Research Article

Classification of Oil Palm Leaf Diseases Using YOLOv8-Nano Algorithm

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Abstract: Early detection of diseases in oil palm leaves is crucial to prevent a decline in productivity and to maintain the quality of crop yields. This study aims to develop an automatic classification model for oil palm leaf images using the YOLOv8-Nano algorithm. The dataset used consists of three classes—Healthy, Fungal, and Brown Spot—which were divided into training, validation, and testing sets with a ratio of 80:10:10. The training process was conducted over 10 epochs using image dimensions of 224×224 pixels, leveraging pretrained weights from YOLOv8n-cls. Evaluation results show that the model was able to classify the images perfectly, achieving 100% accuracy, precision, recall, and F1-score. These findings indicate that YOLOv8-Nano is a lightweight yet highly effective algorithm for the classification task of oil palm leaf images. However, further testing with field data is necessary to ensure the model's generalization ability in real-world scenarios.

Keywords: yolov8-nano, image classification, oil palm leaves, disease detection, deep learning.

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1. Introduction

Oil palm is a strategic agricultural commodity that plays an important role in supporting the national economy, particularly in Southeast Asian regions such as Indonesia. However, oil palm productivity can decline due to disease infections or environmental factors. One of the main threats is brown spot [13], a fungal-induced brown lesion on the leaves that can inhibit the photosynthesis process and lead to decreased crop yields [3][4][16].

The process of identifying oil palm leaf diseases has so far relied on visual inspection by field officers or experts. This method is time-consuming, subjective, and prone to identification errors (human error), especially when applied to large-scale plantations [2][18]. Therefore, a computer vision and deep learning approach is needed to automate the classification of leaf conditions quickly and accurately [6][7][17].

Recent advancements in artificial intelligence, particularly in deep learning and convolutional neural networks (CNN), have opened up significant opportunities for the development of image-based plant disease detection systems. One of the most widely used algorithms is YOLO (You Only Look Once), known for its ability to perform object classification and localization in real time [5][15]. The latest version of this algorithm, YOLOv8-Nano, is designed with a lightweight architecture that is computationally efficient while still maintaining competitive accuracy. This makes it ideal for application in the agricultural sector, especially where hardware resources are limited [8][10][22].

Several studies have successfully implemented YOLO and its variants for leaf disease classification in crops such as rice, sugarcane, and other horticultural plants [2][10][19][21]. However, the specific application of YOLOv8-Nano for classifying diseases in oil palm leaves remains very limited [20]. This approach holds great potential as an efficient, practical, and easily adaptable solution for image-based plant health monitoring systems[9].

This study aims to develop an automatic classification system for oil palm leaf conditions into three categories: leaves affected by brown spot, fungus-infected leaves, and healthy leaves, using the YOLOv8-Nano algorithm. In addition, the study evaluates the model's performance based on metrics such as accuracy, precision, recall, and F1-score. It is expected that this system can serve as an effective early detection tool to assist farmers or plantation managers in making fast and accurate decisions to minimize production losses.

2. Theory

2.1 Image

The image data used in this study consists of oil palm leaf images categorized into three classes:

a) *Healthy leaves*, which have a uniformly green color without spots or discoloration [15][18];
b) *Leaves with brown spots (brownspot)*, characterized by the appearance of brown dots on the leaf surface caused by fungal infection from the genus *Curvularia sp* [11][16]; and
c) *Fungus-infected leaves*, identified by a whitish-gray coloration on the leaf surface.

Each class contains 382 JPG-format images with a resolution of 4000×1800 pixels, resulting in a total dataset of 1,146 images with balanced distribution across classes. The data were obtained as whole images without annotations, as the approach used is image classification rather than object detection. Therefore, each image is directly associated with a single class label based on the leaf condition. Examples of healthy leaves, brown spots, and fungal infections can be seen in Figure 1.

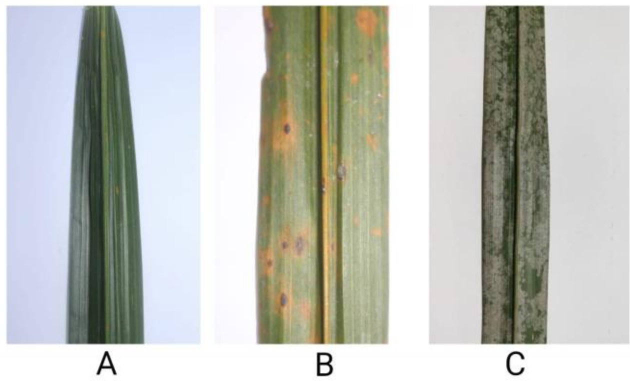

Figure 1. A. Healthy Leaves, B. *Leaves with brown spots (brownspot)*, C. *Fungus-infected leaves*

2.2 Classification

Classification is a stage in data processing that aims to group objects into several categories based on specific characteristics [1][13]. In this study, the classification process is used to differentiate the condition of oil palm leaves into three categories: leaves affected by brown spot, fungus-infected leaves, and healthy leaves. The goal of this classification is to automate plant disease identification with high accuracy, thereby facilitating early detection and efficient disease management [7][17].

This image-based classification system requires the extraction of visual features from the observed objects. Therefore, algorithms such as YOLO are utilized to detect and classify objects by recognizing visual characteristics in leaf images, such as color, texture, and shape [5][6]. Previous studies have demonstrated that approaches using CNN and YOLO are capable of accurately classifying plant disease symptoms, even under suboptimal lighting conditions and background settings [2][7][14].

2.3 Deep Learning dan CNN

Deep learning is a branch of machine learning that utilizes large-scale artificial neural networks to automatically extract and learn data features. A Convolutional Neural Network (CNN) is one of the most commonly used deep learning approaches for visual data analysis and processing. CNN consists of several layers, such as convolution, pooling, and fully connected layers, which enable the model to recognize visual patterns hierarchically. CNN has demonstrated reliable performance in various visual pattern recognition applications, including image-based plant disease identification [1][4][18][12].

2.4 YOLOv8-Nano

YOLO (You Only Look Once) is a one-stage detection algorithm that combines classification and localization into a single prediction process. Its latest version, YOLOv8, supports classification and segmentation tasks thanks to its flexible modular architecture [8][22]. This study utilizes YOLOv8-Nano, the smallest variant of the YOLOv8 family, which is designed for high efficiency on resource-constrained devices. The model is applied to image classification tasks without the need for bounding box annotations, as the focus is not on object detection but on direct image class recognition.

YOLOv8-Nano adopts an anchor-free approach and replaces the C3 structure used in previous versions with the C2f (Cross Stage Partial connection) module, which contains fewer parameters. This adjustment results in improved computational efficiency with a lighter model load. Network activation is carried out using the SiLU function, while the loss function used is Alpha-EIoU—an enhanced version of CIoU and EIoU—which improves stability and accuracy during the training process [10].

The model was initialized with pretrained weights (yolov8n-cls) from Ultralytics, which had been trained on ImageNet, enabling transfer learning to improve accuracy on a limited dataset [12]. Unlike two-stage approaches such as Faster R-CNN [5], YOLOv8-Nano excels in inference speed and efficiency, making it well-suited for direct leaf classification in field environments.

The architectural capabilities and computational efficiency offered by YOLOv8-Nano are the primary reasons for selecting this model in the study. To strengthen the rationale behind this choice, it is important to review the use of similar algorithms in previous studies focused on plant disease classification.

Previous studies have employed deep learning for leaf disease classification, such as YOLO-CNN for sugarcane [2], CNN for oil palm [4][6], and YOLOv8 for rice [10]. Most of these studies classified only two classes and relied on heavy models with high computational demands.

In contrast to previous studies, this research applies YOLOv8-Nano—a lightweight and efficient model—to classify oil palm leaf images into three categories: healthy, fungal-infected, and brown spot. Without the need for bounding box annotations, the use of YOLOv8n-cls becomes more practical and easier to implement.

With the combination of the C2f architecture, anchor-free approach, and Alpha-EIoU loss [8][10][12], along with a balanced, high-resolution original dataset, this approach offers an accurate, fast, and resource-efficient classification solution that represents a research gap yet to be widely explored.

3. Method

The research method used in this study consists of five stages: data preprocessing, model initialization, model training, test image prediction & result visualization, and model evaluation. The flow of the research method can be seen in Figure 2.

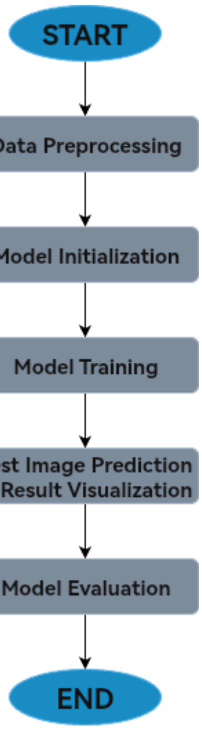

Figure 2. Research Method Flowchart

3.1 *Data Preprocessing*

Several preprocessing steps were carried out in this study. First, data splitting: each class contained a total of 382 images, which were then split into three sets with a ratio of 8:1:1—80% for training, 10% for validation, and 10% for testing. Second, image resizing: all images were resized to a uniform size of 224 pixels. This resizing was done to ensure consistency across image dimensions and to prevent excessively large images from being fed into the model. Additionally, resizing can help improve computational performance [12].

3.2 *Model Initialization*

At this stage, a deep learning model was initialized for the classification of oil palm leaf images. This study uses YOLOv8-Nano, the lightest variant of the YOLOv8 family, designed for fast and efficient detection on devices with limited computational power, such as CPUs and edge devices [8]. The model was initialized using the pretrained weights *yolov8n-cls* from Ultralytics, which had been trained on large datasets such as ImageNet. This transfer learning approach accelerates training and improves accuracy on limited datasets. [12].

YOLOv8-Nano adopts an anchor-free architecture, C2f module, SiLU activation function, and Alpha-EIoU loss function, which enhance bounding box accuracy in multi-scale detection [8][10]. As a single-stage detector, YOLOv8-Nano performs classification and bounding box regression simultaneously, making it more efficient than two-stage models like Faster R-CNN [5], and thus ideal for real-time image-based agricultural applications.

3.3 *Model Training*

The model training stage is the core process in developing a deep learning–based classification system. In this study, the training process was conducted on the YOLOv8-Nano model to recognize and classify oil palm leaf images into several categories, such as healthy, fungal-infected, and brown spot–infected.

3.4 *Test image Prediction and Result Visualization*

After the model has been trained and the best version obtained, the next step is to perform predictions on the test data and then display the results in the form of visualized images that have been classified and labeled in the output. In this stage, the model will be tested using 76 test images from all categories of oil palm leaf classes.

3.5 *Model Evaluation*

Model evaluation is a crucial stage in the research process aimed at measuring how well the classification model can recognize and distinguish between the classes of oil palm leaf images. The evaluation is carried out using test data that were not involved in the training or validation process. The methods used to evaluate the model include accuracy, precision, recall, F1-score, and confusion matrix. Moreover, in this study [10][23], the value of precision (1), Recall (2), Accuracy (3), and F1-score (4) can be calculated using equations (1) – (4).

$$Presisi = \frac{TP}{TP + FP} \; x \; 100\% \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \; x \; 100\% \tag{2}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$F1\text{-}Score = 2 \; x \; \frac{Precision \; x \; Recall}{Precision + Recall} \tag{4}$$

Where TP is the number of target leaves correctly identified, FP is the number of background elements incorrectly identified as target leaves, and FN is the number of target leaves that were not detected.

4. Result and Analysis

4.1 Image Prediction Results and Output Visualization

After the data splitting, model initialization, and training processes were completed, the model was tested using 50 randomly selected samples from all classes. As shown in Figure 3, the testing results indicate that 100% of the samples were correctly predicted.

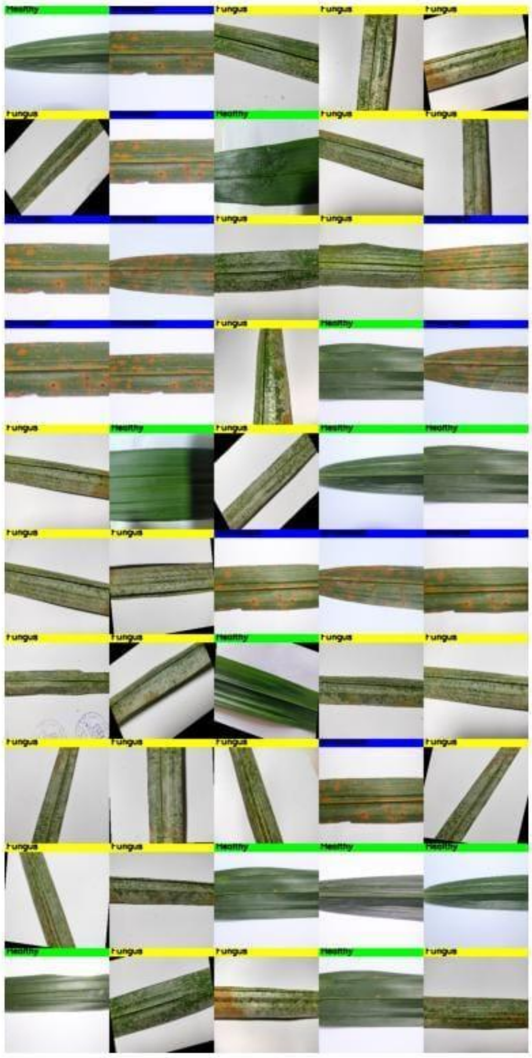

Figure 3. Image Prediction Results and Output Visualization

4.2 Evaluation

The training process of the oil palm leaf image classification model using the YOLOv8-Nano algorithm yielded highly optimal results, as illustrated by the confusion matrix shown in Figure 4.

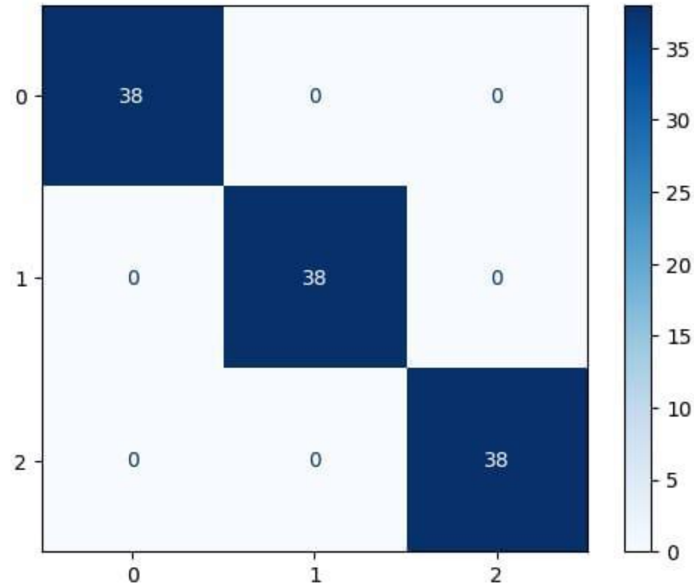

Figure 4. Confusion matrix table results

In Figure 4, label 0 represents “brownspot,” label 1 represents “Healthy,” and label 2 represents “Fungus.” The confusion matrix shows that all classes in the test data were correctly predicted. The training results indicate that the model achieved 100% accuracy at every stage, including training, validation, and testing. In addition to accuracy, the testing phase also yielded perfect values for precision, recall, and F1-score, each reaching 100%. All images from the test data were correctly classified according to their respective classes, without any misclassification. This is further supported by the confusion matrix results, which show no false positives or false negatives, meaning the model's predictions were completely accurate across all classes.

This achievement indicates that the model has a strong generalization capability on the test data. This is supported by the consistent and representative quality of the dataset, where each class possesses distinct visual characteristics that are easily recognizable by the model. Additionally, the proportional and non-overlapping division of training, validation, and testing data allowed the model to learn optimally without experiencing overfitting. In other words, the model did not merely memorize the training data but was truly able to understand and differentiate the key features of each class.

Nevertheless, this perfect performance still needs to be further evaluated, particularly using external test data or field images that were not involved in the training process. This is important to ensure that the model not only performs well on structured data but is also capable of handling real-world variations, such as differences in lighting, camera angles, and more complex leaf damage. Therefore, the use of test data from real-world conditions is highly recommended as a follow-up step in this research.

Overall, the evaluation results demonstrate that the YOLOv8-Nano algorithm is highly effective and efficient for the task of oil palm leaf image classification. With a relatively short training time, lightweight model size, and accurate classification results, this method is well-suited to serve as the foundation for developing an automated and real-time oil palm leaf disease detection system for broader practical applications.

5. Conclusion

This study successfully demonstrates that the YOLOv8-Nano algorithm is capable of classifying oil palm leaf images into three categories—Healthy, Fungus, and Brown Spot—with excellent evaluation results. The model achieved 100% accuracy, precision, recall, and F1-score on the test data, indicating optimal classification performance. These results confirm that YOLOv8-Nano is effective for automatic and efficient detection of oil palm leaf diseases. However, further testing on real-world field data is necessary to ensure the model's generalization capability under actual conditions.

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References

[1] P. Wang, E. Fan, and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning,".Pattern Recognition Letters, vol. 141, pp. 61–67, Jan. 2021, doi: 10.1016/j.patrec.2020.07.042.
[2] I. Kumpala, N. Wichapha, and P. Prasomsab, "Sugar Cane Red Stripe Disease Detection using YOLO CNN of Deep Learning Technique," unpublished.
[3] Y. Priyandari, R. Zakaria, and A. Syakura, "Sistem Pakar Pemupukan Kelapa Sawit Menggunakan Metode Forward Chaining,"PERFORMA: Media Ilmiah Teknik Industri, vol. 16, no. 2, Dec. 2017, doi: 10.20961/performa.16.2.16978.
[4] J. H. Ong, P. Ong, and W. K. Lee, "Image-based Oil Palm Leaf Disease Detection using Convolutional Neural Network,".Journal of Information and Communication Technology. vol. 21, no. 3, pp. 383–410, Jul. 2022, doi: 10.32890/jict2022.21.4.
[5] S. Srivastava, et.al "Comparative analysis of deep learning image detection algorithms,".Journal of Big Data. vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00434-w.
[6] V. G. Dhanya, et.al "Deep learning based computer vision approaches for smart agricultural applications,". Artificial Intelligence in Agriculture. vol. 6, pp. 211–229, Jan. 2022, doi: 10.1016/j.aiia.2022.09.007.
[7] A. Bhargava, et.al "Plant Leaf Disease Detection, Classification, and Diagnosis Using Computer Vision and Artificial Intelligence: A Review,".IEEE Access. vol. 12, pp. 37443–37469, 2024, doi: 10.1109/ACCESS.2024.3373001.
[8] A. F. Rasheed and M. Zarkoosh, "Optimized YOLOv8 for multi-scale object detection,". Journal of Real-Time Image Processing., vol. 2024, no. 1, p. 6, 2024, doi: 10.1007/s11554-024-01582-x.
[9] M. Ariza-Sentís, et.al "Object detection and tracking in Precision Farming: a systematic review,". Computers and Electronics in Agriculture. vol. 219, Apr. 2024, doi: 10.1016/j.compag.2024.108757.
[10] D. C. Trinh, et.al "Alpha-EIOU-YOLOv8: An Improved Algorithm for Rice Leaf Disease Detection,". AgriEngineering. vol. 6, no. 1, pp. 302–317, Mar. 2024, doi: 10.3390/agriengineering6010018.
[11] F. Afriliya and B. A. Fajar, "Keanekaragaman Jenis-Jenis Penyakit dan Cara Pengendaliannya di Pembibitan Kelapa Sawit (Elaeis Guinensis Jacq) PT. Perkebunan Nusantara I Langsa,". Jurnal Biologica Samudra. vol. 1, no. 1, pp. 34–40, Jun. 2019.
[12] H. Talebi, P. Milanfar, and G. Research, "Learning to Resize Images for Computer Vision Tasks," unpublished.
[13] Q. A'yuni and B. Hendrik, "2024, Pages 6589–6596,". Journal of Education Research, vol. 5, no. 4, 2024.
[14] Y. Borhani, J. Khoramdel, and E. Najafi, "A deep learning based approach for automated plant disease classification using

vision transformer," *Scientific Reports*, vol. 12, no. 1, Dec. 2022, doi: 10.1038/s41598-022-15163-0.
[15] W. Z. Hau, et.al "Palm Leaves Image Classification Using Deep Learning," in Proc. IEEE Int. Conf. on Automatic Control and Intelligent Systems (I2CACIS), 2024, pp. 439–444, doi: 10.1109/I2CACIS61270.2024.10649867.
[16] R. R. Cameron, A. Febrianni, and S. R. Yusticia, "Insidensi dan Keparahan Penyakit Bercak Daun Disebabkan oleh *Curvularia* sp. pada Pembibitan Kelapa Sawit di Kabupaten Banyuasin Sumatera Selatan," Jurnal Agro Industri Perkebunan, vol. 12, no. 1, pp. 1–10, Mar. 2024, doi: 10.25181/jaip.v12i1.3303.
[17] N. Hidayat, et.al. "Pemanfaatan Teknologi Smartfarming Berbasis AI untuk Peningkatan Efisiensi dan Produktivitas Pertanian di Desa Watu," unpublished.
[18] G. A. W. Satia, E. Firmansyah, and A. Umami, "Perancangan sistem identifikasi penyakit pada daun kelapa sawit (*Elaeis guineensis* Jacq.) dengan algoritma deep learning convolutional neural networks," Jurnal Ilmiah Pertanian, vol. 19, no. 1, pp. 1–10, Mar. 2022, doi: 10.31849/jip.v19i1.9556.
[19] D. Guna, et.al. "Identifikasi Penyakit pada Daun Mangga Menggunakan Algoritma YOLO V8," unpublished.
[20] K. Kumar, Y. Chen, B. Hu, and Y. Luo, "Assessing Human Visual Attention in Retail Human-Robot Interaction: A YOLOv8-Nano and Eye-Tracking Approach," in Proc. ACM Conf. on User Modeling, Adaptation and Personalization (UMAP), Jun. 2024, pp. 610–615, doi: 10.1145/3631700.3665195.
[21] Y. Miao, W. Meng, and X. Zhou, "SerpensGate-YOLOv8: an enhanced YOLOv8 model for accurate plant disease detection," Frontiers in Plant Science, vol. 15, 2024, doi: 10.3389/fpls.2024.1514832.
[22] Y. Shen, et.al. "Optimization of Improved YOLOv8 for Precision Tomato Leaf Disease Detection in Sustainable Agriculture," Sensors, vol. 25, no. 5, Mar. 2025, doi: 10.3390/s25051398.
[23] M. Nur, et.al. "Klasifikasi Penyakit Mata Berdasarkan Citra Fundus Menggunakan YOLO V8," 2023, unpublished.
[24] J. Sikati and J. C. Nouaze, "YOLO-NPK: A Lightweight Deep Network for Lettuce Nutrient Deficiency Classification Based on Improved YOLOv8 Nano," Engineering Proceedings, vol. 58, no. 1, 2023, doi: 10.3390/ecsa-10-16256.