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RESEARCH ARTICLE

YOLOV9-DBN: HYBRID YOLOV9 AND DBN ARCHITECTURE FOR AUTOMATED BANANA LEAF DISEASE DETECTION & CLASSIFICATION

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Abstract – Banana leaf disease detection (BLDD) is an automated approach used to identify diseases in banana leaves for improving crop health and agricultural productivity. Accurate and real-time diagnosis of banana leaf diseases remains difficult due to environmental variability, visual similarity of symptoms, and the need for computationally efficient models. To address these issues, a YOLOv9 model is proposed, using advanced deep learning architectures for accurate banana leaf disease classification. Adaptive trilateral filtering is used to improve banana leaf image quality by lowering noise while preserving sharp edge information and disease lesion patterns. YOLOv9-based detection is used to correctly locate diseased patches in banana leaves, allowing for exact identification of infection sites. Furthermore, a Deep Belief Network (DBN) is developed to improve multi-level disease classification by learning discriminative representations from identified regions. The proposed framework classifies banana leaf conditions into healthy, cordana, pestalotiopsis, and sigatoka categories based on the extracted features, ensuring accurate and reliable disease severity assessment for precision agriculture applications. The YOLOv9 model achieves an accuracy of 91.9%.

Keywords *– YOLOv9, Deep Learning, Banana Leaf disease, Deep Belief Network, Disease Detection.*

1. INTRODUCTION

Banana Leaf Spot Disease poses a serious threat to banana plants, appearing as spots that range from small specks to large, merging lesions on leaves [1]. Banana crops are affected by many diseases with syndromes visual in leaves, stems, flowers, fruits, roots, and suckers [2]. Among these, major diseases such as Sigatoka, fusarium wilt, and Cordona are significant threats to banana production [3]. In particular, leaf-related diseases significantly reduce overall crop productivity [4].

Despite significant advances in plant disease identification, existing methods still struggle to achieve high accuracy and generalization across various datasets [5]. Furthermore, the combination of machine learning (ML) and DL approaches frequently increases computational complexity, limiting their usefulness in real-time applications [6]. Furthermore, YOLO-based detection models struggle with exact multi-class classification and robustness under changing environmental conditions [7].

Advanced deep learning architectures such as Convolutional Neural Networks (CNN) [8], Long Short-Term Memory (LSTM) [9], RegNet models [10], and real-time object detection frameworks like YOLO [11] have significantly improved the accuracy of banana leaf disease. These approaches capture complex spatial and temporal patterns in leaf images, allowing for accurate disease identification under a variety of environmental conditions. To overcome these limitations, this research proposed a YOLOv9 framework for Banana Leaf Disease Detection. Major contribution of this research are outlined as follows:

- Developed a hybrid YOLOv9-DBN framework for accurate banana leaf disease detection and classification.
- Adaptive Trilateral Filter is employed in the preprocessing stage to minimize noise and preserve leaf texture and lesion details, resulting in accurate feature representation.
- YOLOv9 based detection module is utilized to precisely localize diseased regions on banana leaves improving the quality of extracted regions for subsequent analysis.
- Based on the extracted features from detected regions, a DBN model is employed to perform accurate classification of disease severity into

healthy, cordana, pestalotiopsis, and sigatoka categories.

2. LITERATURE REVIEW

In recent years, researchers have introduced ML and DL approaches for banana leaf disease detection. A overview of numerous existing works on BLDDs presented in this literature sections.

In 2025, Mora, J.J., et al., [12] developed Several foundation models, including YOLONAS, YOLOv8, YOLOv9, and Faster-RCNN, were tested for accurate banana leaf disease detection on various platforms. Among these, YOLOv9 outperformed mAP@50 with precision values ranging from 55% to 86% for detecting healthy leaves, cordonas, and other damaged leaf in aerial images.

In 2025, Lin, S., et al., [13] developed a UAV-based remote sensing approach that significantly reduces labor and time requirements while effectively identifying BFW and evaluating sickness severity over wide areas using a BFW severity detection (BFWSD) model. The experimental findings show the model outperforms standard object detection algorithms, with a 6.5% higher recall than YOLOv8n.

In 2025, Lai, Z., et al., [14] presented an enhanced YOLOv8n model specifically designed for BLDD. In context of networks architecture optimization, CA attention mechanism is introduced after the P5 layer of the backbone network, and an Efficient Multi-scale EMA Attention Mechanism is incorporated after each C2f module in the neck network. The model improves accuracy by 4.24%, according to experimental findings.

In 2024, Nyambo, D., et al., [15] introduced DL methods, particularly the fundamental Convolutional Neural Networks and VGG16 models, which were applied to problem of detecting Black Sigatoka disease in banana leaves. The results of the trials revealed that the basic Convolutional Neural Networks model attained a validation accuracy of 89%.

In 2024, Genet, Y.H., et al., [16] suggested a reliable disease detection model by utilizing Convolutional Neural Network methods, which have produced an advanced system that can precisely recognize and classify diseases in banana plants. During extensive testing with separate datasets, VGG16 model demonstrated an amazing identification accuracy of 81.53%.

3. PROPOSED METHODOLOGY

This research, YOLOv9-DBN model has been proposed for accurate banana leaf disease detection. The overall workflow of YOLOv9-DBN is display in Figure.1.

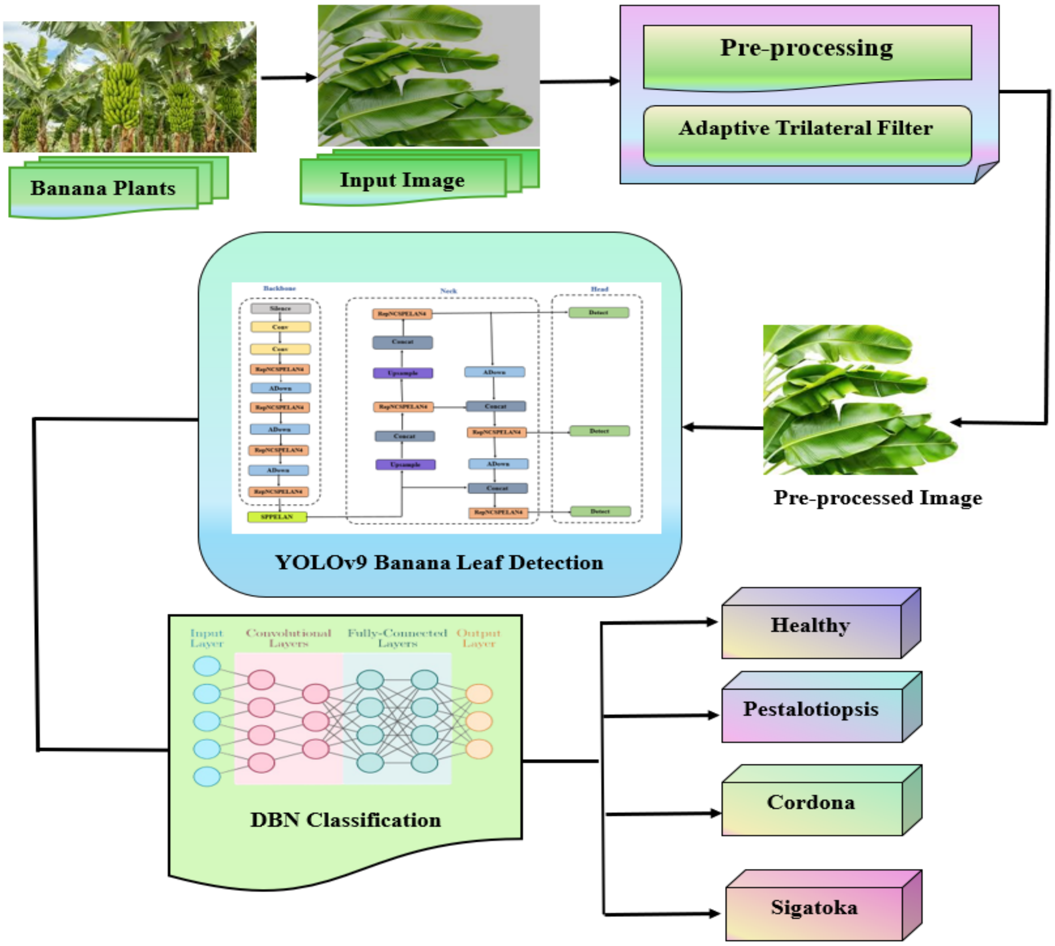

Figure 1. Workflow of YOLOv9-DBN

3.1 Dataset Description

The Banana Leaf Spot Disease dataset includes different varieties of damaged banana leaves: Sigatoka, Pestalotiopsis, and Cordana. They are complemented with image sequence of colorful banana leaves. The four classes contain 937 images. Table 1 depicts the class-wise distribution of sets.

Table 1. Class wise distribution

Class Name	Total
Pestalotiopsis	173
Sigatoka	473
Cordona	162
Healthy	129
Total	937

3.2 Adaptive Trilateral Filter (ATF)

Banana leaf images are preprocessed using an ATF to effectively suppress noise and motion artifacts while preserving important structural and textural details such as lesions, spots, and vein patterns. It implements the bilateral filter's guiding principles.

$$h_\theta\ (q) = \frac{1}{l_\theta} \sum_q \sum_p f_p H(q,p) Z(f_q, f_p) \quad (1)$$

When the kernel is tilted trilateral filter's $H(.)$ and $Z(.)$ functions become non-orthogonal. Equation (1) establishes the value of each pixel at this plane.

$$f(q,p) = f(q) + h_\theta.(||q-p||) \quad (2)$$

Where $|q-p|$ is the multi-dimensional spacing between q and f(q) represented by q at a target pixel, and h_θ is the tilting angle.

$$f_o(q) = f_{in}(Y) + t(Y)\Delta \quad (3)$$

Where Δ denotes the spatial distance between pixels q and p, and $f_o(q)$ is the output function. Tilting improves the filter's capacity to smooth out high gradient zones. This results in improved noise suppression and better preservation of disease-specific features, thereby strengthening the preprocessing stage for accurate banana leaf disease detection and classification.

3.3 YOLOv9 Detection

YOLOv9 is a creative real-time illness diagnosis that combines cutting-edge DL methods with architectural advances to achieve remarkable disease detection performance. The Generalized Efficient Layer Aggregation Network (GELAN) and Programmable Gradient Information (PGI) are used for efficient feature extraction and accurate gradient propagation, respectively. These enhancements mitigate information loss and improve model flexibility, resulting in superior detection accuracy compared to earlier YOLO versions. Backbone utilizes CSPNet and ELAN modules, along with RepNCSP-ELAN blocks, to efficiently extract multi-scale features while maintaining a lightweight design in Fig 2.

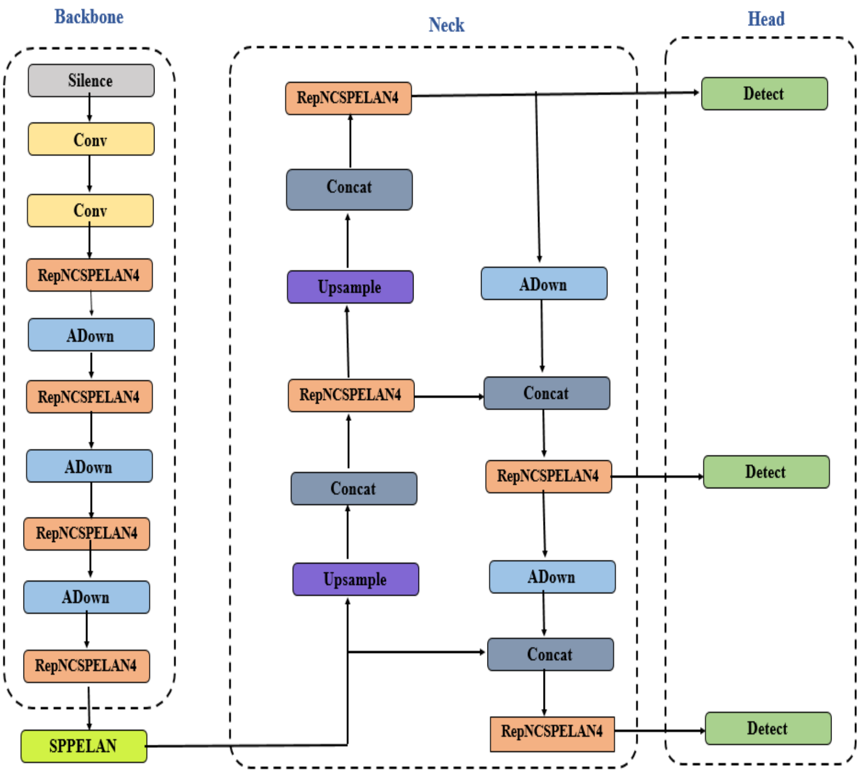

Figure 2. Architecture of YOLOv9

YOLOv9 employs a unique loss function to aid in effective training optimization, and non-maximum suppression (NMS) is used to enhance detection outputs, hence enhancing accuracy and efficiency. This is determined as:

$$L_{YOLOv9} = \lambda_{boxs}.L_{boxs} + \lambda_{clss}.L_{clss} + \lambda_{obj}.L_{obj} \quad (4)$$

The weights λ_{boxs}, λ_{clss}, and λ_{obj} control each component of the model's error contributes during training. L_{boxs} is calculated as follows:

$$L_{boxs} = \frac{1}{N}\sum_{i=0}^{N}[(x_i - x_i^{true})^2 + (y_i - y_i^{true})^2 + (w_i - w_i^{true})^2 + (h_i - h_i^{true})^2] \quad (5)$$

Where L_{boxs} represents the bounding box regression loss and N denotes the total number of bounding boxes. L_{clss} is calculated as follows:

$$L_{clss} = \frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_i^{(c)} log\hat{p}_i^{(c)} \quad (6)$$

Where L_{clss} represents classification loss, N represents no of predicted bounding boxes, and C is no of classes. It improves disease identification by calculating the mean difference between expected and real objectness ratings. L_{obj} is represented as:

$$L_{.obj} = -\frac{1}{N}\sum_{i=1}^{N}[\, y_i^{obj} log\hat{p}_i^{(obj)} + (1.-y_i^{obj})\log(1.-\hat{p}_i^{(obj)})] \quad (7)$$

Where $L._{obj}$ represents the objectiveness loss, and $\hat{p}_i^{(obj)}$ is the predicted objectness score or confidence level.

3.4 DBN Classification

Deep Belief Networks (DBNs) are probabilistic generative models composed of multiple Restricted Boltzmann Machines (RBMs), and they are effectively utilized for banana leaf disease detection. DBNs are trained using a combination of greedy layer to improve classification performance. In this architecture, connections exist only between adjacent layers, while neurons with same layer remain unconnected. During model construction, the hidden layer of one RBM acts as visible layer for RBM. The network typically trained in a bottom-up manner, where each RBM is pretrained sequentially to extract meaningful features from banana leaf images. Subsequently, supervised learning is applied to fine-tune the entire network for accurate disease classification. The final output layer utilizes learned probability distributions from preceding layers to generate predictions. The formula for its energy function for a specific set of states (W, t) as:

$$A_{\emptyset}(w,t) = -\sum_{i=1}^{m_w} p_i w_i - \sum_{j=1}^{m_t} e_j t_j - \sum_{i=1}^{m_w}\sum_{j=1}^{m_t} v_{ij} w_i t_j \quad (8)$$

There is a connection between i neurons in hidden layer and j neurons in visible layer, represented by v_{ij}. The component form is displayed earlier however, matrix form is an alternative:

$$A_{\emptyset}(w,t) = -p^H t - e^H w - Vwt \quad (9)$$

To obtain joint probability distribution of state (W, T) use the following energy function:

$$B_{\emptyset}(w,t) = \frac{1}{X_{\varphi}} * a^{-A_{\varphi}(w,t)} \quad (10)$$

Banana leaf diseases they are healthy, cordana, pestalotiopsis, and sigatoka are classified.

4. RESULTS AND DISCUSSION

This section analyzes performance of banana leaf disease detection model using standard evaluation metrics. The experiments were conducted on a system with Windows 10 operating system, and a minimum of 8GB RAM. The implementation was carried out using Python 3.12 in environments such as Visual Studio Code and Google Colab. Detailed performance analysis of YOLOv9-DBN model with deep learning architectures, including YOLO-based detection and DBN-based classification, is presented this section.

4.1 Performance Analysis

Effectiveness of YOLOv9-DBN was evaluated using specified measures namely like Accuracy (Acy), Recall (Rcl), Precision (Pcn), Specificity (Spy), and F1-score (Fs) respectively.

$$Acy = \frac{\mathrm{Tp+Tn}}{\mathrm{Tp}+Fp+\mathrm{Tn+Fn}} \quad (11)$$

$$Rcl = \frac{Tp}{Tp + Fn} \quad (12)$$

$$Pcn = \frac{Tp}{Tp+Fp} \quad (13)$$

$$Spy = \frac{Tn}{Tn+Fp} \quad (14)$$

$$Fs = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (15)$$

Where Fp represents False positive, Fn represents False negative, Tn represents True negative and Tp represents True positive.

Table 2. Efficiency analysis

Diseases	Accuracy
Healthy	87.9%
cordana	93.5%
pestalotiopsis	89.9%
sigatoka	96.3%

Table 2 presents efficiency analysis of proposed YOLOv9-DBN for diseases that includes healthy, cordana, pestalotiopsis, and sigatoka. The proposed YOLOv9 model achieves higher accuracy of 87.9%, 93.5%, 89.9% and 96.3% for healthy, cordana, pestalotiopsis, and sigatoka.

Figure 3 shows confusion matrix of proposed YOLOv9-DBN for banana leaf disease classification, which includes healthy, cordana, pestalotiopsis, and sigatoka categories. The diagonal values reflect the high predictability of YOLOv9-DBN model.

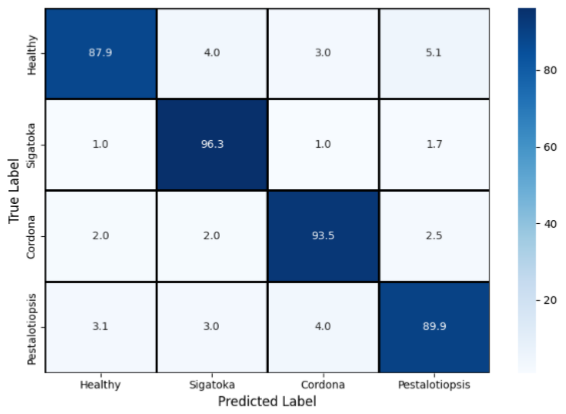

Figure 3. Confusion Matrix

4.2 Comparative Analysis

A comparative analysis was conducted among YOLOv9 model and four other DL networks such as SSD, YOLOv5, YOLOv7, YOLOv8 and YOLOv9.

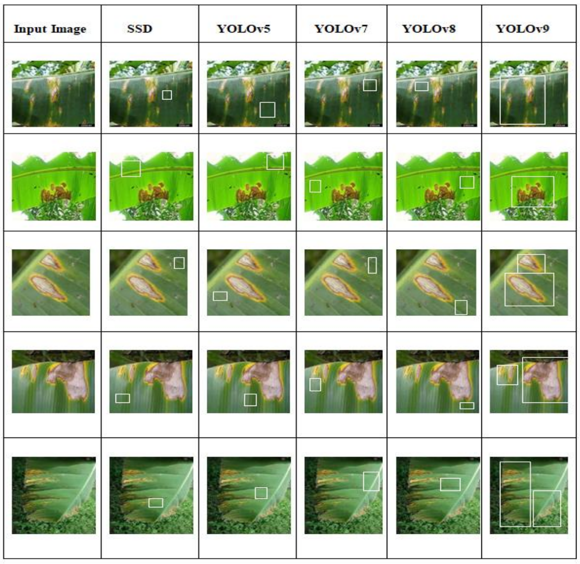

Figure 4. Visualization results of existing and proposed model

This figure 4 compares the five detection networks such as SSD, YOLOv5, YOLOv7, YOLOv8 and YOLOv9 on their ability to identify lesions on banana leaves. While the earlier models SSD through YOLOv8 frequently miss large diseased areas or only detect small, fragmented spots. YOLOv9 demonstrates significantly higher accuracy than other four models. It consistently produces larger, more comprehensive bounding boxes that better represent the actual scale of the leaf damage across all five samples.

Table 3. Comparison of existing models and YOLOv9-DBN model

Authors	Approaches	Acy
Nyambo, D., et al., [15]	CNN and VGG16 models	89%
Genet, Y.H., et al., [16]	CNN	81.53%
Proposed	YOLOV9-DBN	91.9%

Table 3 demonstrates the comparison of existing models and YOLOv9-DBN model. The YOLOV9-DBN performs better than existing methods achieving 91.9% Acy. Moreover, the proposed YOLOV9-DBN model enhances overall Acy by 3.25, and 12.71 compared to CNN and VGG16 models and CNN.

5. CONCLUSION

This research proposed a YOLOv9-DBN for accurate banana leaf disease detection and severity classification by efficiently classifying leaf images. The YOLOv9-based detection system effectively localizes sick spots on banana leaves via multi-scale collecting features, ensuring accurate identification under changing situations. A deep neural network is used to extract discriminative characteristics more efficiently and accurately. The DBN model is utilized for classification by learning complicated patterns from extracted characteristics, allowing for precise categorization of Banana Leaf Diseases. The proposed YOLOv9-DBN model was validated with the metrics like Acy, Pcn, Rcl, Spy and Fs respectively. The proposed YOLOv9-DBN achieves an Acy 91.9%. Future work may concentrate on expanding the system to detect many diseases and implementing it on mobile or edge devices for real-time field applications, with larger and more complex datasets. Future research may potentially look into advanced or hybrid models, as well as the integration of IoT and cloud-based systems, to improve agricultural monitoring accuracy, scalability, and decision-making.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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