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Sugarcane Leaf Disease Detection and Classification Using Deep Learning

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Abstract:

Sugarcane is one of the most important commercial crops and plays a vital role in the agricultural economy. However, sugarcane production is often affected by various leaf diseases that reduce crop quality, yield, and overall productivity. Early and accurate disease identification is essential for effective crop management and minimizing economic losses. Traditional disease diagnosis mainly depends on manual inspection by agricultural experts, which is time-consuming, labour-intensive, and prone to human error. This paper presents an intelligent Sugarcane Leaf Disease Detection and Classification System using Deep Learning techniques. The proposed system combines YOLOv10 for leaf detection and localization with MobileNetV2 for disease classification. Initially, YOLOv10 identifies the leaf region from the uploaded image and extracts the region of interest. The detected leaf is then pre-processed and passed to the MobileNetV2 model, which classifies the leaf into the corresponding disease category or healthy class. MobileNetV2 is selected because of its lightweight architecture, computational efficiency, and strong classification performance. The system is deployed through a Flask-based web application, enabling users to upload sugarcane leaf images and receive disease predictions along with confidence scores and annotated output images. The deep learning models are implemented using the TensorFlow framework, while image processing operations are performed using OpenCV. The proposed system provides a fast, accurate, and user-friendly solution for automated disease diagnosis. By assisting farmers and agricultural professionals in identifying diseases at an early stage, the system contributes to improved crop management, reduced crop losses, and enhanced agricultural productivity. The integration of object detection, disease classification and web-based deployment makes the system suitable for practical agricultural applications and future smart farming solutions.

Keywords:

Sugarcane Leaf Disease Detection, Deep Learning, YOLOv10, MobileNetV2, Disease Classification, Object Detection, Computer Vision, Tensor Flow, Smart Farming.

1. Introduction

Agriculture plays a vital role in ensuring food security and supporting the economic growth of many countries. Among the major commercial crops, sugarcane is widely cultivated because of its importance in the production of sugar, ethanol, jaggery, and several other industrial products. The productivity and quality of sugarcane largely depend on the health of the crop. However, sugarcane plants are susceptible to various diseases such as Bacterial Blight, Mosaic Disease, Red Rot, Rust Disease, and Yellow Disease, which can significantly reduce crop yield and negatively impact farmers' income [1], [4], [5].

Traditionally, the identification of sugarcane diseases relies on visual inspection by agricultural experts. Although this method can be effective, it is often time-consuming, labor-intensive, and not readily accessible to farmers in many rural regions. Consequently, diseases may remain undetected until they reach advanced stages, leading to severe crop damage and economic losses. With recent advancements in Artificial Intelligence (AI), Deep Learning, and Computer Vision, automated disease detection systems have emerged as a promising solution. These technologies enable the analysis of plant images and provide accurate disease diagnosis in a faster and more efficient manner [1], [5], [12], [13].

The proposed system employs YOLOv10 for sugarcane leaf detection and MobileNetV2 for disease classification [2], [3]. The framework automatically processes sugarcane leaf images and predicts the corresponding disease category along with a confidence score. YOLOv10 efficiently detects and localizes the leaf region, while MobileNetV2 performs accurate disease classification using its lightweight and computationally efficient architecture [2], [3]. By providing rapid and reliable disease diagnosis, the system enables timely intervention, supports better crop management decisions, and contributes to improved agricultural productivity [5], [6], [7].

The main objectives of this research are:

- To develop an intelligent deep learning-based system for automatic sugarcane leaf disease detection and classification.
- To detect and localize sugarcane leaf regions using YOLOv10.
- To classify sugarcane leaf diseases using MobileNetV2 transfer learning.
- To generate confidence scores for disease predictions using a Softmax-based classification layer.
- To assist farmers and agricultural experts in early disease diagnosis and crop management.

2. Background and Related Work

2.1 Conventional Plant Disease Diagnosis

Traditional plant disease diagnosis mainly relies on visual inspection by agricultural experts. Although effective, this process is time-consuming, subjective, and difficult to scale for large agricultural fields. The lack of expert availability in remote farming regions further limits timely disease identification.

2.2 Deep Learning-Based Plant Disease Detection

Recent studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) and transfer learning techniques for automated plant disease detection. **Mohanty et al** [1]. employed deep CNN architectures for image-based plant disease identification and achieved high classification accuracy across multiple crop species. **Ramcharan et al** [4]. demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for cassava disease detection. **Ferentinos** compared several deep learning architectures and reported superior performance over conventional machine learning approaches [5].

Object detection models such as YOLO have also gained popularity for agricultural applications. **Liu and Wang** proposed an improved YOLO-based framework for detecting plant diseases and pests in real-time environments [11]. Recent YOLO variants have further improved localization accuracy and computational efficiency.

2.3 Sugarcane Disease Detection Research

Recent sugarcane-specific studies introduced transformer-based and lightweight CNN architectures for disease diagnosis. While some approaches focus only on classification, others emphasize disease localization. However, few systems combine efficient leaf localization with lightweight disease classification suitable for real-world deployment.

2.4 Research Gap

Most existing systems focus either on disease classification or disease localization independently. Most lightweight classification models do not perform localization, while object detection models often require higher computational resources. To address these limitations, the proposed system combines YOLOv10 for leaf detection and MobileNetV2 for disease classification, providing an efficient and practical solution for sugarcane disease diagnosis.

3. Data and Methods

3.1 Dataset

The study utilizes the Sugarcane Plant Disease Dataset containing approximately 19,926 images distributed across six classes:

• Bacterial Blight Disease – 4,800 images
• Healthy Leaves – 3,132 images
• Mosaic Disease – 2,772 images
• Red Rot Disease – 3,108 images
• Rust Disease – 3,084 images
• Yellow Disease – 3,030 images

The dataset contains images collected under different conditions and includes healthy as well as diseased sugarcane leaves. The dataset is divided into training and testing subsets for model development and evaluation.

3.2 Image Pre-processing

Before classification, images undergo pre-processing operations including:

• Image resizing to 224 × 224 pixels
• RGB colour conversion
• Pixel value normalization

These operations improve input consistency and classification performance.

3.3 Leaf Detection Using YOLOv10

YOLOv10 is used to detect and localize the sugarcane leaf region from the uploaded image. The model generates bounding box coordinates corresponding to the leaf region and removes irrelevant background information.

3.4 Feature Extraction and Classification

The detected leaf image is processed by MobileNetV2, a lightweight convolutional neural network based on transfer learning. The network extracts discriminative features from the leaf image and classifies it into one of six categories.

The classification pipeline consists of:

• MobileNetV2 feature extraction layers

• Global Average Pooling layer

• Fully Connected layers

• Softmax classification layer

3.5 Confidence Score Generation

The Softmax layer generates prediction probabilities for all disease classes. The class with the highest probability is selected as the final prediction, while the corresponding probability is reported as the confidence score.

3.6 Experimental Setup

The proposed Sugarcane Leaf Disease Detection and Classification System is implemented using Python, TensorFlow/Keras, YOLOv10, MobileNetV2, OpenCV, NumPy, and Flask. The model is trained and tested on a sugarcane leaf disease dataset containing six classes. Input images are resized to 224 × 224 pixels and normalized before classification. Model performance is evaluated using classification accuracy**,** confidence scores**.**

3.7 System Architecture

The System Architecture Diagram illustrates the complete workflow of the Sugarcane Leaf Disease Detection and Classification System. The system enables users to upload sugarcane leaf images through a Flask-based web application, where the images are processed using deep learning models. The system integrates YOLOv10 and MobileNetV2 to automatically detect sugarcane leaves, classify diseases, and provide visual explanations of the prediction results.

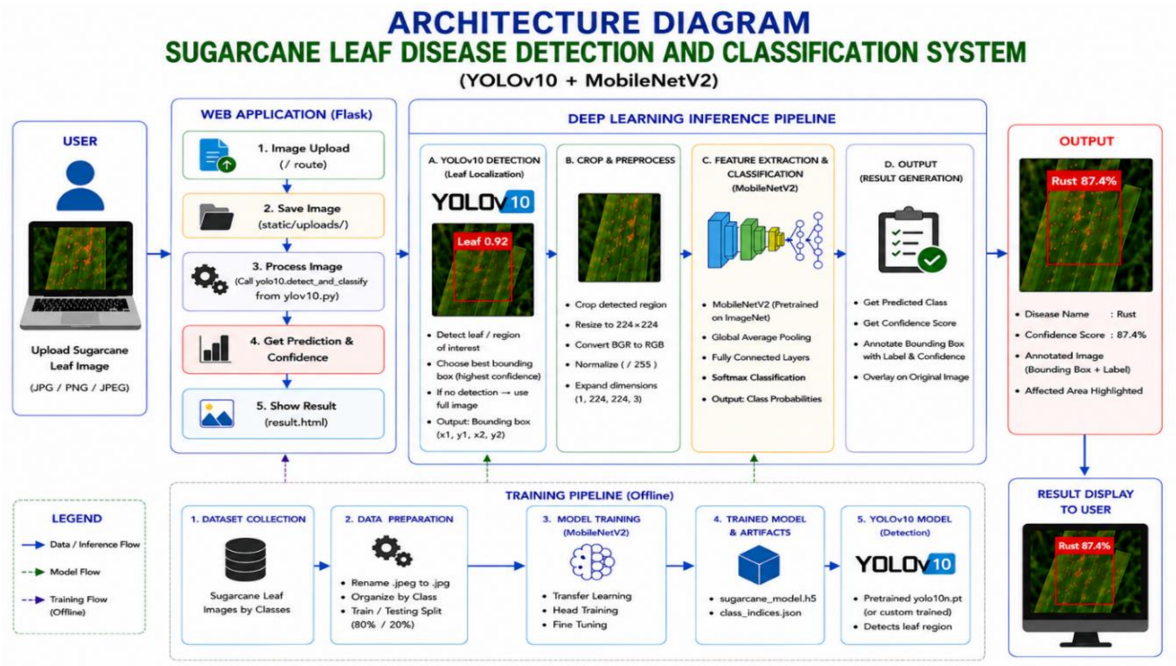

Figure 1: Architecture Diagram for Sugarcane disease Detection & Classification System

The architecture is divided into five major layers: User Layer, Web Application Layer, Deep Learning Inference Layer, Training Pipeline Layer, and Output Layer. The models are trained using a labelled sugarcane disease dataset and the trained model files are utilized during inference. The final output includes the predicted disease name, confidence score, and annotated image highlighting the detected leaf region.

4. Outcomes and Discussion

4.1 Disease Detection Interface

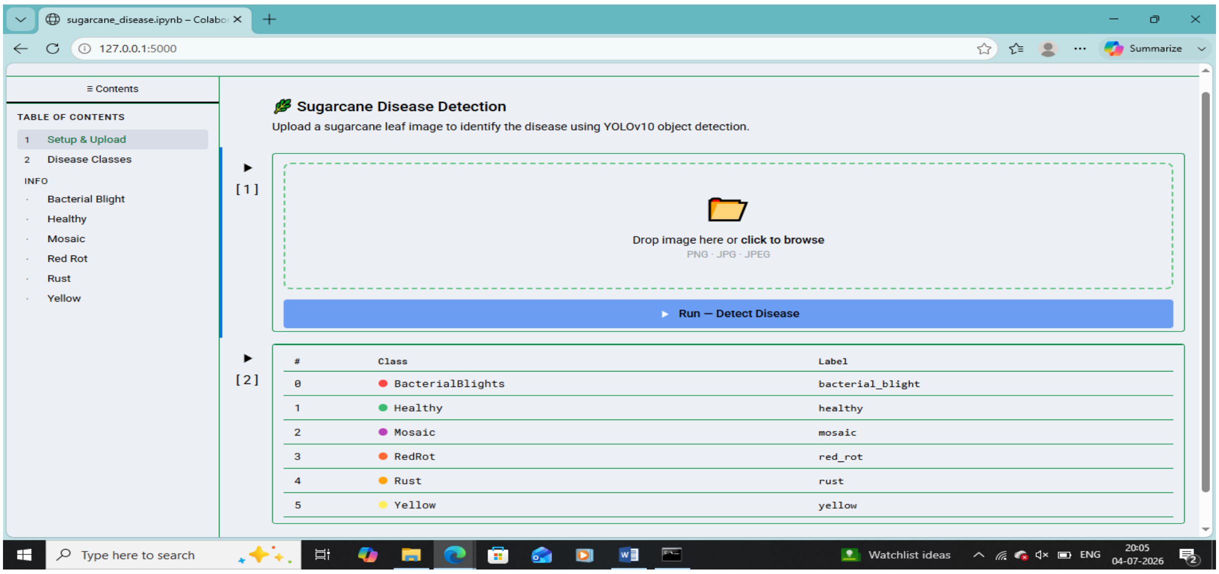

Figure 2: Image upload interface of Sugarcane Leaf Disease

The above figure 2 shows the home page of the Sugarcane Leaf Disease Detection and Classification System, which provides a user-friendly web interface for disease identification. Users can upload sugarcane leaf images in JPG, JPEG, or PNG format through the upload section. The navigation panel displays information about the six supported disease classes: Bacterial Blight, Healthy, Mosaic, Red Rot, Rust, and Yellow Disease. After uploading an image, the user can click the "Run – Detect Disease" button to initiate disease detection and classification using YOLOv10 and MobileNetV2 models. The page also includes a disease class table that serves as a reference for understanding the prediction results generated by the system.

4.2 Prediction Results

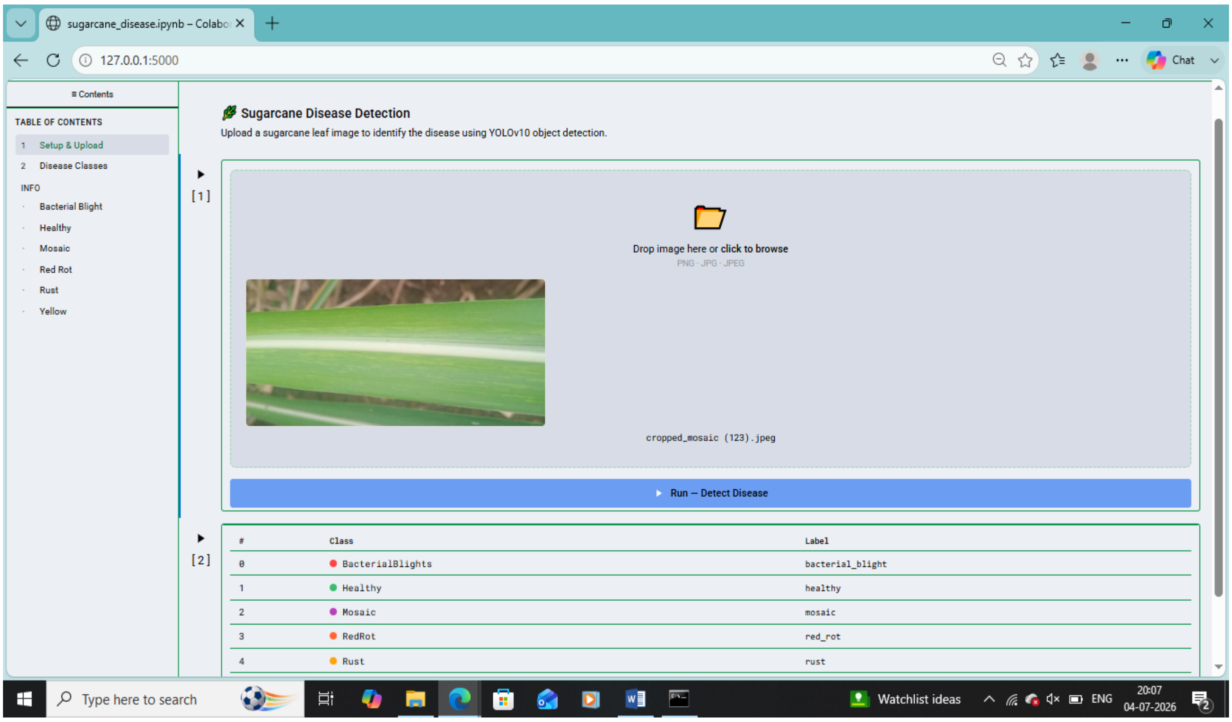

Figure 3: Image upload stage of the Sugarcane Leaf Disease

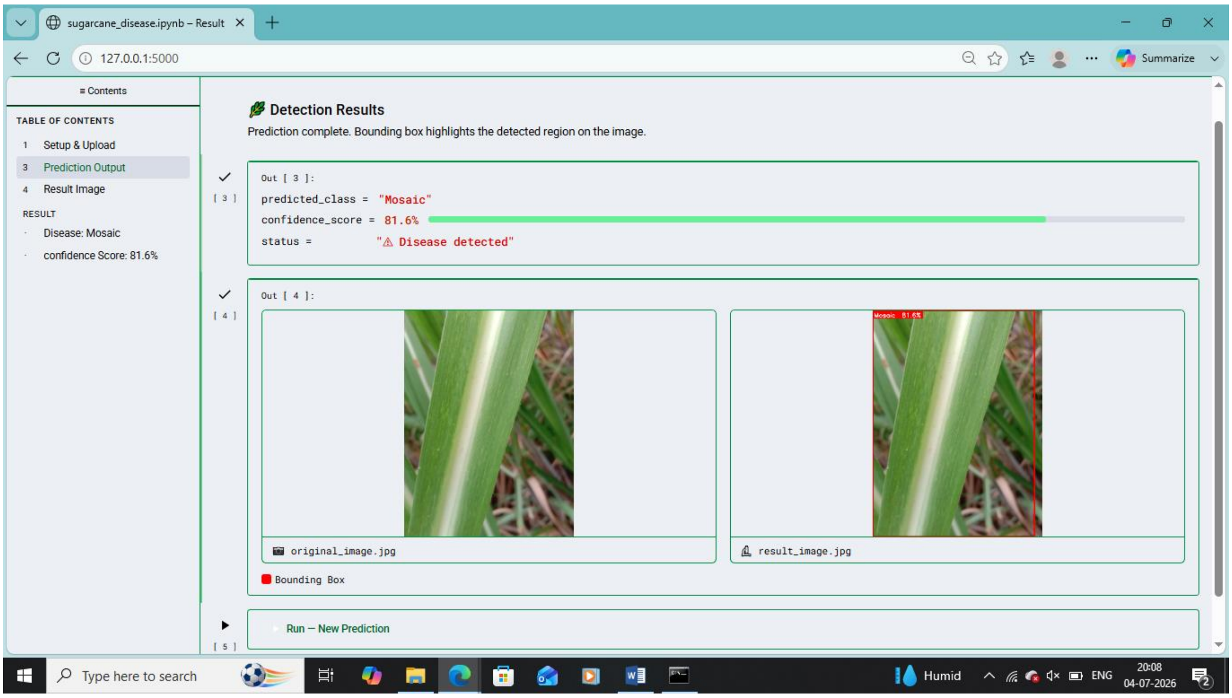

Figure 4: Mosaic Disease

The above figures 3 and 4 illustrate the image upload and prediction stages of the Sugarcane Leaf Disease Detection and Classification System**.** After a sugarcane leaf image is uploaded through the web interface, the system processes it using YOLOv10 for leaf detection and MobileNetV2 for disease classification**.** The final output displays the predicted disease name, confidence score, and an annotated image with a bounding box around the detected leaf region, providing an accurate and user-friendly disease diagnosis.

In the illustrated example, the uploaded sugarcane leaf is identified as **Mosaic Disease** with a confidence score of 81.6%. The system also displays the **leaf image name** used for analysis, allowing users to easily track and verify the uploaded sample. This output demonstrates the effectiveness of the proposed system in accurately detecting and classifying sugarcane leaf diseases while providing a clear visual representation of the analysed leaf region.

4.3 Discussion

The integration of YOLOv10 and MobileNetV2 improves the efficiency of disease diagnosis by focusing classification only on the detected leaf region. The lightweight architecture of MobileNetV2 enables faster inference while maintaining reliable classification performance. The proposed system reduces dependency on manual inspection and provides a practical solution for smart agriculture applications.

4.4 Disease Types

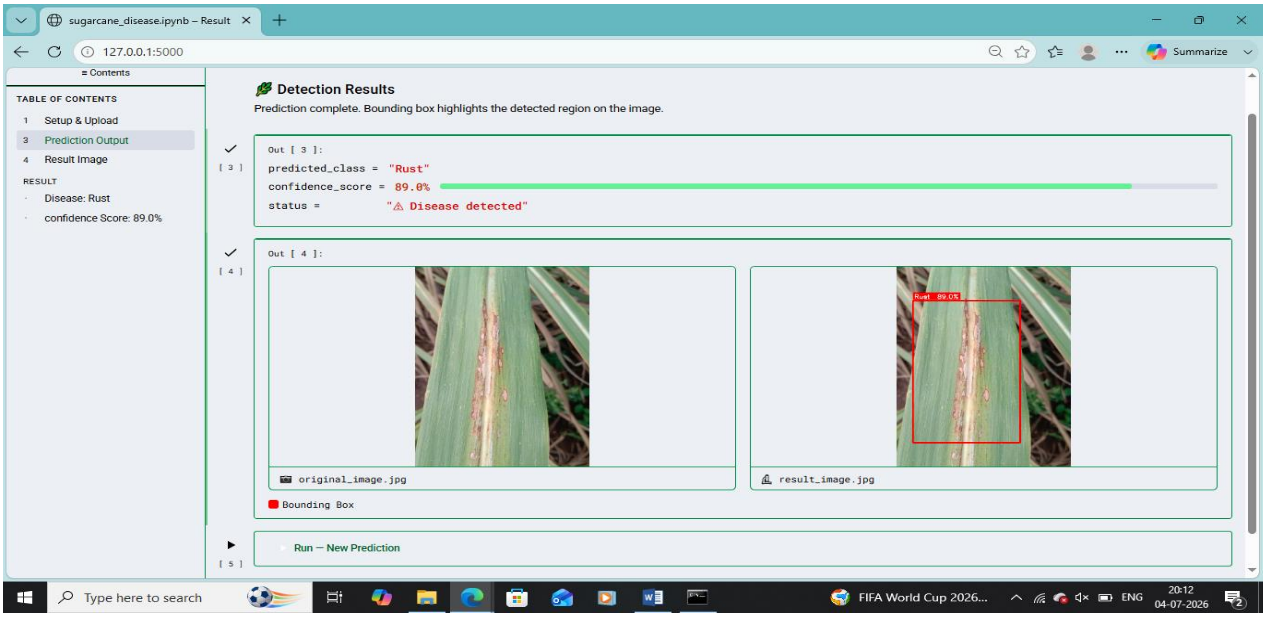

Figure 5: Rust Disease

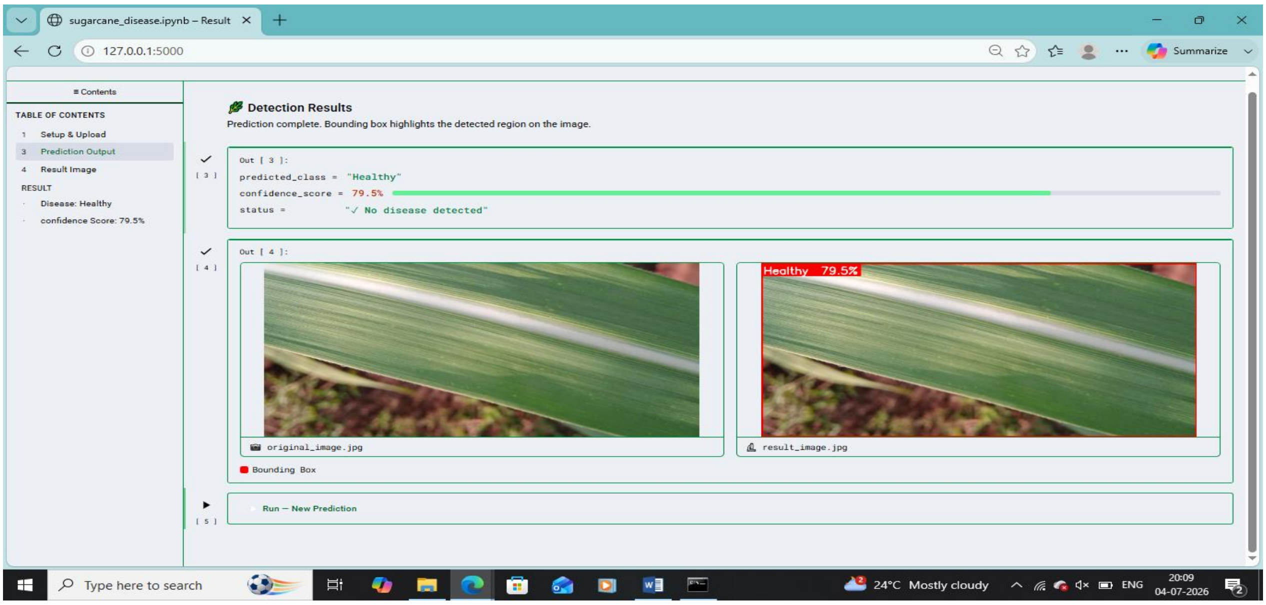

Figure 6: Healthy Leaf

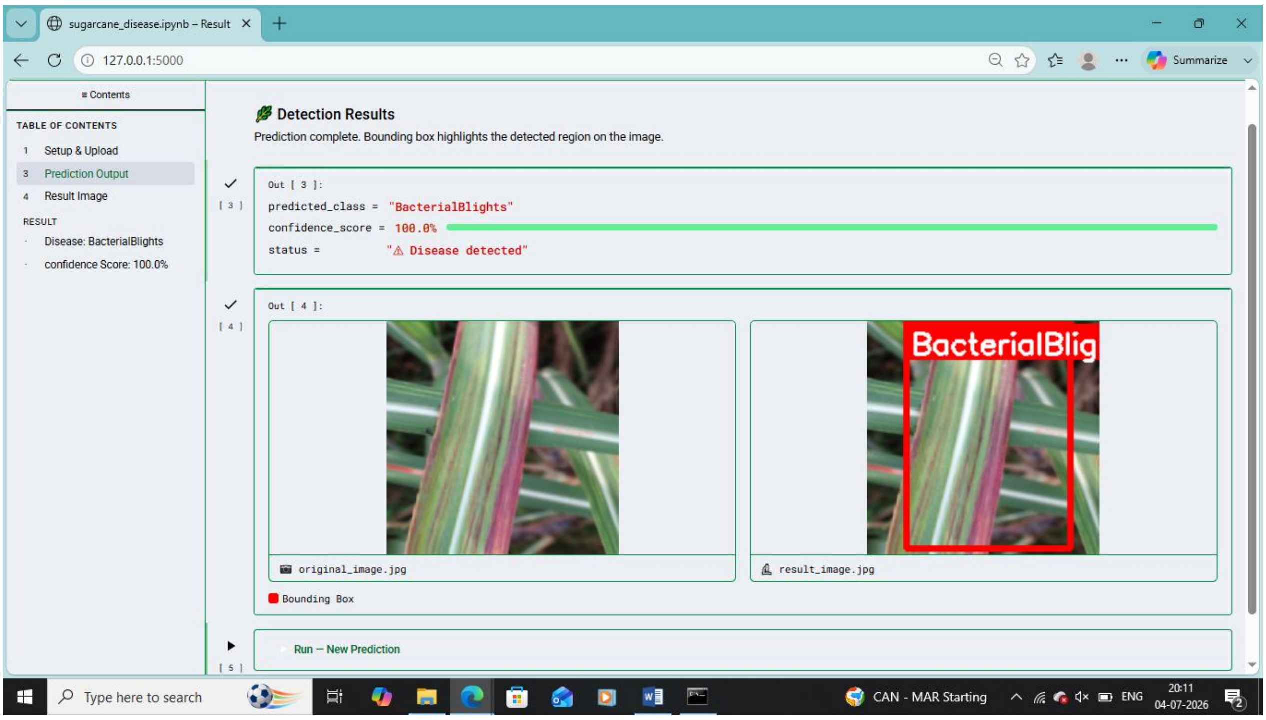

Figure 7: Bacterial Blight Disease

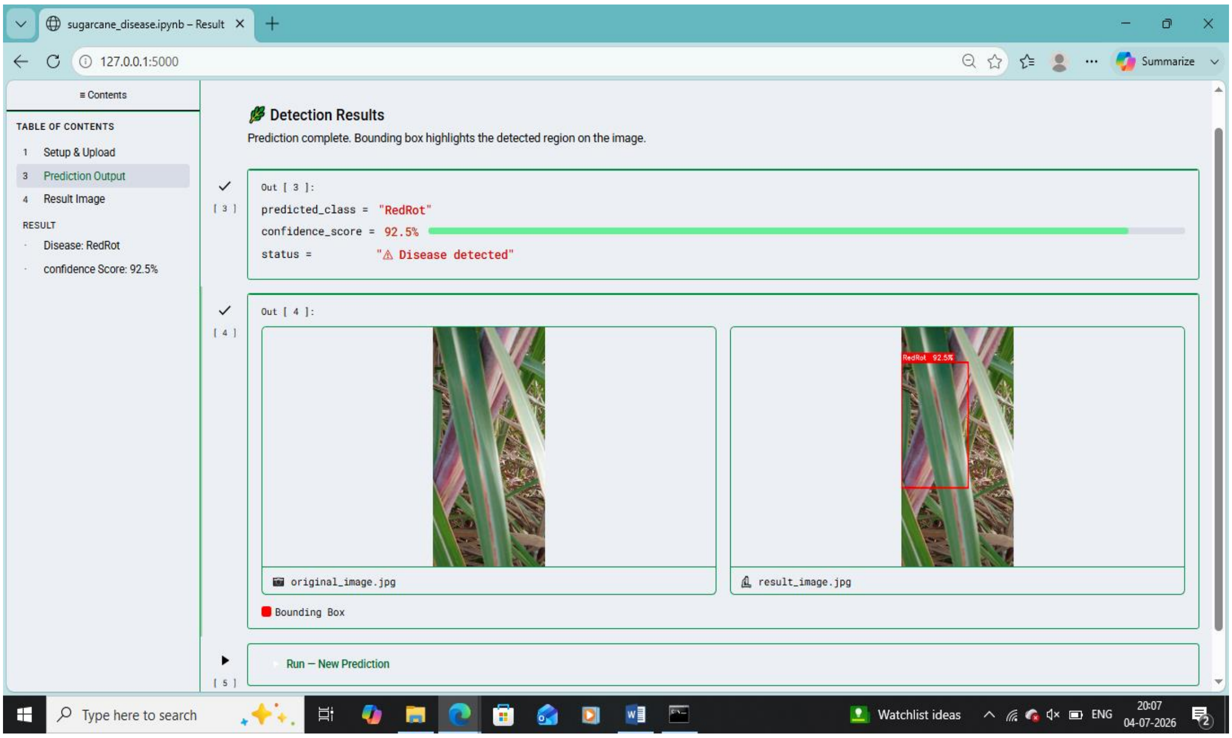

Figure 8: RedRot Disease

5. Conclusion and Future Work

This paper presented a deep learning-based Sugarcane Leaf Disease Detection and Classification System that integrates YOLOv10 and MobileNetV2 for automated disease diagnosis. YOLOv10 effectively localizes sugarcane leaf regions, while MobileNetV2 accurately classifies diseases into six categories:

Bacterial Blight, Healthy, Mosaic, Red Rot, Rust, and Yellow Disease. The proposed framework provides confidence scores and annotated outputs through a user-friendly web interface.

The developed system demonstrates the potential of Artificial Intelligence and Computer Vision in agricultural disease diagnosis. By enabling early disease identification, the framework can support farmers in improving crop health monitoring, reducing crop losses, and enhancing agricultural productivity.

Future work will focus on expanding the sugarcane leaf disease dataset by collecting more images from different regions and environmental conditions. Additional disease categories and nutrient deficiency symptoms can be incorporated to improve the system's diagnostic capabilities. A mobile-based application can be developed to enable farmers to perform disease detection directly using smartphones. Real-time disease detection using live camera feeds can also be implemented for continuous crop monitoring. The system can be enhanced with disease severity estimation to determine the level of infection. Treatment recommendation modules can be integrated to provide disease-specific management suggestions and preventive measures. Future versions may also support cloud-based deployment for remote access and large-scale usage. Integration with IoT devices and smart farming technologies can further improve monitoring and decision-making. Advanced deep learning models may be explored to increase detection accuracy and efficiency. These improvements will make the system more practical, scalable, and beneficial for modern agriculture.

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