requirement is provided by object detection models. YOLO (You Only Look Once) family of algorithms has become popular because of its capability to operate in real-time and high accuracy. The last release, YOLOv8, consists of architectural enhancements that make the detector more accurate, faster to inference, and allowing more deployment options. It is especially lightweight and modular, which is why it would be used in real-time agricultural monitoring systems and can have a potential edge-device implementation.

This paper presents a proposal of an automated leaf curl disease detection system based on YOLOv8 to overcome the shortcomings of traditional and classification-oriented solutions.

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The system will identify and locate disease-affected areas in leaf images in different environmental conditions. The proposed approach helps to facilitate the use of precision agriculture, obviate the use of manual inspection, and implement timely intervention strategies to enhance crop productivity by fostering the accurate and real-time detection of diseases.

II. Literature review

Detecting plant diseases has become an important research topic because it directly affects the agricultural output and food security. The initial methods were based on the manual inspection and the conventional methods of the image processing, but the development of deep learning has changed the process of the plant pathology diagnosis since it is now possible to extract the features automatically and create the effective classification models [6]-[8]. Object detectors like YOLO and Faster R-CNN also evolved this field of work in recent years as they combine both disease classification and localization of the disease into a single architecture [9], [13]. Long-standing developments of detection architectures such as anchor free models and enhanced approaches to loss optimization has been very effective in advancing real-time monitoring of agriculture [10], [11].

2.1 Deep Learning–Based Plant Disease Detection

Deep learning has completely revolutionized the area of plant disease diagnostics through the automation of feature extraction and the less use of manual inspection. The application of CNNs to plant health and disease classification has demonstrated itself as a popular method because it can be trained to identify scalable visual features without manual features. As an illustration, multiple leaf diseases have been demonstrated to be highly classified using pre-trained CNN architectures such as VGG16, which shows that the model has the capability to differentiate intricate visual symptoms and enhance the efficiency of diagnosing the disease in comparison to conventional approaches. Although these CNN-based systems are effective in terms of classification, they do not usually have the localization of disease in space which is required in precision agriculture to be targeted[6], [7], [8].

2.2 YOLO and Object Detection in Plant Disease Identification

Models of object detection like You Only Look Once (YOLO) have become popular as real-time object detection and localization beyond classification.

Previous researchers used YOLOv4 to detect and identify different plant leaf diseases with a greater number of plants being detected and recognized compared to classification-only methods. Recent studies have generalized the YOLO family models to plant disease scenarios, e.g., the detection of cotton leaf disease by deep learning with the help of the YOLO framework demonstrates the potential of the approach to the task of agricultural monitoring. Moreover, there are deep learning architectures that combine YOLOv8 and demonstrate high scores in detecting various forms of leaf disease with accuracy and speed to be applied in smart farming settings in real-time. These works highlight how classification has been replaced by detection models to accomplish both disease areas identification and localization.

2.3 Improvements and Hybrid Models for Enhanced Detection

In addition to simple applications, scholars have come up with improved YOLO-based models which are used in an agricultural setting. In a recent research, the authors came up with a better version of YOLOv8, called SerpensGate-YOLOv8, which is specially crafted to detect plant diseases and is suggested to be better in complex field settings, with higher mean Average Precision (mAP) due to the additions of better convolutional and attention mechanisms. In other studies, architectural optimizations and support modules are also included to further improve the detection accuracy and computational efficiency of object-detection systems in the condition of plants health inspection. These developments show continuous innovation in implementing object detection systems to be suitable to precision agriculture and complete monitoring of leaf diseases.

III. Existing System

The current leaf curl disease detection methods mainly used are traditional viewing systems and simple image recognition systems. In conventional agriculture, the identification of disease is manually done by a farmer or plant pathologist, depending on the observation of the disease manifestations that include deformities, color changes, and curling of the leaves. Even though this method has been used extensively over the decades, it is very subjective and relies on the expertise. The process of manual inspection is slow, irregular and cannot be applied to a large scale farming setup where extensive scale monitoring is needed. Moreover, the initial signs are not always significant and can be confused with the lack of certain nutrients or stresses in the environment, contributing to the wrong diagnosis**[6], [7]**.

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As digital imaging and machine learning were developed, automated systems of plant disease detection were implemented to enhance the accuracy and efficiency. Most of these models make use of Convolutional Neural Networks (CNNs) to classify images at an image-level. Under these methods, images of leaves are inputted in deep-learning and are categorized into healthy or diseased leaves. Although these models are highly classified in cases of controlled datasets, most of them are usually incapable of localizing the infected regions [6], [8]in the leaf. Consequently, they do not offer much actionable data to precision agriculture applications where the localization of diseased regions is essential. [9], [12]

Other researchers have used object detection models like previous versions of YOLO and Faster R-CNN to localize the disease. Despite having better detection capacity than the classification-only techniques, these models, nevertheless, encounter several issues with small object detection, interference with the background, and complexity. Moreover, prior detection systems need a lot of hyperparameter optimization and do not necessarily need optimization to run in the field.

IV. PROPOSED WORK

The suggested system presents a real-time leaf curl disease detection system, which is based on the YOLOv8 object detector. The system has been developed to identify and pinpoint infected leaf areas with very high precision and at the cost of very low computation efficiency to be implemented in precision agriculture settings. The proposed framework is a type of classification, unlike the traditional classification-based methods, which carry out spatial localization of disease-affected areas, thus, permitting specific crop management measures.

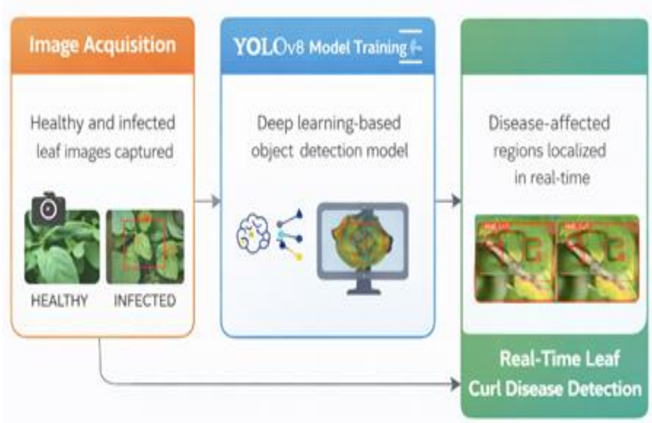

Fig. 4.0 illustrates the overall working principle of the proposed work

4.1. System Architecture

The architecture proposed is made of image acquisition, preprocessing, annotation, model training, and inference. Images of leaves have been acquired at different environmental settings to make them resistant to the variability of illumination, background clutter, and leaf orientation. The sample is equipped with healthy and infected samples. Bounding boxes are used to mark disease regions that are visible in the images. The annotated data is then manipulated as to be used in the training of YOLOv8. The methods of augmenting the data include rotation, horizontal flipping, scaling, and adjusting the brightness to enhance the generalization and decrease the overfitting. [9], [10].

4.2 YOLOv8-Based Detection Framework

YOLOv8 is chosen because it has an anchor-free detection network, better feature extraction backbone and lightweight structure. The model works with a single-stage detection pipeline, which, at the same time, predicts the coordinates of bounding boxes, class probabilities, and confidence scores. [10] The training process makes the process optimize the composite loss which involves localization loss, classification loss and objectness confidence loss. The model is trained to tell the difference between small texture differences, color distortions and structural deformities of leaves with leaf curl disease. The trained model produces bounding boxes of infected areas with the associated values of confidence which then allows the localization and accurate classification in real time. [11]

4.3. Deployment Strategy

The trained model will be able to be integrated with edge devices, mobile platforms or smart farming systems based on IoT. YOLOv8 has a lightweight architecture, which allows inference with low latency to be used in real-time field surveillance. The system can be extended further to be used in drone-based surveillance and automated crop health assessment. [10]

V. METHODOLGY

The suggested framework of leaf curl disease detection adheres to a systematic deep learning pipeline so that the proposed system can have accurate localization, strong generalization, and the ability to detect the disease in real-time. The data preparation, annotation, model training, inference, and evaluation procedures are incorporated in the methodology that is realized based on the YOLOv8 object detection architecture [10].

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5.1 Dataset Preparation

The data is composed of images of plant leaf leaves that are healthy and those affected by leaf curl at varying environmental conditions. Standard digital cameras were employed to take pictures to replicate actual-field agricultural conditions, such as changes in illumination, complexity of the background, and orientation of the leaves. The obtained data was partitioned into training, validation, and testing sets to achieve adequate model testing and avoid data leak. Augmentation was applied to enhance fine-tuning of the model and enhance the diversity of the dataset by using rotation, horizontal flipping, scaling, translation, and brightness adjustment. These changes assist the model in acquiring invariant characteristics as well as enhancing resistance to real-world variability [9], [10].

5.2 Data Annotation and Formatting

Disease-affected area was annotated manually with the help of bounding boxes on each infected image of a leaf. The standard labeling tools were used to perform the annotation process and the coordinates were stored in YOLO-compatible format. The annotation contains class labels and normalized bounding box parameters of object center coordinates, width and height. Such organized labeling allows the YOLOv8 model to learn object classification and localization in one training phase.

5.3 YOLOv8 Model Training

The YOLOv8 object detection model was chosen based on the fact that it has an anchor-free detection mechanism, better backbone network, and effective computational design. The model uses single-stage detection and it predicts the bound box coordinates, object confidence scores and class probabilities in a single forward pass and operates in one step. The annotated dataset was used to train with the optimized hyperparameters such as learning rate, batch size and number of epochs. The loss functional that is applied in training is a composite function consisting of localization loss, classification loss, and objectness confidence loss [9], [10]. The multi component loss allows the model to effectively learn both spatial and categorical information related to the symptoms of leaf curl disease.

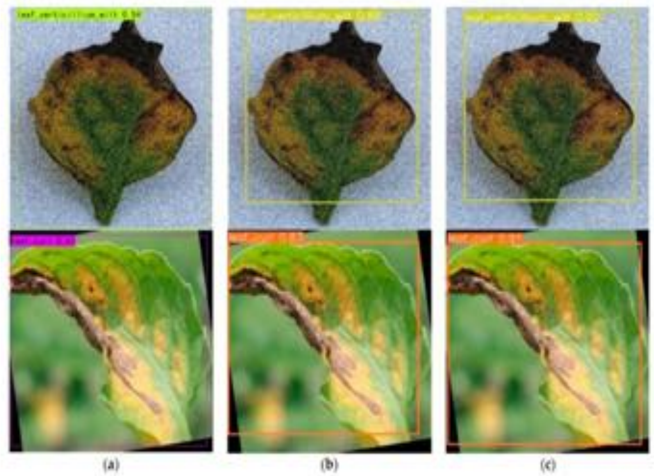

Fig 5.1 Showing the dataset sample for training the model

5.4 Inference and Real-Time Detection

Upon training, the model was made to inference on unseen test images. The YOLOv8 network takes each image during inference and creates bounding boxes of disease areas found and confidence scores. Non-Maximum Suppression (NMS) is used to eliminate duplicate overlapping predictions and only the most confident ones are kept. YOLOv8 has a lightweight architecture that guarantees low inference latency and consequently, the system can be used in real-time agricultural surveillance systems[12].

5.5 Performance Evaluation

The metrics that were used to measure the performance of the proposed system were standard object detection metrics such as Precision, Recall, F1-Score, and average Average Precision (mAP). Precision measures the percentage of correctly detected disease detections of all predicted disease detections and Recall measures the percentage of correctly detected disease regions of all real infected regions. Testing subcomponent was evaluated to determine the generalization ability of the model in unseen conditions. The results obtained show a high level of detection and localization of areas of leaf curls [11].

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VI. Results And Discussion

The proposed Yolo8-based system of detecting leaf curl disease was tested to determine its accuracy, localization, and robustness in the real-field conditions. The assessment was performed with the use of the unseen test data in order to guarantee the unbiased performance measurement[11].

6.1 Quantitative Performance Evaluation

The tested trained YOLOv8 model was determined with typical object detection performance measurements such as Precision, Recall, F1-Score and mean Average Precision (mAP). The choice of these metrics relied on the fact that they allowed a balanced evaluation of both the classification accuracy and the localization accuracy. The experimental findings reveal that the model had high accuracy levels, which showed a low false positive value in detecting disease-infected areas. The recall value proves the model to be successful in detecting most infected locations that are present in the images. F1-Score is used to indicate balanced performance as a point of precision and recall, which implies that it is a matter of stable detection behavior. Also, the mAP score confirms the model stability of the detection model to different thresholds of Intersection over Union (IoU). The good values of the metrics verify that the YOLOv8 architecture is a good predictor of the discriminative visual cues of the leaf curl symptoms such as texture distortion, edge curling, and color anomalies.The high metric values confirm that the YOLOv8 architecture effectively captures discriminative visual features associated with leaf curl symptoms, including texture distortion, edge curling, and color irregularities.

6.2 Localization Performance Analysis

The proposed method also does not involve the provision of a single image prediction as is the case with traditional CNN-based classification methods, but rather, they offer a spatial localization of the disease-affected locations. The model correctly produces bounding boxes on infected areas of the leaf as well as confidence scores. The anchor-free mechanism of detecting objects in YOLOv8 makes it a more beneficial tool in enhancing the ability of the framework to detect small and irregularly shaped disease patches. Localization accuracy is further promoted by the Non-Maximum Suppression (NMS) process to remove redundant overlapping detections. The ability to detect the spatial aspect of the system renders it more applicable to precision agriculture application where it is necessary to do specific pesticide application and localized treatment. [10]

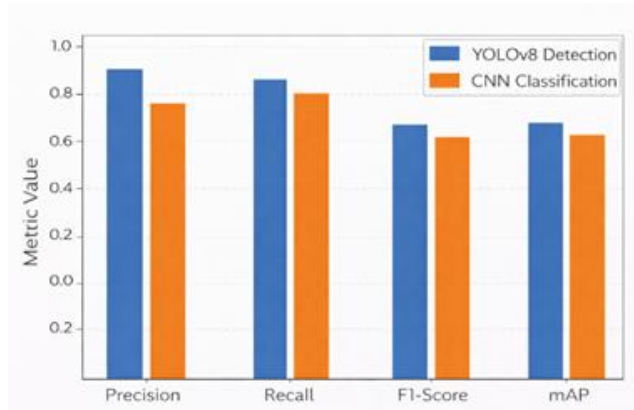

Fig 6.1 Comparison of performance metrics between YOLO v8 based detection and CNN based classification

6.3 Comparative Analysis with CNN-Based Classification

The proposed YOLOv8 detection framework was compared to the conventional CNN-based classification models in terms of their performance. Although CNN classifiers proved to be appropriate in terms of identifying whether a leaf is a healthy or infected one, they failed to localise disease regions. The YOLOv8-based model was more practically applicable than the classification models because both localization and detection are offered in the forward pass [6], [7]. Also, YOLOv8 was less inference-latency, which is beneficial in real-time agricultural applications. The above comparative findings vividly show that the object detection frameworks are more interpretable and can be used by the field than classification only systems [9], [10].

6.4 Discussion

The results of the experiment prove that the offered system demonstrates a high level of detection accuracy and is computationally efficient. Generalization in different environmental conditions was enhanced by the introduction of data augmentation techniques. YOLOv8 has a lightweight architecture, which guarantees low inference time and makes it possible to deploy the system in the field at real-time or to be used on edge devices or agricultural platforms backed by IoT. The fact that one can precisely identify areas of diseased crops offers a great opportunity to smart farming systems. The proposed approach helps to minimize the loss of crops, the efficient use of pesticides, and the enhanced agricultural productivity by allowing early diagnosis and accurate planning of the treatment. On the whole, the findings confirm the usefulness of the suggested YOLOv8-based framework as a scalable and feasible method of automated leaf curl disease detection.

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VII. CONCLUSION

In the current paper, an automated leaf curl disease detection and localization system in smart agriculture was proposed based on YOLOv8. In contrast to the traditional CNN-based classification methods, which perform the image-level disease detection only [6], [7], the developed framework allows the accurate localization of the infected area at a plane level with the help of a real-time object-detecting framework [9], [10]. The mechanism of anchor-free detection and optimized backbone structure of YOLOv8 make it easier to achieve higher detection accuracy and lower computational costs [10]. The study of experimental performance based on conventional object detection metrics, including Precision, Recall, F1-Score, and the average Average Precision (mAP), shows that the proposed model has a strong and stable performance across the different environmental conditions [11]. The localization stability is further improved with the integration of Non-Maximum Suppression (NMS) that minimizes redundant predictions [12]. The system produced is helpful in the precision agriculture by providing the ability to detect disease early, lessening the manual inspection intensive processes, and providing the chance to implement custom treatment plans. Future research can be dedicated to developing several crop diseases, drone-based monitoring systems, and deploying the framework to the edge device to use it in large-scale agriculture.

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