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An Efficient YOLO26-Based Framework for Banana Leaf Disease Identification

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Abstract: *Banana cultivation is affected by several leaf diseases that can alter leaf colour, texture and visible surface patterns. Identifying these symptoms early is useful for crop monitoring and disease management. In practice, diagnosis based only on visual inspection can be time-consuming and may vary with the experience of the observer. This study presents a deep-learning approach based on YOLO26 for automatic identification of banana leaf diseases. We consider four categories: Cordana, Healthy, Pestalotiopsis, and Sigatoka. The study uses banana leaf images obtained from the BananaLSD/Kaggle-related collection and a separate set of 768 segmented leaf images prepared using Roboflow. In the available four-class evaluation, 1,600 images were assessed, with 400 images in each class. The experiment achieved 96.88% accuracy, 96.93% precision, 96.88% recall and 96.88% F1-score. The class-wise F1-scores were 0.98 for Cordana, 0.96 for Healthy, 0.96 for Pestalotiopsis and 0.98 for Sigatoka. These results indicate that the proposed approach can distinguish the selected banana leaf disease categories with high consistency. The work is intentionally limited to one research objective: accurate identification of banana leaf diseases. Detection of disease location, object localisation and segmentation are not treated as separate research objectives.*

Keywords: Banana leaf disease; YOLO26; deep learning; disease identification; computer vision; agricultural informatics; plant disease classification

I. INTRODUCTION

Banana is an important crop in tropical and subtropical agriculture and provides food as well as income for farming communities. The health of the leaf canopy is closely related to plant development because healthy leaves contribute to photosynthetic activity. Diseases affecting banana leaves can produce characteristic spots, streaks, lesions and areas of discolouration. Cordana, Pestalotiopsis and Sigatoka are among the leaf diseases that can create visually similar symptoms at different stages of infection.

Traditional disease identification generally depends on visual examination by farmers, field workers or plant-health experts. Although expert inspection remains valuable, it becomes difficult to apply consistently when large plantations or large image collections have to be examined. Variations in illumination, background, disease severity and leaf orientation can further complicate visual recognition. These challenges have encouraged the use of image-based machine-learning methods for plant-health assessment.

Deep learning has changed the way agricultural images can be analysed. Instead of relying entirely on manually selected colour or texture features, convolutional neural networks learn useful visual patterns from training examples. Previous studies have shown that deep-learning models can classify plant diseases effectively, while also noting that performance obtained on controlled images may not always transfer directly to field conditions [9]–[11].

Artificial intelligence has also been useful in banana-specific research. Selvaraj et al. [1] designed an AI based system for detection of banana disease and pests using field images. Then, it provided a curated dataset for banana leaf spot disease research, including Cordana, Pestalotiopsis and Sigatoka [2]. Such studies are an important basis for developing automated banana disease identification systems. The present work explores YOLO26 as a recent deep-learning

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architecture to identify four categories of banana leaf images. The main goal of the research is intentionally limited to the development and testing of a model for recognition of banana leaf diseases. This allows us to study disease-class discrimination clearly, without the additional objectives of localization or segmentation. The present work investigates YOLO26 as a recent deep-learning architecture for identifying four banana leaf image categories. The central research objective is deliberately narrow: to develop and evaluate a model for banana leaf disease identification. This focus makes it possible to examine disease-class discrimination clearly without presenting localisation or segmentation as additional objectives.

II. RELATED WORK

A. Artificial Intelligence for Plant Disease Identification

The application of artificial intelligence to agricultural image analysis is increasing. Ferentinos evaluated convolutional neural networks for plant disease detection and demonstrated that learned image representations can provide good classification performance across crop and disease classes [9]. Mohanty et al. demonstrated the potential of deep learning for image-based plant disease recognition and also emphasized the necessity of considering the difference between laboratory style and realistic images [10]. Kamilaris and Prenafeta-Boldú surveyed deep-learning applications in agriculture and identified crop-health analysis as an important application area [11].

B. Banana Leaf Disease Studies

Banana disease identification presents a useful computer-vision problem because symptoms can differ in colour, shape, size and severity. Selvaraj et al. investigated AI-powered detection of banana diseases and pests using field photographs and showed the potential of deep learning for practical banana-health monitoring [1]. The BananaLSD dataset was developed specifically around banana leaf spot diseases and includes Cordana, Pestalotiopsis and Sigatoka [2].

C. YOLO Models

YOLO models were originally developed for fast object detection and have evolved through several generations. YOLOv4 provided an effective balance between speed and detection accuracy [3]. YOLOX introduced an anchor-free design and a decoupled detection head [4]. YOLOv7 improved the efficiency of real-time detection through architectural and training improvements [5]. YOLOv9 introduced programmable gradient information and GELAN [6], and YOLOv10 further developed end-to-end real-time detection [7]. YOLO26 represents a later generation in the Ultralytics YOLO family and supports multiple computer-vision tasks [8].
Although the YOLO family is primarily associated with detection, the present research uses the model within a disease-identification study. The main comparison is therefore based on the model's ability to distinguish the four banana leaf categories. Published results from unrelated datasets are not treated as direct evidence that one model is superior, because dataset composition, preprocessing, class definitions and experimental settings differ.

III. MATERIALS AND METHODS

A. Research Objective

The study has one specific objective: to develop and evaluate a deep-learning model for identification of banana leaf diseases from images. The target categories are Cordana, Healthy, Pestalotiopsis and Sigatoka. All experimental procedures and evaluation measures are selected to support this single objective.

B. Image Dataset

For the four-class evaluation, the available experimental record consists of 1,600 images, evenly distributed between the four classes. The disease classes are Cordana, Pestalotiopsis and Sigatoka, and Healthy as the non-diseased reference category. Also, a separate Roboflow collection of 768 segmented banana leaf images was prepared and is

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considered supporting image data. The two sources are not assumed to be the same, and the counts for each are reported separately.

Class	Category	Images
Cordana	Disease	400
Healthy	Reference	400
Pestalotiopsis	Disease	400
Sigatoka	Disease	400

TABLE I. DISTRIBUTION OF IMAGES IN THE FOUR-CLASS EVALUATION.

C. Preprocessing

The images were sorted by class labels and were ready for deep-learning analysis. After the segmentation of leaves, images from the Roboflow workflow were used to keep the relevant leaf content. Preprocessing is meant to enhance the consistency of the image inputs while maintaining visual symptoms useful for differentiating disease classes. The last experiment log should contain the exact final training split, augmentation settings, image size and training epochs.

D. YOLO26-Based Identification

The proposed workflow consists of preparing labelled banana leaf images. The images are then fed into the YOLO26 learning pipeline. During inference, the trained model predicts classes of input images. The known class label is compared to the predicted class to determine if the disease has been correctly identified. Outcomes were not differentiated for the performance of localization or segmentation.

E. Evaluation Metrics

Accuracy is the ratio of the number of images correctly classified to the total number of images tested. Precision is a measure of how many of the images that are assigned to a class actually belong to that class. Recall measures how many of the members of the class are correctly identified. F1-score is a combination of precision and recall. These measures are reported because they provide additional information about disease-class identification.

IV. RESULTS AND DISCUSSION

A. Overall Performance

The available evaluation contains 1,600 images. The model correctly classified 1,550 images and misclassified 50 images. The resulting accuracy is 96.88%. The overall precision, recall and F1-score are 96.93%, 96.88% and 96.88%, respectively.

Measure	Value	Measure	Value	Images
Accuracy	96.88%	Precision	96.93%	1,600
Recall	96.88%	F1-score	96.88%	1,600

TABLE II. OVERALL FOUR-CLASS IDENTIFICATION PERFORMANCE.

B. Class-Wise Performance

Class	Precision	Recall	F1-score	Support
Cordana	0.98	0.97	0.98	400
Healthy	0.94	0.98	0.96	400
Pestalotiopsis	0.97	0.94	0.96	400
Sigatoka	0.99	0.98	0.98	400

TABLE III. CLASS-WISE PERFORMANCE.

Cordana and Sigatoka got 0.98 for F1-score. Sigatoka had the highest precision with 0.99, showing that very few images predicted as Sigatoka were of other categories. Healthy images had a recall of 0.98, indicating that most healthy

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examples were recognized correctly. Pestalotiopsis had the lowest recall (0.94), indicating that this class was relatively more difficult to identify in the current dataset.

C. Confusion Matrix

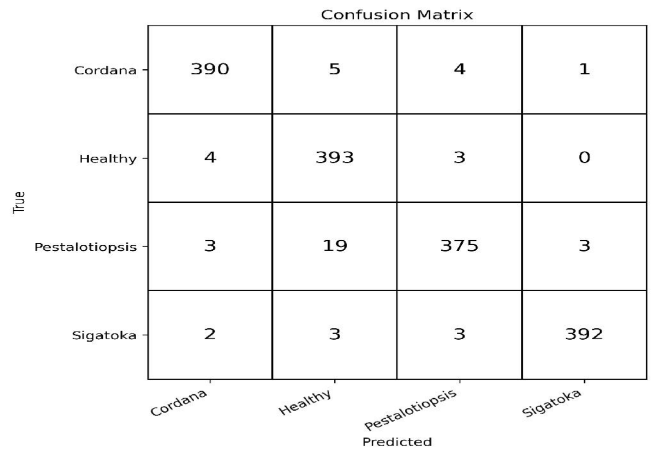

Fig. 1. Confusion matrix for the 1,600-image evaluation.

The confusion matrix obtained from the evaluation contains 390 correct Cordana predictions, 393 correct Healthy predictions, 375 correct Pestalotiopsis predictions and 392 correct Sigatoka predictions. The largest single confusion occurs when 19 Pestalotiopsis images are classified as Healthy. This result suggests that some Pestalotiopsis symptoms have visual characteristics that overlap with the healthy class in the available images.

D. Interpretation

The results indicate that the model is able to classify the four target categories with a high degree of consistency on the set of images evaluated. In contrast, the class-wise results explain why the overall accuracy should not be used solely to describe the quality of disease identification. Pestalotiopsis has lower recall among the other disease categories and hence deserves special attention in future data collection and model refinement. The confidence of a displayed prediction should also be distinguished from accuracy. The system had a total confidence of 77.08% in one supplied YOLO26 inference image. This value describes how confident you are about that particular inference and not the accuracy of the whole dataset.

V. COMPARISON WITH PREVIOUS YOLO GENERATIONS

Model	Year	Relevant contribution
YOLOv4	2020	Real-time speed and accuracy improvements [3]
YOLOX	2021	Anchor-free design and decoupled head [4]
YOLOv7	2022/2023	Improved real-time detection efficiency [5]
YOLOv9	2024	PGI and GELAN [6]
YOLOv10	2024	End-to-end real-time detection [7]
YOLO26	2026	Recent unified YOLO vision architecture [8]

TABLE IV. SELECTED YOLO GENERATIONS.

The table provides historical context rather than a direct accuracy ranking. A valid numerical comparison would require the earlier YOLO models to be trained and tested on the same banana dataset using the same split and evaluation procedure. This is especially important in agricultural image studies because reported accuracy can change substantially with dataset size, image quality, class balance and collection conditions.

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VI. CONCLUSION

This paper proposed a deep-learning approach for banana leaf disease identification based on YOLO26. The study uses four categories, which are Cordana, Healthy, Pestalotiopsis and Sigatoka. On the available 1,600-image evaluation, the approach achieved 96.88% accuracy, 96.93% precision, 96.88% recall and 96.88% F1-score. The class-wise results were also good, but the recall for Pestalotiopsis was lower compared to other categories. Thus, the main contribution of the study is focused on one objective, which is to identify diseases of banana leaves from images. Roboflow segmentation is considered a pre-processing step for the image, not a separate research goal. In future work, larger field datasets, more disease stages, further geographic conditions and controlled comparisons with earlier YOLO versions under identical experimental settings can be explored.

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