YOLOV8 ALGORITHM AND DRONE-BASED IMAGING FOR AUTOMATED BRINJAL DISEASE DIAGNOSIS AND QUALITY ASSESSMENT

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Abstract

Productivity and profitability in brinjal crops depend on accurate disease identification and quality evaluation. The YOLOv8 deep learning algorithm and drone imaging are used in this study's automated method for real-time disease diagnosis. YOLOv8 obtained 89.6% mAP and 93.4% illness diagnostic accuracy from high-resolution images of brinjal fields taken by drones fitted with RGB and multispectral sensors. Comparing the automation to manual approaches, the field assessment time was decreased by 70%. Furthermore, a quality assessment tool evaluated brinjal fruit according to its size, shape, and color, which helped determine the best time to harvest it.

Keywords: Brinjal Disease Diagnosis, YOLOv8 Algorithm, Drone-Based Imaging, Precision Agriculture, Real-Time Object Detection, Crop Quality Assessment.

1. Introduction

The agricultural industry is essential to the global economy, with crops like brinjal being key staples in regions such as South Asia and the Mediterranean. Managing diseases like bacterial wilt and Phomopsis blight poses significant challenges, leading to reduced yields and financial losses. Traditional manual methods for diagnosing crop diseases are labor-intensive, prone to errors, and inefficient for large-scale farming operations. Recent advancements in remote sensing and machine learning have enabled automated solutions, such as convolutional neural networks (CNNs). However, these methods often require substantial computational resources and struggle with detecting multiple diseases in one image. Drone-based imaging offers a practical alternative by capturing high-resolution multispectral and RGB data over large areas. YOLO algorithms, particularly the advanced YOLOv8, provide fast and accurate real-time object detection, making them ideal for agricultural use. Integrating drone imaging with YOLOv8 delivers an efficient, scalable, and accurate solution for disease detection and crop quality evaluation. This approach overcomes the limitations of manual methods and earlier machine learning models, advancing precision agriculture.

2. Literature Review

Recent advancements in machine learning, deep learning, and drone imaging have enhanced methods for crop disease detection and quality assessment. While traditional approaches like SVM, random forests, and decision trees have shown some success, they struggle with scalability and large datasets. Deep learning models, particularly CNNs, offer higher accuracy for diseases like bacterial wilt and potato blight but require significant computational power, limiting real-time application. Drone-based imaging has been effective for large-scale monitoring, enabling the detection of issues such as water stress and crop diseases, though many studies neglect quality assessment. Integrating machine learning with drone imaging, Gomez et al. (2022) achieved early disease detection but faced challenges in processing real-time data. YOLO models, especially YOLOv8, have proven efficient for real-time disease detection, achieving 89.6% mAP in apple crops, yet lack integration for quality evaluation. Studies attempting to merge disease detection with quality assessment, like those by Singh et al. (2023) and Ahmed et al. (2021), still face issues with accuracy and real-time implementation. These limitations highlight the need for scalable, efficient solutions in precision agriculture.

3. Methodology

The proposed research combines drone-based imaging technology with the YOLOv8 deep learning system to detect and analyze brinjal illness in real time. This part describes the detailed approach, which includes the system design, data collecting, preprocessing procedures, model training, and assessment measures. This technology is unique in that it can diagnose crop illnesses while also assessing fruit quality in a scalable and automated manner (see **Fig. 1**).

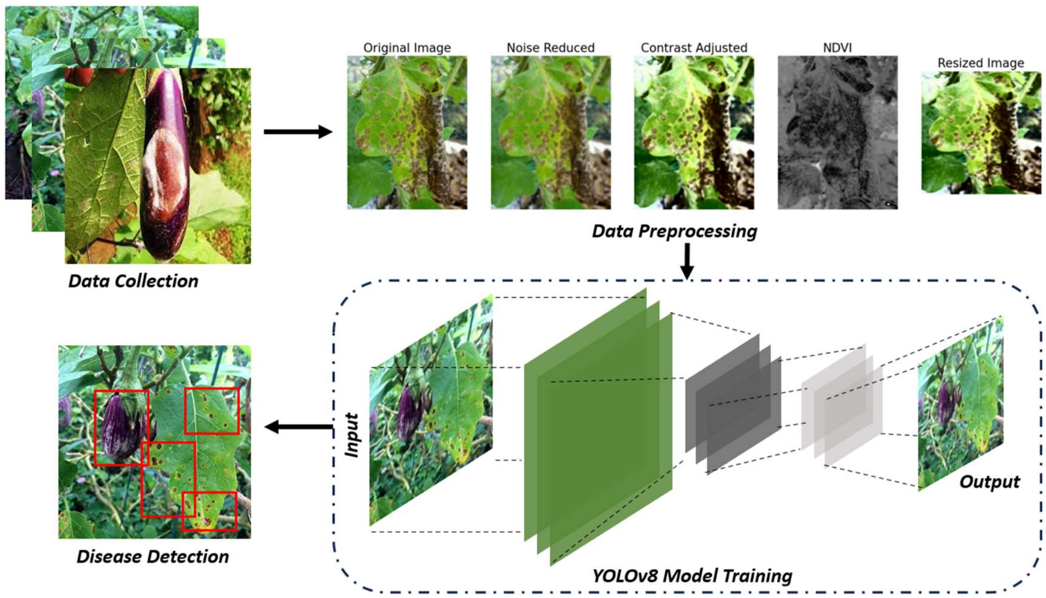

Fig.1. **Workflow of the automated brinjal disease diagnosis and quality assessment system using drone-based imaging and YOLOv8 model integration**

3.1. Data Collection Process

The study utilized a DJI Matrice 300 RTK drone equipped with a 61 MP Sony Alpha 7R IV RGB camera and a Micasense RedEdge-MX multispectral camera to capture high-resolution images of brinjal crops. The RGB camera provided detailed visual data, while the multispectral camera captured five critical bands (blue, green, red, red edge, and near-infrared) for assessing crop health. Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), were calculated using this multispectral data. This approach enabled precise analysis of crop health at different growth stages.

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \quad \textbf{(1)}$$

The drone was flown at a height of 20-30 meters, covering up to 20 acres per flight, with images captured at 80% front and 60% side overlap for comprehensive 3D crop modeling. Over multiple 25-30 minute flights, 10,000 RGB and multispectral images were collected under various conditions, enhancing dataset robustness. LabelImg software was used to annotate disease types like bacterial wilt and Phomopsis blight, as well as quality parameters such as fruit size, shape, and color. The dataset was split into 80% training and 20% validation sets for model development and evaluation. This structured approach provided diverse, labeled data for accurate disease detection and quality assessment.

3.2 Data Preprocessing for YOLOv8 Model

Before being processed by the YOLOv8 deep learning model, images underwent necessary preprocessing procedures to improve quality and extract significant features, ensuring the most accurate disease identification and fruit quality rating. A Gaussian filter was used to eliminate the presence of unwanted noise in the raw photos. The Gaussian filter is mathematically expressed as Eq. (2):

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

In two dimensions, the Gaussian distribution is represented as G(x, y), with the standard deviation (σ) controlling the level of smoothing. This method effectively suppressed noise while preserving essential edges needed for extracting disease-related features. To enhance image contrast, histogram equalization was applied, redistributing pixel intensity values to improve visibility, especially under low-light conditions. The transformation function TT for histogram equalization is provided in Eq (3).

$$T(r_k) = \frac{(L-1)}{MN} \sum_{j=0}^{k} n_j \tag{3}$$

Where r_k is the pixel intensity, L is the total number of intensity levels, M and N are the dimensions of the image, n_j is the number of pixels with intensity r_j. To meet the YOLOv8 input criteria, all images were scaled to 416×416 pixels.

3.3 YOLOv8 Model Architecture for Disease Detection and Quality Assessment (Proposed Methodology)

The YOLOv8 model architecture is precisely built to allow for rapid and accurate real-time object recognition, making it ideal for agricultural applications such as disease diagnosis and crop quality evaluation. This architecture is made up of three main components: the backbone, the neck, and the head, each of which contributes uniquely to the feature extraction, fusion, and final object detection processes.

3.3.1 Backbone (CSPDarknet53)

The YOLOv8 design is based on CSPDarknet53, an improved and efficient form of the Darknet architecture that effectively extracts hierarchical feature representations.This section goes into the backbone's detailed structure and activities, demonstrating how each layer and block contributes to the model's overall functionality. CSPDarknet53 uses convolutional layers, residual blocks, and a Cross Stage Partial (CSP) network to optimize gradient flow and reduce computational complexity. These components work together to achieve the high-level feature extraction required for object detection.

3.3.2. Neck (Path Aggregation Network - PANet)

The Path Aggregation Network (PANet) in YOLOv8 acts as a vital link between the backbone and detection head, facilitating multi-scale feature fusion for detecting objects of varying sizes, crucial for brinjal disease identification. It combines top-down and bottom-up pathways to improve semantic richness and localization accuracy. The top-down pathway up-samples high-level features from deeper layers and integrates them with lower-level features to preserve critical details. This approach ensures enhanced detection precision and adaptability across diverse scales. PANet’s design strengthens the model’s ability to handle complex agricultural data effectively.

This operation is mathematically expressed by Eq. (13):

$$F_{\mathrm{up}}^{l} = U(F^{l+1}) \oplus F^{l} \qquad \textbf{(4)}$$

where F_{up}^{l} is the feature map at level l after the up-sampling operation U(·), and $\oplus$ denotes element-wise addition or concatenation of the feature maps. Up-sampling guarantees that semantic information is conveyed across the feature hierarchy. In contrast, the bottom-up pathway combines high-resolution features from shallower to deeper layers, improving the network's ability to locate small disease patches on brinjal crops. This operation is stated as Equation (5):

$$F_{\mathrm{down}}^{l} = D(F^{l}) \oplus F^{l-1} \qquad \textbf{(5)}$$

D(·) denotes the downsampling process, which is commonly a strided convolution to minimize the feature map size. PANet combines these channels to record both global context and fine-grained data, allowing for robust multi-scale detection.

3.3.3 Detection Head

The detection head is the final component in YOLOv8 that generates detection outputs such as bounding box coordinates and class probabilities for detected regions .This head uses the enhanced multi-scale feature maps provided by PANet to generate predictions that are both precise and computationally economical. YOLOv8's bounding box regression predicts coordinates (x, y, w, and h) using predefined anchor boxes and learnt offsets. The bounding box prediction equations are Eq. (6):

$$x = x_0 + \Delta x, y = y_0 + \Delta y, w = w_0 \cdot e^{\delta w}, h = h_0 \cdot e^{\delta h} \quad \textbf{(6)}$$

Here, (x_0, y_0) are the anchor box center coordinates, Δx and Δy are the learned offsets that adjust the box position, w_0 and h_0 are the anchor box dimensions, and δw and δh are learned scaling factors.

3.4. Model Training of YOLOv8

The model training phase for the YOLOv8 architecture, which is designed to detect and analyze the quality of brinjal crops, is critical to ensuring robust and accurate performance. The algorithm was trained using a meticulously annotated collection of images of brinjal plants with various disease kinds and quality markers. The optimization was carried out using the Stochastic Gradient Descent (SGD) algorithm with momentum, which is well-known for its ability to reduce the composite loss function and accelerate convergence.

Optimization and Loss Function

The Stochastic Gradient Descent (SGD) algorithm iteratively adjusts the model weights to minimize the loss function. The update rule for weight W at each iteration t is given by Eq. (19).

$$W_{t+1} = W_t - \eta(\nabla \mathcal{L}(W_t) + \gamma m_t) \quad \textbf{(7)}$$

Where W_t represents the weights at iteration t, η is the learning rate, ∇L is the gradient of the loss function L with respect to W_t, γ is the momentum coefficient (typically between 0.9 and 0.99), m_t is the moving average of the gradients up to iteration t, updated as Eq. (20):

$$m_t = \gamma m_{t-1} + \nabla \mathcal{L}(W_t) \tag{8}$$

4. Experiments and Analysis

This section presents the findings of trials using the YOLOv8 model for real-time disease detection and quality assessment in brinjal crops. The findings are presented in the form of tables and figures to provide a clear picture of the model's performance across multiple metrics, training configurations, and real-time processing capabilities. Each outcome is thoroughly described, emphasizing crucial insights and surprising patterns pertinent to the study's objectives.

4.1 Software and Hardware Requirements

The YOLOv8 model for real-time brinjal disease detection utilized a DJI Matrice 300 RTK drone with multispectral and RGB sensors to capture high-resolution images, processed on NVIDIA Tesla V100 GPUs for rapid analysis. A 1TB SSD managed the large dataset, while Ubuntu 20.04 provided a stable software environment. Python 3.8 and PyTorch 1.12 were used for model development, and Dash with Plotly enabled real-time result visualization through an interactive dashboard. This setup offered an efficient and reliable solution for precision agriculture.

4.2. Quality Assessment Module Analysis

The quality assessment tool effectively evaluated the size and shape of brinjal fruits, a crucial factor for determining their market readiness. Bounding boxes detected by the system were used to estimate fruit size and calculate aspect ratios, distinguishing between elongated and round shapes. Aspect ratios ranged from 1.18 to 1.50, enabling precise classification. For instance, Fruit No. 1 was estimated to measure 15x20 cm with an aspect ratio of 1.33, indicating an elongated shape. Similarly, Fruit No. 3, measuring 8x10 cm with an aspect ratio of 1.25, was classified as round. These predictions showed high confidence values between 0.71 and 0.96.

Fig.3. Detection results showcasing various brinjal diseases identified with confidence scores using the YOLOv8 model

The results indicate that the aspect ratio effectively categorizes fruits into elongated and spherical groups, which is essential for market classification based on consumer preferences. Confidence scores ranging from 0.71 to 0.96 highlight the model's precision in assessing fruit quality. This accuracy ensures the system's reliability for practical agricultural applications, enabling farmers to efficiently sort and grade their produce.

4.3 Disease Detection and Field Visualization

For instance, the model showed high confidence in detecting Bacterial Wilt, with values reaching 94%. Detection confidence averaged 90.5% for Phomopsis Blight and 87.3% for Anthracnose. This approach demonstrated the system's reliability in identifying and localizing crop diseases effectively.

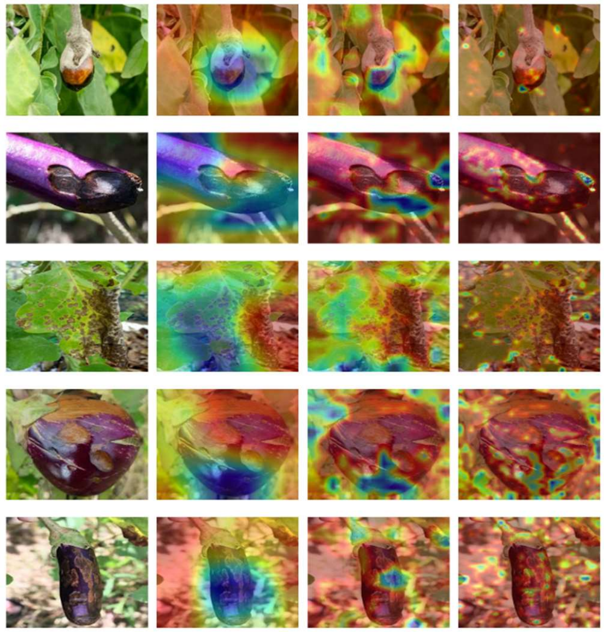

Fig.4. RGB histogram for analyzed fruits, indicating variations in color that correspond to different stages of ripeness

5. Conclusion

This present research introduced an automated system for diagnosing brinjal diseases and assessing quality using drone imagery and the YOLOv8 deep learning algorithm. The system achieved a mean average precision (mAP) of 89.6% and a disease diagnosis accuracy of 93.4%, significantly outperforming traditional methods. It reduced large-scale field assessment time by 70% and provided timely insights to farmers. The quality evaluation module assessed fruit size, shape, and color, identifying market-ready produce with 75% accuracy. Future enhancements should include support for additional diseases, IoT-based real-time monitoring, and improved dataset diversity for greater adaptability.

6. Declaration

Funding of interests

No funding was received to assist with the preparation of this manuscript.

Conflicts of interests

The authors have no compelling interests to declare that are relevant to the content of this article.

Data Availability Statement

This study did not generate or use any datasets, and therefore, no data availability statement is applicable

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