Crop Disease Prediction and Stage Risk Assessment using YOLO v11

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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. This research presents an AI-powered system that integrates YOLO v11 for crop disease detection, Long Short-Term Memory (LSTM) for stage-wise risk assessment, and a recommendation engine for treatment guidance. The system identifies disease symptoms through leaf image analysis, classifies severity levels, and suggests optimized treatments based on the predicted stage. The use of deep learning techniques allows for real-time detection and classification, significantly reducing farmers' dependency on manual diagnosis. The solution's web and mobile interface ensures ease of accessibility for rural communities. This model promotes precision agriculture by minimizing losses, optimizing pesticide use, and contributing to sustainable farming practices.**

Index Terms: **Agriculture, Crop Disease Detection, YOLO v11, LSTM, Risk Assessment, Precision Agriculture, Image Based Detection.**

I. 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 *YOLO v11*, *LSTM*, 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.

II. 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 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.

III. 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.

IV. METHODOLOGY

A. Dataset Collection:

Fig.1 Sample diseased crop leaf images

The dataset used in this research is collected from the PlantVillage repository, which contains a large number of crop leaf images representing both healthy and diseased plants. The dataset includes different crop species and various disease categories such as early blight, late blight, leaf mold, and bacterial infections. In addition to publicly available datasets, some field images can also be incorporated to represent real agricultural conditions such as varying lighting, background noise, and environmental variations. These images help in improving the robustness of the model and make the system suitable for real-time agricultural applications.

B. Data Preprocessing:

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 so that they can be processed efficiently by the neural network. 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. YOLO v11 Architecture:

The YOLO v11 (You Only Look Once version 11) architecture is used for real-time crop disease detection. YOLO is an advanced object detection algorithm that processes the entire image in a single pass through a convolutional neural network. Unlike traditional detection methods that analyze different regions separately, YOLO divides the input image into multiple grid cells and predicts bounding boxes along with class probabilities simultaneously. In this research, YOLO v11 is trained to detect diseased regions on crop leaves and classify the type of disease present in the image. The model provides fast and accurate detection, making it suitable for real-time agricultural monitoring systems.

D. LSTM Model for Severity Prediction:

To analyze the progression and severity of crop diseases, a Long Short-Term Memory (LSTM) model is incorporated into the system. LSTM is a type of recurrent neural network designed to handle sequential data and capture long-term dependencies. In the proposed system, the LSTM model processes features extracted from the detected diseased regions and predicts the severity stage of the infection. The severity is classified into different levels such as early stage, moderate stage, and severe stage. This stage-wise prediction allows farmers to understand the seriousness of the disease and take appropriate preventive actions at the right time.

E. Recommendation Engine:

The recommendation engine is designed to provide treatment suggestions based on the detected disease and its predicted severity stage. Once the YOLO v11 model identifies the disease and the LSTM model determines the severity level, the system generates suitable treatment recommendations. These recommendations may include pesticide usage, organic treatment methods, or preventive agricultural practices. The recommendation module acts as a decision-support system for farmers, helping them take timely and effective actions to control crop diseases and reduce potential yield losses.

V. SYSTEM DESIGN AND IMPLEMENTATION

A. System Architecture:

The proposed system architecture automates crop disease detection, severity prediction, and treatment recommendation using deep learning techniques. The system consists of several modules that process crop leaf images and generate useful insights for farmers.

The process begins when a farmer uploads or captures a leaf image through a web or mobile interface. The image undergoes preprocessing steps such as resizing and normalization to improve model performance.

The pre-processed image is analysed using the YOLOv11 object detection model, which identifies diseased regions and predicts the disease class by generating bounding boxes. The extracted features are then processed by an LSTM model to classify the disease severity as early, moderate, or severe.

Finally, a rule-based recommendation module suggests suitable treatments based on the detected disease and severity level. This modular design ensures efficient and scalable system performance.

B. Application Workflow:

The application workflow describes the sequence of operations performed by the system.

1. The farmer uploads or captures a crop leaf image using the application interface.
2. The image undergoes preprocessing steps such as resizing and normalization.
3. The YOLOv11 model detects diseased regions and predicts the disease class.
4. The LSTM model analyses extracted features to determine the severity stage.
5. Based on the predicted disease and severity level, the system generates treatment recommendations.
6. The final results are displayed to the user through the application interface.

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 LSTM 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 and user-friendly so that farmers can easily use the system. Users can capture crop leaf images using a mobile camera or upload images from their device. After processing the image, the system displays the detected disease, severity stage, and recommended treatments. The interface focuses on clarity and ease of use, enabling farmers to quickly understand the results and take appropriate action.

VI. EXPECTED OUTCOMES

The system is expected to deliver real-time disease detection with over 95% accuracy and provide reliable stage-wise risk assessment. Through its recommendation module, farmers will receive customized treatment guidance that reduces unnecessary pesticide application, thereby cutting down costs and environmental impact. The integration of YOLO and LSTM ensures fast and precise analysis that aids in decision-making and proactive disease control. Moreover, the solution aims to empower farmers with the knowledge-driven insights, reducing their dependence on expert availability and improving long-term crop health monitoring. The project also contributes to the field of smart farming and precision agriculture by demonstrating how AI can bridge technological gaps in developing nations like India.

VII. CONCLUSION

In conclusion, this research proposes a comprehensive AI-based framework for crop disease management by integrating YOLO v11 and LSTM models. The system not only detects and classifies diseases but also assesses severity and recommends appropriate treatments, creating a holistic solution for farmers. By enhancing accessibility through mobile and web platforms, it promotes large-scale adoption of AI in agriculture. The implementation promises to reduce yield losses, increase efficiency, and support sustainable agricultural practices. Future enhancements may include the integration of additional models for weather-based prediction, multilingual interfaces for regional users and cloud-based data sharing for large-scale analysis.

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