Sustainable Farming Through Intelligent Leaf Disease Monitoring Using Yolov8 and Leafnet Deep Learning Models

R.Senthil Kumar[1], R.Sasmedha[2], J.Shri Shadha[2], K.Subhageetha[2]
[1]*Assistant Professor, Department of Electronics and Communication Engineering, SSM Institute of Engineering and Technology, Dindigul, Tamil Nadu, India*
[2]*Final Year Student, Department of Electronics and Communication Engineering, SSM Institute of Engineering and Technology, Dindigul, Tamil Nadu, India*

Abstract: ***In the modern era of rapid technological advancement, agriculture must adopt intelligent systems to enhance crop productivity and minimize losses caused by plant diseases. Conventional disease identification methods depend largely on manual inspection by agricultural experts, which is time-consuming, costly, and often inaccessible to farmers, particularly in rural areas. To address these challenges, this work presents an Intelligent Leaf Disease Detection and Farmer Assistance System based on deep learning techniques. The proposed system automatically processes leaf images acquired from real-time field conditions or standard datasets to detect plant diseases. YOLOv8 is employed to accurately localize diseased regions on the leaf surfaces, while a customized LeafNet deep learning model is used to classify the disease with high accuracy. The identified disease name and confidence score are displayed through a Graphical User Interface (GUI) along with suitable fertilizer and treatment recommendations. To improve usability, the system provides voice-based output in both English and Tamil, and all detection results are stored in a history database for future reference and crop health monitoring. The proposed approach enables early-stage disease detection, reduces dependency on agricultural experts, and supports precision farming, thereby improving agricultural productivity and promoting sustainable agriculture.***

***Keywords:** Leaf Disease Detection, Deep Learning, YOLOv8, LeafNet, Precision Agriculture, Voice Assistance System, Image Processing, Sustainable Farming.*

I. INTRODUCTION

Agriculture is the backbone of many developing countries, and crop health plays a crucial role in ensuring food security. Plant diseases are one of the major challenges faced by farmers, as they reduce crop productivity and lead to economic losses. Traditional disease identification methods rely on manual inspection by experts, which is time-consuming, expensive, and prone to human error.

With the advancement of artificial intelligence and computer vision, automated disease detection systems have gained attention. Leaf diseases often exhibit visible symptoms such as discoloration, spots, and texture variations, which can be effectively analyzed using image processing and deep learning techniques. Early detection enables farmers to take preventive measures and apply appropriate remedies at the right time.

This project focuses on developing an intelligent leaf disease detection system that automatically identifies diseased regions and classifies the disease type. The proposed system aims to reduce dependency on agricultural experts and provide an efficient decision-support tool for farmers.

II. LITERATURE SURVEY

In the year 2025, a study titled "A Leaf Disease Detection Using Machine Learning and Deep Learning: Comparative Study" was presented by Moaad Al-Shalout, Mohamed Elleuch, and Ali Douik. In this work, Support Vector Machine (SVM) and VGG19 deep learning models were employed along with SIFT and Gabor filters on a dataset consisting of

25,272 leaf images of crops such as corn, potato, and tomato. The results demonstrated that SVM achieved an accuracy of 96%, while VGG19 achieved 95%, proving the effectiveness of both machine learning and deep learning approaches for accurate plant disease detection.

In 2024, Sri M. Chilaka Rao, Sharun Kumar, Kishore, Rakesh Kumar, and Sravan Kumar proposed a method titled "Enhancing Plant Leaf Identification using Machine Learning Techniques with the Random Forest Algorithm". The study utilized the Random Forest algorithm to classify plant leaf diseases. The results indicated high accuracy and precision, highlighting the algorithm's efficiency, scalability, and resistance to overfitting in agricultural applications.

Another work in 2024 by G. Tejaswi, G. Ramya, G. Sreeja, G. Abhi Rami, and Komal Bonde focused on "Plant Leaf Disease Detection Using Machine Learning". This research implemented a Convolutional Neural Network (CNN) model for leaf disease classification. The proposed system achieved an accuracy of 92.5%, demonstrating the reliability and effectiveness of CNN-based approaches in identifying plant diseases.

In the same year, D. Tejaswi et al. proposed a deep learning-based plant disease detection system using a CNN model developed with Teachable Machine and TensorFlow Lite. The system was implemented as an Android application for real-time disease detection. The experimental results showed an accuracy of 94%, enabling efficient disease identification and providing treatment guidance to farmers.

In 2022, Asha Patil presented a study titled "Plant Leaf Disease Classification Using SVM and CNN Algorithms". This work compared Support Vector Machine and Convolutional Neural Network models for leaf disease classification. The results showed that the CNN model achieved an accuracy of 95.33%, outperforming the SVM model and confirming the superiority of deep learning techniques in plant disease detection.

From the above studies, it is observed that deep learning-based approaches provide higher accuracy and better generalization compared to traditional machine learning methods. However, most existing systems focus mainly on classification and lack real-time localization, multilingual assistance, and historical data storage. To overcome these limitations, the proposed system integrates YOLOv8 for disease localization, a customized LeafNet model for classification, voice-based assistance in Tamil and English, and history storage, making it more effective and farmer-friendly.

III. BLOCK DIAGRAM

The proposed system is developed using a deep learning framework for automatic plant leaf disease detection and diagnosis. Leaf images are captured using a digital camera or mobile device and are first subjected to preprocessing operations such as resizing, noise removal, normalization, and contrast enhancement to improve image clarity and ensure uniformity. These steps standardize the input data and enhance important visual features, enabling more accurate analysis by the detection model.

The preprocessed images are then passed to the YOLOv8 model, which localizes the diseased regions on the leaf surface by identifying abnormal patterns such as spots, discoloration, and lesions. The extracted regions are further classified using a customized LeafNet convolutional neural network (CNN) model to determine the specific disease type. The system displays the detected disease name, confidence score, and recommended remedies through a graphical user interface. Additionally, voice-based output is provided in both English and Tamil to improve accessibility for farmers. All detection results are stored in a history database for future reference, monitoring, and crop health analysis.

Agriculture plays a vital role in the economic development of many countries, and crop diseases remain one of the major challenges affecting yield and quality. Plant leaf diseases are typically caused by bacteria, fungi, viruses, and pests, and early identification is essential to prevent their spread and minimize losses. Traditional detection methods rely on manual inspection by experts, which is time-consuming, expensive, and often inaccessible to farmers in rural areas. With recent advancements in artificial intelligence and deep learning, automated disease detection systems have emerged as reliable and efficient solutions.

In this work, a YOLOv8-based detection system integrated with a web application is proposed to provide an easy-to-use and accessible platform. The web-based design eliminates the need for dedicated mobile applications and allows the system to be used on any device with a browser. By combining real-time detection, remedy recommendations, and multilingual voice support, the proposed system offers a practical, farmer-friendly, and efficient solution for smart agricultural disease management.

Furthermore, the proposed system contributes to sustainable farming practices by enabling continuous crop monitoring and timely intervention. Early disease detection helps reduce excessive pesticide usage, lowers operational costs, and prevents large-scale crop damage. The stored historical data can also assist in analyzing seasonal disease trends and improving future decision-making. Thus, the system not only enhances detection accuracy but also supports precision agriculture and long-term agricultural productivity.

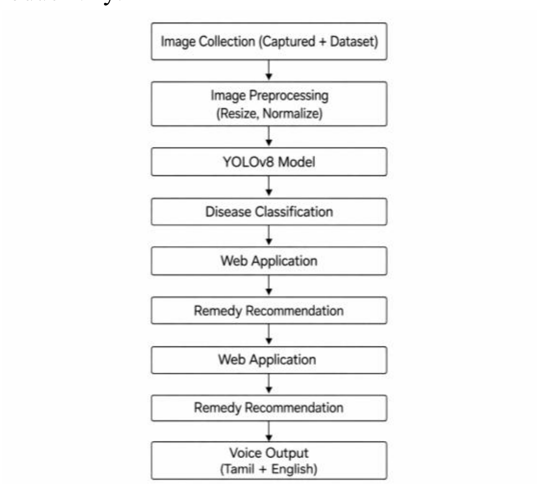

Fig -1: Block diagram of proposed method

1. Image Collection (Captured + Dataset)

Image collection is a critical phase of the leaf disease detection system, as the overall performance of the system depends heavily on the quality and variety of images used. In this stage, plant leaf images are obtained from two primary sources: real-time captured images and publicly available datasets. Real-time images are captured using digital cameras or mobile devices directly from agricultural fields. These images reflect real environmental conditions such as varying lighting, shadows, complex backgrounds, and different stages of disease severity. Capturing images under real-world conditions helps the system perform reliably when deployed for practical usage by farmers.

In addition to real-time captured images, standard plant leaf disease datasets are used to increase the size and diversity of the data. These datasets contain labeled images of healthy and diseased leaves across multiple plant species. The dataset images help the system learn distinct visual patterns associated with different diseases, including color discoloration, texture deformation, and spot formation. By combining captured images with dataset images, the system reduces data imbalance, improves robustness, and ensures better generalization across different leaf types and disease conditions.

Fig 2: Image Collection

2. Image Preprocessing

Image preprocessing is a crucial stage in the proposed leaf disease detection system, as the accuracy of deep learning models strongly depends on the quality and consistency of input images. The raw images collected from real-time field capture and public datasets often exhibit significant variations in resolution, size, lighting conditions, orientation, and background complexity. Such inconsistencies can negatively affect the learning capability of the detection model and lead to poor classification performance. Therefore, preprocessing techniques are applied to standardize and enhance the images before they are provided to the YOLOv8 model.

The first preprocessing step involves image resizing. Since images obtained from different cameras or datasets may have varying dimensions, they are resized to a fixed resolution (for example, 640 × 640 pixels) to maintain uniformity. Standardizing the image size simplifies batch processing, reduces memory requirements, ensures compatibility with the neural network input layer, and decreases computational overhead, enabling faster training and real-time detection.

Next, normalization is performed to scale pixel intensity values to a common range, typically between 0 and 1 or −1 and 1. This stabilizes the training process by preventing large intensity variations, accelerates gradient descent optimization, and improves detection accuracy. In addition, image enhancement operations such as noise reduction, smoothing, and filtering help remove distortions caused by camera sensors or environmental conditions. Contrast enhancement improves the visibility of important leaf features, while background suppression minimizes irrelevant objects like soil, sky, or surrounding plants. Together, these steps improve visual clarity and allow the model to focus on disease symptoms such as spots, lesions, discoloration, and mold patches.

Fig 3: Preprocessed images

3. YOLOv8 Model

The YOLOv8 (You Only Look Once version 8) model serves as the core intelligence of the proposed leaf disease detection system. It is a state-of-the-art deep learning–based object detection algorithm that performs feature extraction and detection in a single forward pass. Unlike traditional multi-stage methods that depend on separate region proposal and classification steps, YOLOv8 integrates all operations into a unified architecture, reducing processing time while maintaining high detection accuracy.

In this system, preprocessed leaf images are provided as input to the YOLOv8 network, where the model automatically learns discriminative features such as color variations, edges, texture abnormalities, and shape distortions associated with plant diseases. Symptoms like yellowing, spots, fungal patches, and lesions are identified without manual feature extraction, improving efficiency and adaptability.

The YOLOv8 architecture consists of three main components: backbone, neck, and head. The backbone extracts deep features, the neck performs multi-scale feature fusion, and the head predicts bounding boxes, class labels, and confidence scores for diseased regions. This multi-scale detection enables accurate identification of both small and large disease spots on leaves.

Additionally, YOLOv8 supports real-time processing and low memory usage, allowing fast analysis and easy deployment on web or mobile platforms. Farmers can upload images and receive instant results, making the system practical and effective for real-world agricultural applications.

4. Disease Classification

Disease classification is the stage where the system determines the health condition of the plant leaf based on the analysis performed by the YOLOv8 deep learning model. After feature extraction and detection, the model compares the visual characteristics of the input leaf image with the learned disease patterns obtained during training. Based on this comparison, the leaf is classified into predefined categories such as healthy or diseased.

The proposed system is trained to identify multiple plant leaf diseases, including Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Target Spot, Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, and Spider Mite (Two-Spotted Spider Mite). Each disease exhibits unique visual symptoms such as color discoloration, irregular spots, lesions, mold growth, curling of leaves, and texture variations. The YOLOv8 model effectively learns these distinguishing features to accurately classify the disease type.

Once the classification is completed, the system provides a clear and meaningful output by identifying the exact disease affecting the leaf along with its confidence level. This classified information plays a crucial role in guiding further actions such as remedy recommendation, treatment planning, and preventive measures. Accurate disease classification enables farmers to understand the condition of their crops at an early stage and take timely corrective actions, thereby reducing crop loss and improving agricultural productivity.

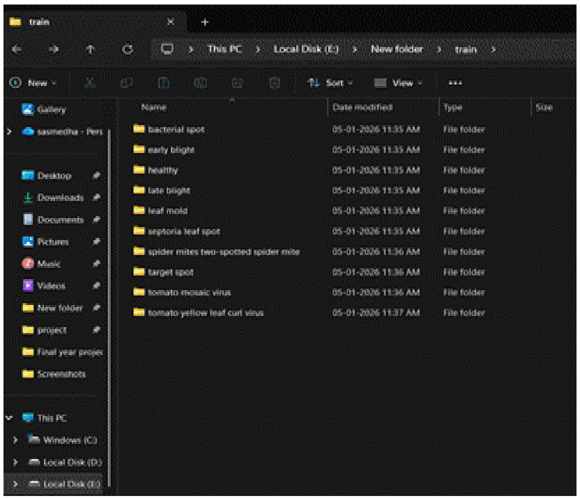

Fig 5: Classified Disease List

5. Web Application

The web application serves as the main interaction layer between the user and the proposed leaf disease detection system. It provides a simple and accessible platform that allows users to upload plant leaf images and quickly receive detection results. As a web-based solution, it removes the need for installing dedicated software or mobile applications and can be accessed from any device with a standard web browser, ensuring convenience and wider usability for farmers and agricultural workers.

The application communicates with the backend server, where preprocessing, YOLOv8-based detection, and classification are performed. After image upload, results such as the detected disease, confidence level, and remedy suggestions are displayed in a clear and user-friendly format. Its simple design ensures easy operation even for users with limited technical knowledge, making it well suited for rural and agricultural environments.

Fig 6: Web Application

6. Remedy Recommendation

Once the disease is identified, the system provides appropriate remedy recommendations based on the detected disease type. The remedy information is retrieved from a predefined database that contains treatment guidelines, preventive measures, and basic crop care practices. These recommendations assist farmers in taking immediate corrective actions to control the disease and prevent further spread.

Providing remedy suggestions along with disease detection increases the practical value of the system. Farmers not only gain information about the disease but also receive guidance on how to manage it effectively. This integrated approach supports better crop health management and improves agricultural productivity.

The remedy module is designed to deliver simple, clear, and actionable instructions that can be easily followed by farmers without requiring expert supervision. The recommendations may include suitable pesticides, organic treatments, irrigation adjustments, and preventive measures to minimize future infections. By combining accurate detection with timely treatment advice, the system helps reduce crop damage, lower costs, and promote sustainable farming practices.

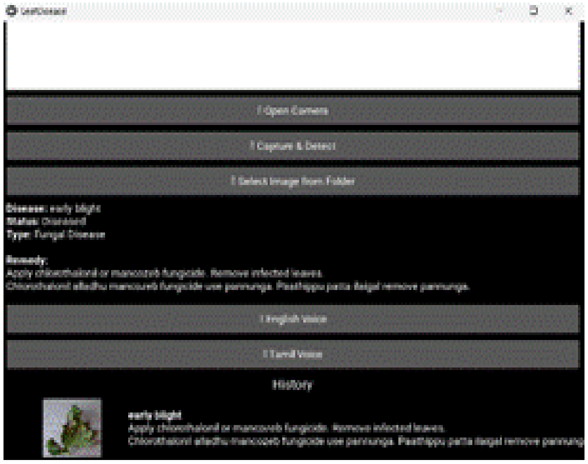

Fig 7: Remedy

7. Voice Output (Tamil + English)

The final stage of the system focuses on improving accessibility through voice output. The detected disease details and remedy recommendations are converted into speech using a text-to-speech mechanism. The system supports voice output in both Tamil and English, making it suitable for users with different language preferences.

This feature is particularly beneficial for farmers who may have difficulty reading text-based information. By delivering information through voice output, the system ensures clear communication and improves user engagement. The bilingual voice support enhances usability and ensures that critical information reaches users in an easily understandable manner.

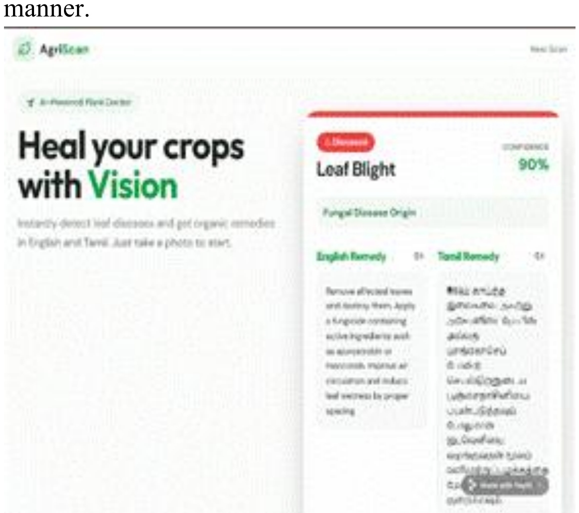

Fig 8: Voice Output

IV. CONCLUSION

This plant leaf disease detection system automatically identifies diseases in plant leaves using image processing and a web-based platform. Leaf images collected from real fields and standard datasets are preprocessed to improve clarity and consistency, and the YOLOv8 deep learning model analyzes them to classify leaves as healthy or diseased based on features such as discoloration, spots, and texture changes. The system includes a user-friendly web application that allows farmers to upload images and view results easily without installing any software. It also provides remedy suggestions and voice output in both Tamil and English for better understanding. Overall, the solution enables early disease detection, timely treatment, and improved crop health, with potential for future expansion to support more crops and higher accuracy.

REFERENCES

[1] M. Al-Shalout, M. Elleuch, and A. Douik, “Comparative study on leaf disease detection using machine learning and deep learning techniques,” *Journal of Agricultural Informatics*, vol. 16, no. 2, pp. 45–56, 2025.

[2] S. M. Chilaka Rao, S. Kumar, K. Kumar, R. Kumar, and S. Kumar, “Plant leaf identification using Random Forest algorithm,” *International Journal of Computer Applications*, vol. 185, no. 6, pp. 12–18, 2024.

[3] G. Tejaswi, G. Ramya, G. Sreeja, G. Abhi Rami, and K. Bonde, “Plant leaf disease detection using convolutional neural networks,” *Procedia Computer Science*, vol. 218, pp. 210–217, 2024.

[4] D. Tejaswi et al., “Mobile-based plant disease detection using CNN and TensorFlow Lite,” *IEEE Access*, vol. 12, pp. 10234–10245, 2024.

[5] A. Patil, “Comparative analysis of SVM and CNN for plant leaf disease classification,” *International Journal of Advanced Research in Computer Science*, vol. 13, no. 4, pp. 95–101, 2022.

[6] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” *Frontiers in Plant Science*, vol. 7, pp. 1–10, 2016.

[7] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” *Computers and*

Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[8] J. Too, L. Yujian, S. Njuki, and Y. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.

[9] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.

[10] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.

[11] G. Jocher et al., "YOLOv8: Real-time object detection and segmentation framework," Ultralytics, 2023.

[12] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE CVPR*, pp. 770–778, 2016.

[13] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. International Conference on Learning Representations (ICLR)*, 2015.

[14] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017.

[15] L. Liu, S. Ouyang, Y. Wang, et al., "Deep learning for generic object detection: A survey," *International Journal of Computer Vision*, vol. 128, pp. 261–318, 2020.

[16] P. Brahimi, A. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: Classification and symptoms visualization," *Applied Artificial Intelligence*, vol. 31, no. 4, pp. 299–315, 2017.

[17] H. Durmuş, E. Güneş, and M. Kırcı, "Disease detection on the leaves of plants using deep learning approach," *International Journal of Advanced Computer Science and Applications*, vol. 8, no. 10, pp. 291–298, 2017.

[18] S. Sladojevic et al., "Deep neural networks based recognition of plant diseases by leaf image classification," *Computational Intelligence and Neuroscience*, vol. 2016, pp. 1–11, 2016.

[19] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.

[20] R. Picon, A. Bereciartua, A. Alvarez-Gila, and A. Seitz, "Deep convolutional neural networks for mobile capture device-based crop disease classification," *Computers and Electronics in Agriculture*, vol. 161, pp. 280–290, 2019.