A YOLOv10-based Approach for Banana Leaf Disease Detection

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ABSTRACT

Leaf disease detection plays a crucial role in modern agricultural management, enabling early intervention to minimize crop losses. This paper explores the application of the YOLOv10 model for detecting and classifying banana leaf conditions with high accuracy. A publicly available dataset of 938 images was used, categorized into five classes, namely Black-Sigatoka, Healthy-Leaf, Panama-Disease, Potassium-Deficiency, and Yellow-Sigatoka. The model achieved a mean Average Precision (mAP@0.5) of 88.85%, a precision of 91.22%, and a recall of 85.06%, demonstrating strong detection capabilities. These findings highlight the effectiveness of YOLOv10 in advancing automated disease detection, providing a reliable tool for precision agriculture. The model's ability to accurately classify multiple leaf conditions can aid farmers in proactive disease management, ultimately enhancing crop health and sustainability.

Keywords-object detection; deep learning; YOLOv10

I. INTRODUCTION

Banana is a vital crop, providing not only a key source of nutrition but also playing an important role in the economy, particularly in tropical and subtropical regions [1]. However, banana cultivation is threatened by various diseases and nutrient deficiencies that can significantly reduce yields and affect the quality of the fruit. Identifying and addressing these issues is crucial for sustaining banana production and minimizing economic losses. Among the most prevalent conditions affecting banana leaves are fungal diseases such as Black-Sigatoka and Yellow-Sigatoka, physiological disorders like Potassium Deficiency, and devastating diseases like Panama Disease. The existence of healthy leaves is a primary indicator of the plant's vigor and productivity.

Traditional methods of banana disease detection are time-consuming, subjective, and prone to error, underscoring the need for automated and real-time solutions [2]. Recent advancements in Machine Learning (ML) and Deep Learning (DL) techniques have shown great promise in detection and classification of banana diseases. For instance, Hyper-Spectral Imaging (HSI) combined with ML classifiers like k-Nearest Neighbors (kNN) achieved high accuracy in detecting banana leaf diseases by capturing detailed spectral and spatial features [3]. Similarly, Convolutional Neural Networks (CNNs) such as AlexNet, VGG16, and ResNet have demonstrated remarkable success, achieving classification accuracies of up to 99%, highlighting their effectiveness in automating disease identification processes [4-7]. Among traditional machine learning approaches, Support Vector Machines (SVM) have emerged as a robust choice, with accuracies ranging from 80% to 99.61% in detecting diseases like Black Sigatoka and Banana Streak Virus. These methods excel in leveraging texture-based features extracted from images, enabling precise disease classification [8-11, 14]. For instance, authors in [8] employed k-means clustering and feature extraction techniques to detect banana leaf diseases. They used color, texture, and shape features to classify diseases achieving an average accuracy of 85%. The study highlighted the importance of feature extraction in improving disease detection accuracy. Authors in [9] utilized high spatial resolution aerial photographs to monitor yellow Sigatoka infestation in banana crops. The study employed SVM for disease classification, achieving an accuracy of 99.28%. The research demonstrated the potential of UAV-based imaging for large-scale disease monitoring in banana plantations. Furthermore, techniques employing texture analysis, such as Local Binary Patterns (LBP), have further contributed to improving the reliability of classification when combined with classifiers like SVM and kNN [10-12]. The recent success of ML and DL models in agricultural disease detection highlights their potential for real-time implementation in precision agriculture, significantly reducing the reliance on manual inspections and improving the productivity and sustainability of banana farming [13]. In [15], the authors proposed a novel Heap Auto Encoders (HAEs) technique for classifying banana leaf diseases, achieving a Classification Accuracy (CA) of 99.35%. This method reduced the need for handcrafted features and addressed overfitting issues, making it superior to traditional methods. The study used datasets such as Godliver, Scotnelson, PlantVillage, and real-field data to validate the approach. Authors in [16] applied the Discrete Orthonormal Stockwell Transform (DOST) and LBP features for banana leaf disease classification. The study achieved a CA of 95.9% using an Artificial Neural Network

(ANN) classifier. The authors emphasized the effectiveness of combining DOST with LBP-based features for accurate disease classification.

Authors in [17] explore the use of transfer learning to accurately classify banana leaf diseases, a critical issue for banana farmers aiming to maintain crop yield and quality. The study's main objective is to adapt pre-trained CNN models for classifying different banana leaf diseases, thereby minimizing the need for extensive labeled data and reducing computational demands. Using popular CNN architectures like VGG16, ResNet50, and InceptionV3, the authors fine-tune these models on a dataset of labeled banana leaf images, enabling the networks to identify specific diseases effectively. The evaluation of the models demonstrates that transfer learning enhances classification accuracy, making it a practical solution for agricultural disease identification. The study concludes that transfer learning is a scalable and effective tool for plant disease classification, offering a feasible approach for early disease detection in agriculture. This approach holds promise for aiding farmers in managing diseases proactively, ultimately contributing to improved crop management and yield through accessible AI-driven solutions.

The YOLOv10 [18] model was chosen for this research due to its high efficiency and flexibility in object detection tasks. The considered dataset [19] includes five classes, and the model is evaluated based on its performance in detecting these distinct banana leaf conditions, contributing to improved disease management in agriculture.

II. BACKGROUND

This section provides an overview of the dataset categories, describing both the symptoms and impacts on banana plants.

Healthy-Leaf: A healthy banana leaf is crucial for the optimal growth and development of the banana plant. It is typically large, broad, and vibrant green in color, indicating efficient photosynthesis and nutrient absorption. As shown in Figure 1(a), healthy leaves are free from spots, discoloration, or any signs of disease or deficiency. Maintaining healthy foliage is essential for maximizing fruit production and ensuring the plant's resilience against environmental stressors and diseases.

Black-Sigatoka: It is also known as black leaf streak disease, is a fungal disease caused by Mycosphaerella fijiensis, which primarily affects banana leaves. As shown in Figure 1(b), the disease is characterized by dark streaks and spots that gradually expand into large black patches on the leaves, leading to significant leaf tissue damage. As the infection progresses, it reduces the plant's ability to photosynthesize, resulting in lower fruit yields and premature ripening. If left untreated, Black-Sigatoka can severely impact banana plantations, making it one of the most destructive diseases in banana production.

Yellow-Sigatoka: It is a leaf spot disease caused by the fungus Mycosphaerella musicola. This disease causes yellow streaks or spots on banana leaves (Figure 1(c)), which can merge to form larger patches, gradually turning brown or black. Like Black-Sigatoka, it reduces the leaf's ability to photosynthesize, leading to lower fruit production and yield loss. Although less aggressive than Black-Sigatoka, the Yellow-Sigatoka poses a significant threat to banana cultivation, especially if not controlled through proper agricultural practices.

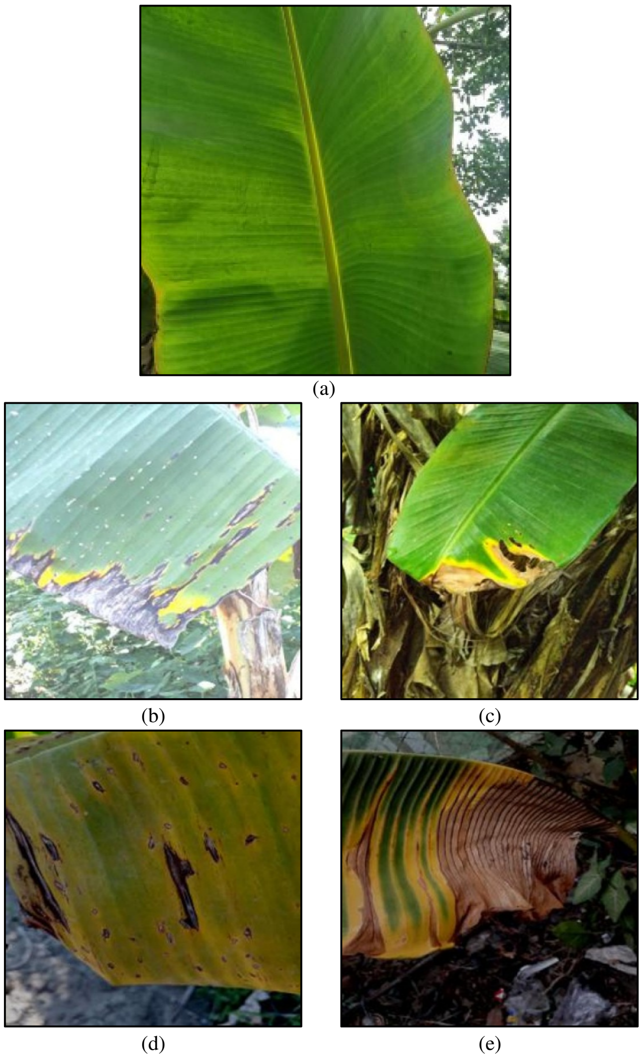

Fig. 1. Banana leaf classes: (a) Healthy, (b) Black-Sigatoka, (c) Yellow-Sigatoka, (d) Panama-Disease, (e) Potassium-Deficiency.

Panama-Disease: It also known as Fusarium Wilt. It is caused by the soil-borne fungus Fusarium oxysporum f. sp. cubense. As shown in Figure 1(d), it infects the banana plant through its roots, leading to wilting and yellowing of the leaves, particularly the older ones, while younger leaves may appear pale and stunted. Over time, the disease obstructs water and nutrient transport, resulting in the plant's death. Panama Disease is one of the most aggresive banana diseases, capable of wiping out entire plantations, and is particularly threatening to the Cavendish banana variety.

Potassium-Deficiency: Potassium deficiency in banana plants manifests as a yellowing of the leaf margins, starting with the older leaves, followed by necrosis or browning (Figure

1(e)). Potassium is an essential macronutrient for banana plants, aiding in various physiological processes like water regulation, enzyme activation, and nutrient transport. A deficiency in potassium can weaken the plant's structure, reduce fruit quality, and make the plant more susceptible to environmental stress and diseases. Addressing potassium deficiency through appropriate fertilization is key to ensuring healthy banana crop yields.

III. DATASET AND METHODOLOGY

A. Dataset

The dataset used in this research [19], has been curated specifically for detecting various banana leaf conditions. It consists of a total of 938 images, categorized into five classes: Black-Sigatoka, Healthy-Leaf, Panama-Disease, Potassium-Deficiency, and Yellow-Sigatoka. The dataset was divided into three subsets for training, validation, and testing purposes. As shown in Table I, out of the total 938 images, 657 images (70%) were designated for the training set, 188 images (20%) for the validation set, and 93 images (10%) for the testing set.

TABLE I. SUMMARY OF DATASET

Category	Number of Images
Training dataset	657 (70%)
Validation dataset	188 (20%)
Testing dataset	93 (10%)
Total images	938

- Training Set: This set was used to train the YOLO model, allowing it to learn the unique patterns and features associated with different banana leaf conditions.
- Validation Set: This set helps fine-tune the model and optimize hyperparameters, giving an indication of how well the model generalizes beyond the training data.
- Testing Set: The final evaluation of the model's performance is carried out on this set, assessing its accuracy in detecting leaf conditions in previously unseen images.

Figure 2 provides a bar chart of the distribution of different classes within the dataset. It can be seen that Potassium-Deficiency is the most prevalent condition, while the Healthy and Panama-Disease are the least represented classes.

B. YOLOv10 Model Architecture

Real-time object detection seeks to effectively predict object categories and positions in images with low latency. The YOLO series [20] has led the way in this research due to its combination of performance and efficiency. YOLOv10 [18] improves real-time object detection by correcting inefficiencies from previous versions. It eliminates the need for Non-Maximum Suppression (NMS) using a new dual assignment technique, lowering latency and increasing efficiency. Key enhancements include an upgraded CSPNet-based backbone for improved feature extraction, a PAN-based [21] neck for multiscale feature fusion, and specialized training and inference heads. Furthermore, YOLOv10 incorporates large-kernel convolutions and partial self-attention, resulting in great accuracy with little computational cost. With these modifications, YOLOv10 is now a powerful, efficient model for rapid and accurate object recognition.

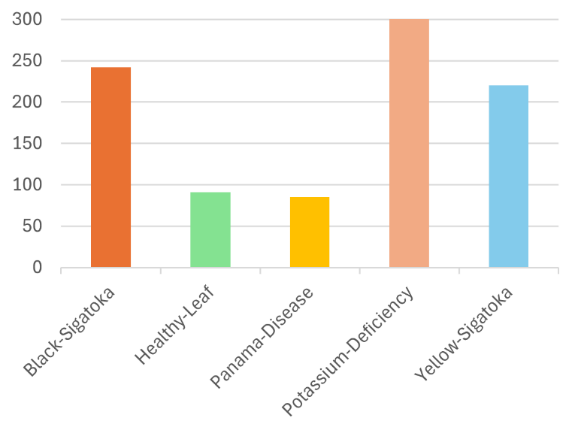

Fig. 2. Dataset's annotation distribution per class.

C. Evaluation Metrics

Evaluation metrics are essential for assessing the performance of ML models, particularly in object detection tasks like the one handled by the YOLO model. The metrics used in this study are Precision, Recall, Mean Average Precision at 0.5 IoU (mAP@0.5), and Mean Average Precision at multiple IoU thresholds (mAP@0.5:0.95).

Precision (P) measures the accuracy of the model in detecting objects by calculating the ratio of correctly identified objects (True Positives, TP) to the total detections made (sum of True Positives and False Positives, FP), as shown in (1). A higher P value indicates that the model produces fewer FP, leading to more reliable detections.

$$P = \frac{TP}{TP+FP} \tag{1}$$

Recall (R) evaluates the model's ability to capture all relevant objects by calculating the ratio of TP detections to the actual objects present in the image (sum of TP and False Negatives, FN), as shown in (2). High R values signify that the model missed fewer objects.

$$R = \frac{TP}{TP+FN} \tag{2}$$

mAP@0.5 considers the model's ability to correctly predict objects with an Intersection over Union (IoU) threshold of 0.5. IoU is calculated as the ratio of the overlap between predicted and actual bounding boxes to their union, as shown in (4). mAP@0.5 evaluates the model's performance by taking the average precision across all classes at this IoU threshold.

$$mAP@0.5 = \frac{1}{N}\sum_{i=1}^{N} P(i) \times R(i) \tag{3}$$

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{4}$$

mAP@0.5:0.95 is a more rigorous measure, taking an average of mAP scores over a range of IoU thresholds from 0.5 to 0.95, with a step of 0.05:

$$\text{mAP@0.5:0.95} = \frac{1}{10}\sum_{t=0.5}^{0.95} \text{AP}(t) \tag{5}$$

The considered metrics provide a comprehensive assessment of the model's ability to accurately detect and classify banana leaf conditions.

IV. RESULTS AND DISCUSSION

The evaluation was conducted on a test dataset, and the results highlight the strengths and areas for improvement across different disease classes.

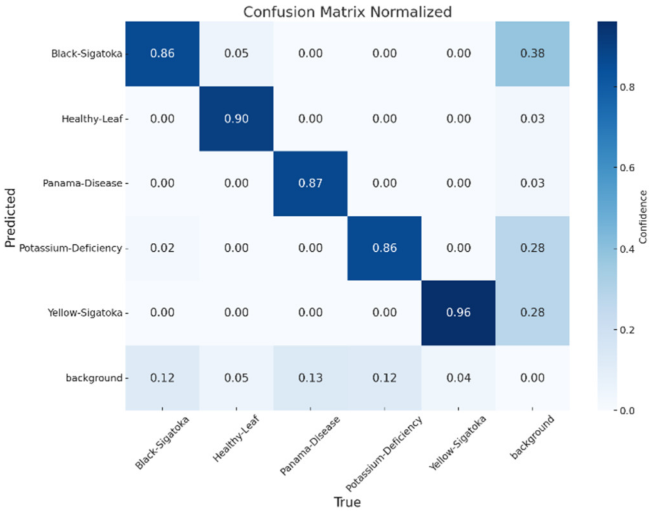

Fig. 3. Normalized confusion matrix.

Figure 3 shows the normalized confusion matrix of the proposed system on the utilized dataset. The normalized confusion matrix shows that the model generally performs well in distinguishing between specific classes, with the highest accuracy observed for Yellow-Sigatoka at 0.96. This indicates that the model has a strong ability to identify this condition correctly. Healthy-Leaf also shows a high accuracy rate of 0.90, suggesting effective classification of healthy leaf samples. For Panama-Disease, the model achieves an 0.87 correct classification rate, reflecting reasonable accuracy in identifying this condition. Both Black-Sigatoka and "Potassium-Deficiency" have an accuracy of 0.86, which, while slightly lower, still indicates reliable performance. These results suggest that the model is well-tuned to classify these leaf conditions, with the highest success in recognizing Yellow-Sigatoka. Nonetheless, slight variations in accuracy across classes point to potential areas for further model refinement, especially for conditions like Potassium-Deficiency and Black-Sigatoka. The charts in Figure 4 illustrate the performance metrics values over the training epochs for the model.

Starting with recall materic, as indicated in the first chart from the top left, we see a quick climb from an initial low position to above 0.80 in the early epochs. This increasing trend indicates that the model soon learned to detect a higher proportion of TP, detecting relevant items more accurately as training progressed. Moving to mAP@50, we notice a similar improvement trend. Beginning with a low mAP, the model gradually improved its accuracy, reaching around 0.85 by the 100th epoch. This demonstrates the model's increasing ability to accurately recognize objects, as assessed by the 50% IoU threshold. The mAP@50-95 metric increased progressively, similar to the other metrics, and by the last epoch, it was close to 0.80. This consistent increase across IoU levels suggests the model's robust detection capabilities across various levels of overlap between predicted and actual object locations. Precision had risen progressively from its low starting point to approximately 0.9. This improvement highlights the model's growing accuracy in identifying TP while minimizing FP as training advanced. These values illustrate that the model consistently improved its detection capabilities with training, achieving high levels of recall, precision, and mAP by the 100th epoch, suggesting that the model is well-optimized for accurate and reliable object detection.

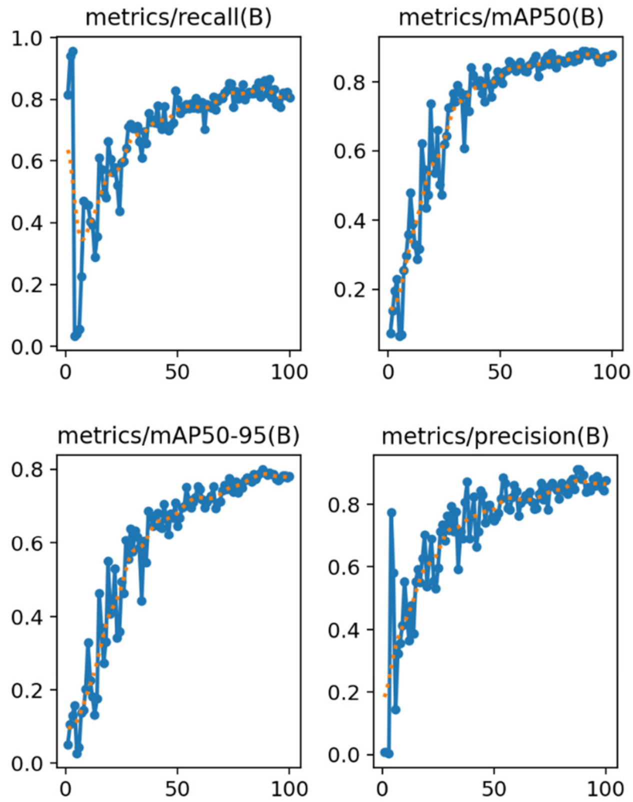

Fig. 4. Model's performance.

V. CONCLUSION

This paper demonstrated the effectiveness of the YOLOv10 framework in detecting various conditions affecting banana leaves, achieving high accuracy rates across five categories. The model's performance indicates that YOLOv10 is a robust tool for precision agriculture, capable of accurately identifying and classifying banana leaf conditions, including Black-Sigatoka, Healthy-Leaf, Panama-Disease, Potassium-Deficiency, and Yellow-Sigatoka. The mean Average Precision (mAP@0.5) reaching 0.88 across all categories underscores the model's ability to distinguish these conditions effectively. The results highlight YOLOv10's strengths in identifying and classifying distinct leaf conditions, demonstrating its potential for real-world agricultural applications where early and accurate disease detection is critical. However, while the model performs well overall, future work could focus on refining the dataset to address any class imbalances that may exist, as these could affect generalization across less frequent conditions. Additionally, further improvements could explore ways to enhance detection for leaves that may appear in varied orientations, lighting, or partial visibility in the field, thus broadening the model's applicability in diverse agricultural environments. Moreover, a future work of this study would be to conduct an extensive comparative study using the same dataset, evaluating YOLOv10 against other established models to further validate its performance.

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