

Crop Disease Prediction and Stage Risk Assessment using YOLOv11

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Abstract - Agriculture is the cornerstone of the India's economy, contributing substantially to national GDP and employment. However, crop diseases remain a major obstacle to food security and economic stability. These diseases often go undetected until the later stages, leading to significant yield loss. The detection of crop diseases at an early stage is crucial for improving agricultural productivity and reducing financial losses. Traditional methods of disease identification rely on manual inspection, which is time-consuming and prone to errors. This research presents an intelligent crop disease detection system using deep learning techniques. The system integrates MobileNetV2 for leaf validation and YOLOv11 classification model for identifying crop diseases from leaf images. MobileNetV2 ensures that the uploaded image is a valid leaf before passing it to the disease detection model. The YOLOv11 model is trained on the PlantVillage dataset containing multiple classes of tomato leaf diseases. A web-based application is developed using Flask for backend processing and HTML, CSS, and JavaScript for the frontend interface. The system allows users to upload images and receive disease predictions along with confidence scores in real time. Experimental results show that the model achieves high accuracy, making it suitable for precision agriculture and smart farming applications.

Key Words: Agriculture, Crop Disease Detection, YOLOv11, MobileNetV2, Risk Assessment, Precision Agriculture.

1. INTRODUCTION

India, being an agrarian economy, depends heavily on crop productivity to sustain its population and economy. Despite technological progress, agricultural yield continues to be affected by diseases such as bacterial blight, powdery mildew, and viral infections. According to FAO estimates, global crop losses due to diseases account for 20 – 30% of total production annually. Conventional methods of disease detection, primarily manual inspection, are time – consuming, subjective and prone to errors. Hence, there is a pressing need for automated systems that can detect and classify crop diseases accurately and in real time. Advances in artificial intelligence, computer vision and deep learning models such as YOLO (You Only Look Once) have provided new opportunities for developing such tools. This research aims to create an end-to-end framework combining YOLOv11, MobileNetV2, and a recommendation engine to not only detect diseases but also evaluate risk stages and recommend suitable treatments, bridging a critical gap in precision agriculture.

In this research, a two-stage deep learning approach is proposed. The first stage uses MobileNetV2 to validate whether the input image is a leaf. The second stage uses YOLOv11 to classify the disease present in the leaf image. This approach improves system reliability and ensures accurate predictions.

2. RESEARCH OBJECTIVES

The main objective of this research is to develop an intelligent crop disease detection system that can automatically identify plant diseases, assess their severity, and recommend appropriate treatments using deep learning techniques. The specific objectives of this research are as follows:

- To develop a leaf validation system using MobileNetV2 to filter non-leaf images.
- To develop an automated crop disease detection system using the YOLOv11 object detection model to identify diseased regions in crop leaf images.
- To develop a web or mobile-based application interface that allows farmers to easily upload crop images and receive disease diagnosis and treatment recommendations.
- To contribute to precision agriculture by enabling early disease detection and reducing crop losses through intelligent decision support.

3. LITERATURE REVIEW

Recent advancements in artificial intelligence and computer vision have significantly improved the automation of crop disease detection. Many researchers have applied deep learning models to identify plant diseases using leaf images.

Kumar et al. [1] proposed a crop disease detection system using the YOLOv8 object detection model. The system was trained on agricultural image datasets to detect disease symptoms directly from leaf images. The YOLO-based approach demonstrated high detection speed and accuracy in identifying diseased regions. However, the study mainly focused on disease detection and did not address the problem of predicting the severity stage or recommending appropriate treatments.

Patil and Manohar [2] introduced a hybrid deep learning model for potato leaf disease identification. Their approach

combined convolutional neural networks with additional feature extraction techniques to improve classification accuracy. The proposed system achieved promising results in identifying potato leaf diseases under controlled conditions. However, the model primarily focused on classification and lacked real-time object detection capabilities required for field applications.

Earlier work by Chakravarthy and Raman [3] focused on detecting early blight disease in tomato leaves using deep learning techniques. Their model analyzed leaf images to classify infected and healthy plant samples, demonstrating the potential of deep learning for agricultural disease detection. Despite its effectiveness, the approach was limited to a specific disease and crop type, reducing its scalability to multiple crop diseases.

Similarly, Sharma et al. [4] performed a performance analysis of deep learning CNN models for plant disease detection using image segmentation techniques. Their study evaluated multiple CNN architectures and demonstrated that segmentation of infected leaf regions improves classification accuracy. However, the approach mainly focuses on disease classification and does not support real-time detection or severity prediction.

Although these studies demonstrate the effectiveness of deep learning models for crop disease detection, most existing systems primarily focus on identifying disease types. Very few approaches address disease severity prediction and treatment recommendation, which are crucial for practical agricultural decision-making. To overcome these limitations, the proposed system integrates YOLOv11 for disease detection and LSTM for stage-wise risk assessment, along with a recommendation module to suggest suitable treatments.

4. METHODOLOGY

A. Data Collection:



Fig.1 Sample Diseased Crop Leaf Images

The dataset used in this research is obtained from two sources. The first dataset is used for leaf detection and is collected from Kaggle, containing 13,000 images with equal

distribution of leaf and non-leaf images. The second dataset is the PlantVillage dataset, specifically the tomato subset, which contains approximately 18,000 labeled images across 10 disease classes (9 diseases and 1 healthy class). Following are the diseases on which we have trained our model some of which are shown in Fig. 1

1. Bacterial Spots
2. Early Blight
3. Late Blight
4. Leaf Mold
5. Septoria Leaf Mold
6. Spider Mites
7. Target Spot
8. Yellow Leaf Curl Virus
9. Mosaic Virus

The dataset is divided into training and validation sets. The training set is used to train the model, while the validation set is used to evaluate performance.

B. Data Processing:

Before training the deep learning models, the collected dataset undergoes several preprocessing steps to improve the quality and consistency of the images. First, all images are resized to a fixed resolution (224 x 224 pixels), so that they can be processed efficiently by the neural network and also converted to RGB format. Image normalization is applied to scale pixel values to a standard range, which helps in faster convergence during training. Data augmentation techniques such as image rotation, horizontal flipping, brightness adjustment, and cropping are also applied to increase dataset diversity. These techniques help prevent overfitting and improve the generalization ability of the detection model.

C. Leaf Detection using MobileNetV2:

MobileNetV2 is used as a lightweight convolutional neural network for binary classification to determine whether the uploaded image contains a leaf or not. This step acts as a validation layer before performing disease detection. The model is trained on a balanced dataset consisting of leaf and non-leaf images, enabling it to distinguish relevant agricultural inputs from irrelevant images such as human faces, objects, or backgrounds.

MobileNetV2 is chosen due to its efficiency and low computational requirements, making it suitable for real-time applications and deployment on systems with limited resources. The model uses depth wise separable convolutions and inverted residual blocks, which significantly reduce the number of parameters while maintaining high accuracy.

By filtering out non-leaf images at an early stage, the system reduces false predictions and ensures that only valid inputs

are processed by the disease classification model. This improves the overall robustness and reliability of the system.

D. Disease Classification using YOLO:

The YOLOv11 classification model is used for detecting and classifying crop diseases from leaf images. YOLOv11 is a state-of-the-art deep learning model known for its high speed and accuracy. In this research, the classification variant of YOLOv11 (yolov11n-cls) is used, which is optimized for image classification tasks.

The model is trained using transfer learning, where pretrained weights (trained on large-scale datasets such as ImageNet) are fine-tuned on the PlantVillage tomato dataset. This approach allows the model to learn disease-specific features such as leaf color variations, texture patterns, and spot formations more efficiently.

During inference, the model takes a preprocessed image as input and outputs the predicted disease class along with a confidence score. The model is capable of distinguishing between multiple disease categories, including bacterial spot, early blight, late blight, and healthy leaves. The use of YOLOv11 ensures fast and accurate predictions, making the system suitable for real-time agricultural applications.

5. ASSUMPTIONS

The proposed system is developed based on certain assumptions to ensure proper functionality and usability:

- The user (farmer) has access to a smartphone or a device with a camera to capture crop images.
- The user has basic internet connectivity to access the web application.
- The uploaded image contains a clear view of a single leaf.
- The image is captured under reasonably good lighting conditions.
- The user is able to interact with a basic web interface.

6. SYSTEM DESIGN AND IMPLEMENTATION

A. System Architecture:

The proposed system architecture is designed as a multi-stage pipeline that ensures accurate and efficient crop disease detection. The architecture consists of two primary modules: leaf validation and disease classification.

Initially, the user uploads an image through the web interface. The image is preprocessed and then passed to the MobileNetV2 model, which determines whether the image contains a leaf. If the image is classified as a non-leaf, the system rejects the input and prompts the user to upload a valid image.

If the image is confirmed as a leaf, it is forwarded to the YOLOv11 classification model. This model analyzes the

image and predicts the type of disease present in the leaf along with a confidence score.

The final result is then sent to the Flask backend, which processes the output and displays it on the user interface. This modular architecture ensures efficient processing, reduces unnecessary computation, and improves overall

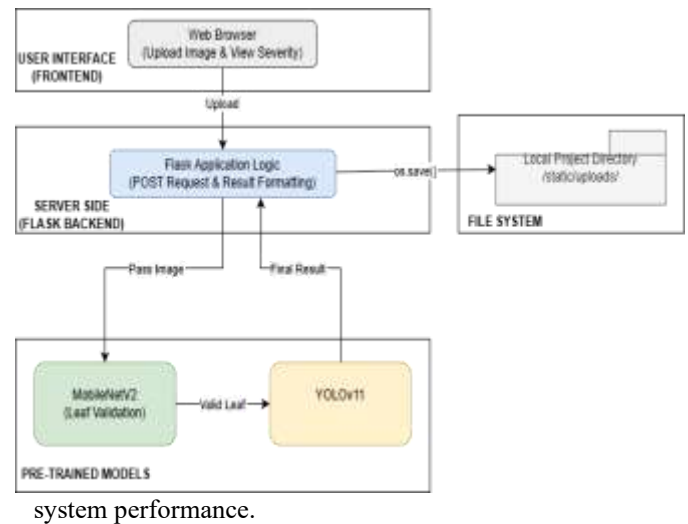


Fig.2 System Architecture Diagram

B. Application Workflow:

The application workflow describes the sequence of operations performed by the system from input to output. The workflow is designed to ensure that only valid leaf images are processed for disease classification, thereby improving the reliability and accuracy of the system.

1. **Image Upload:** The user uploads a crop leaf image through the web interface, and the image is sent to the Flask backend for processing.
2. **Image Preprocessing:** The uploaded image is preprocessed by resizing and normalizing it to meet the input requirements of the deep learning models.
3. **Leaf Validation using MobileNetV2:** The preprocessed image is passed to the MobileNetV2 model to verify whether it contains a valid plant leaf.
4. **Invalid Image Handling:** If the image is identified as a non-leaf, the system stops further processing and displays an error message asking the user to upload a valid leaf image.
5. **Disease Classification using YOLOv11:** If the uploaded image is successfully validated as a leaf, it is forwarded to the trained YOLOv11 classification model. The model analyzes the leaf image and identifies the most probable disease category by extracting and evaluating its visual features.
6. **Prediction Generation:** After processing the image, the YOLOv11 model generates the predicted disease

class along with a confidence score indicating the certainty of the prediction.

7. **Backend Response Processing:** The Flask backend receives the prediction results from the model, formats the output, and prepares it for display on the web application.
8. **Display of Results:** Finally, the predicted disease name and its corresponding confidence score are presented to the user through the web interface, allowing quick and easy interpretation of the diagnosis.

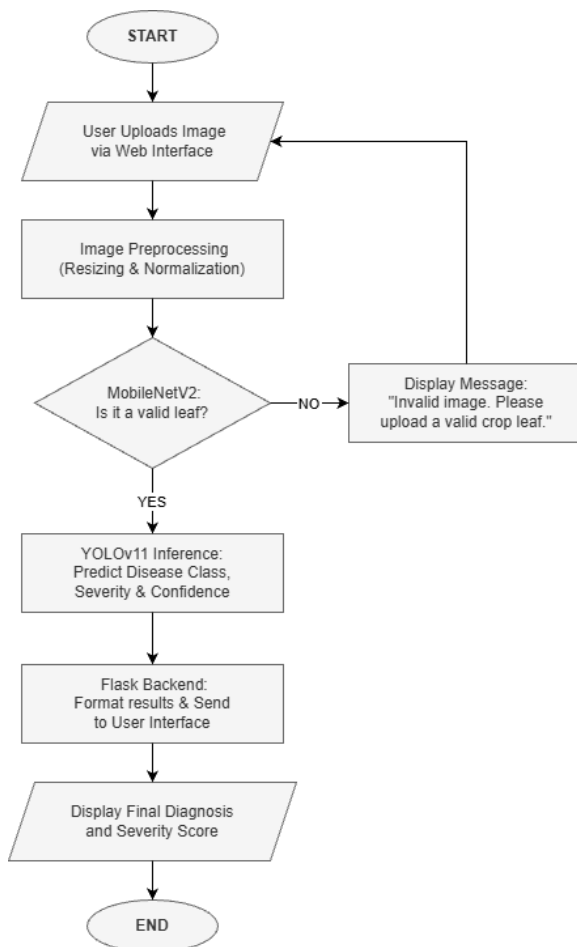


Fig.3 Application Workflow

This workflow enables quick disease diagnosis and helps farmers take timely preventive measures.

C. Software Tools and Technologies:

The system is implemented using Python, which provides extensive support for machine learning and image processing. Deep learning models such as YOLOv11 and MobileNetV2 are developed using PyTorch and TensorFlow frameworks. For image processing tasks including resizing and normalization, the OpenCV library is used. These tools enable efficient handling and analysis of crop leaf images.

The system can be deployed on web or mobile platforms, allowing farmers to easily upload images and receive results. The minimum hardware configuration required for running the system includes 8 GB RAM and 256 GB SSD.

D. User Interface Design:

The user interface is designed to be simple, intuitive, and user-friendly, ensuring ease of use for individuals with minimal technical knowledge. The interface allows users to upload crop leaf images either by selecting files from their device or using drag-and-drop functionality.

Once the image is uploaded, the system processes the input and displays the prediction results, including the detected disease and confidence score. The interface is designed to clearly present the results in an understandable format, enabling users to quickly interpret the output.

The frontend is developed using HTML, CSS, and JavaScript, ensuring responsiveness and compatibility across different devices such as desktops and smartphones. Special attention is given to layout, button design, and result display to enhance user experience.



Fig.4 Application Landing Page



Fig.5 Interface with Drag and Drop Functionality

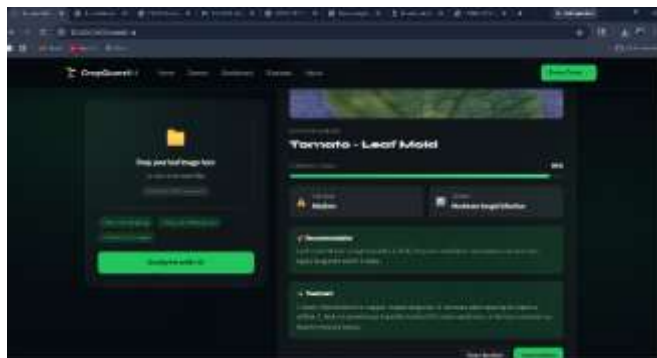


Fig.6 Output Screen

7. OUTCOMES

The performance of the proposed crop disease detection system is evaluated using standard classification metrics. The YOLOv11 classification model was trained on the PlantVillage tomato dataset and evaluated on a validation dataset.

The model achieved a Top-1 Accuracy of 98.87%, indicating that the model correctly predicts the disease class in the majority of cases. This demonstrates the effectiveness of the model in identifying crop diseases with high precision.

The confusion matrix further illustrates the classification performance, showing that most predictions are correctly classified with minimal misclassification. Some minor confusion is observed between visually similar disease classes such as early blight and late blight.

Overall, the results demonstrate that the proposed system achieves high accuracy and performs reliably for crop disease detection.

8. CONCLUSION

The proposed research presents an efficient and reliable crop disease detection system using deep learning techniques. The system integrates MobileNetV2 for leaf validation and YOLOv11 for disease classification, ensuring that only relevant inputs are processed and accurately analyzed.

The use of the PlantVillage dataset enabled the model to learn distinct disease patterns and achieve high accuracy. The experimental results demonstrate that the system performs effectively in identifying multiple crop diseases with a high level of precision.

The implementation of a web-based application using Flask further enhances the usability of the system by allowing users to upload images and receive real-time predictions. This makes the system practical for deployment in agricultural environments.

Overall, the proposed solution contributes to the field of precision agriculture by providing an automated, fast, and accurate method for crop disease detection. It has the potential

to assist farmers in early diagnosis, reduce crop losses, and improve agricultural productivity.

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