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Performance Analysis of YOLOv11: Nano, Small, and Medium Models for Herbal Leaf Classification †

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Abstract

Indonesian people, especially the younger generation, often overlook the great potential of herbal leaves that are easily found around their homes. These leaves not only offer health benefits but also hold significant economic value. This research developed a system to classify 10 types of herbal leaves (*Annona muricata*, *Anredera cordifolia*, *Piper betle*, *Ocimum basilicum*, *Peperomia pellucida*, *Psidium guajava*, *Isotoma longiflora*, *Coleus scutellarioides*, *Ageratum conyzoides*, and *Syzygium polyanthum*) using artificial intelligence (AI). The study employed the Convolutional Neural Network (CNN) method and the You Only Look Once (YOLO) v11 algorithm, focusing on evaluating the performance of YOLOv11 in three variants, Nano, Small, and Medium. The results showed that the YOLOv11 Medium variant achieved the best performance, with the highest mAP50-95 value of 0.743 and mAP50 of 0.974 at the last epoch. The YOLOv11 Small variant outperformed Nano in precision (0.947 vs. 0.933) and mAP50 (0.973 vs. 0.972), while YOLOv11 Nano had slightly higher recall (0.921 vs. 0.906). Confusion Matrix results for YOLOv11 Medium showed precision (P) = 0.932, recall (R) = 0.928, mAP50 = 0.974, and mAP50-95 = 0.743. Based on these metrics, YOLOv11 Medium stood out as the best-performing variant, followed by Small and Nano. This research highlights the potential of AI technology to enhance the utilization of herbal leaves, which can provide broader health benefits and support the local economy.

Keywords: YOLOv11 algorithm; herbal leaves classification; Convolutional Neural Network; performance evaluation

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1. Introduction

Indonesia has great potential in providing medicinal plant resources or herbal plants that can be utilized properly as a medium for traditional medicine. Traditional medicine is an old heritage passed down from ancient times, both in the form of concoctions and herbs [1]. Herbal leaves are a type of plant used as a natural remedy without chemicals. Leaves are one part of the plant that have benefits for humans, especially for the health of the body. Leaves are used as herbal medicines that can be an alternative to help increase immunity and endurance. However, not all leaves have medicinal properties; therefore, knowledge of the types of leaves that have medicinal properties is important [2]. Each herbal leaf contains unique active compounds, such as flavonoids, alkaloids, saponins, and tannins, which contribute to specific health benefits [3]. For example, Kitolod (*Isotoma longiflora*) is

used in traditional medicine to treat headaches and respiratory problems [4]. Furthermore, the methods of processing and utilizing herbal leaves vary, ranging from boiling, drying, and being processed into extracts that are more easily consumed [5].

Well-utilized herbal leaves have a small risk of side effects compared to synthetic drugs [6]. Public knowledge about the types of herbal plants is still minimal [7]. Thus, the development of a technology base system that is able to accurately detect and classify herbal leaves is very important [8]. The Convolutional Neural Network (CNN) method is used in the herbal plant recognition process, because this method is quite reliable for object recognition [9]. This is the first study to thoroughly assess the performance of YOLO11, the latest addition to the YOLO family. YOLOv11 offers improved accuracy and efficiency compared to previous versions. In this study, the three variants of YOLOv11 used are Nano (n), Small (s), and Medium (m), each of which has different resource requirements and detection capabilities. YOLOv11 Nano is suitable for devices with limited resources, YOLOv11 Small offers a balance between efficiency and accuracy, while YOLOv11 Medium provides higher performance for devices with larger computing capacity. While there are other versions, such as YOLOv11 Large (l) and Extra Large (x) that offer higher accuracy, they require more resources. [10] By using these YOLOv11 variants, the developed system can detect and classify herbal leaf types efficiently and accurately and contribute to increasing public awareness of the benefits of herbal plants, which have great potential for both health and economy [11].

2. Related Works

2.1. Previous Related Research

Recent research has focused on using deep learning techniques to classify herbal five types of herbs, respectively, Mehndi, Betel, Mint, Basil, and Aloe Vera. Several studies have used CNN with various architectures to classify herbal leaves from images, including a real-time herb leaf localization and classification system using a YOLO neural network that achieves 95% accuracy [12]. Only segmented leaves of *Basella alba* (alugbati), *Mentha* (mint), *Moringa oleifera* (malungay), *Nerium oleander* (adelfa), and *Psidium guajava* (bayabas) are used to identify medicinal leaves. The images were identified using an inference approach in a real time application based on the extracted features from YOLOv3. The results of the test demonstrate an optimal outcome in the detection of various medicinal leaves. The optimal model performance yields mAP 98.63% [13].

This study uses the YOLOv11 algorithm in detecting 10 types of herbal leaves, using the YOLOv11 Nano, YOLOv11 Small, and YOLOv11 Medium algorithms. This model is used to determine the effectiveness value of each in detecting objects, which is then calculated to obtain recall, effectiveness, and mAP values. The YOLOv11 model also supports various computer vision tasks, such as pose estimation, instance segmentation, and oriented object detection (OBB), which provides flexibility in its application in various fields.

2.2. Herbal Leaf

Herbal leaves are parts of plants that are often used by people, especially in Indonesia, as ingredients for herbal medicines [14]. Some plants such as Annonamuricata, *Anredera cordifolia*, *Piper betle*, *Ocimum basilicum*, *Peperomia pellucida*, *Psidium guajava*, *Isotoma longiflora*, *Coleus scutellarioides*, *Ageratum conyzoides*, and *Syzygium polyanthum*, reflect the biodiversity around us. These leaves contain bioactive compounds, such as flavonoids, alkaloids, and saponins, which have antioxidant, antibacterial, and anti-inflammatory activities. This dataset will be used to recognize and classify herbal leaf types. Included among these herbs are the following:

- *Annona muricata* contains bioactive compounds such as acetogenins, alkaloids, flavonoids, and sterols that play an important role in health benefits, including anticancer, antioxidant, antimicrobial, and anti-inflammatory activities [15].
- *Anredera cordifolia* contains active compounds such as flavonoids, alkaloids, terpenoids, and saponins. Flavonoids function as antibiotics by disrupting the function of microorganisms such as bacteria and viruses. In addition, this plant also has antimicrobial properties that can prevent bacterial growth. Its antibacterial activity is proven to help heal wounds infected with *Staphylococcus aureus*, while its antifungal activity is effective against Candida albicans [16,17].
- *Piper betle* L. contains active compounds such as flavonoids, polyphenols, tannins, and essential oils that have antibacterial activity against Gram-positive and Gram-negative bacteria through certain mechanisms [18,19].
- *Ocimum basilicum* L. are plants that are easily available in Indonesia [20]. *Ocimum basilicum* L. contain flavonoids, saponins, and tannins that have antibacterial activity [21].
- *Peperomia pellucida* L. contains flavonoid, alkaloid, tannin, and saponin compounds that function as natural antibacterials, especially to inhibit the growth of *Propionibacterium acnes* bacteria [22,23]
- *Psidium guajava* contains important compounds such as tannins, triterpenes, flavonoids (quercetin), saponins, and ursolic acid, which have various benefits, including antioxidant, hepatoprotective, antimicrobial, antidiabetic, anti-inflammatory, and antiallergic activities. The plant also supports the treatment of rotavirus enteritis in children, diarrhea, and diabetes [24].
- *Isotoma longiflora* contains compounds such as flavonoids, alkaloids, saponins, and polyteros, which are used in traditional medicine to relieve headaches and respiratory problems [4].
- *Coleus scutellarioides* contains compounds such as alkaloids, steroids, tannins, saponins, and flavonoids. This plant is used in traditional medicine as an antibacterial, anthelmintic, antidiabetic, and appetite enhancer, as well as to treat coughs, hemorrhoids, stomach ulcers, fever, and diarrhea and facilitate the menstrual cycle [25,26].
- *Ageratum conyzoides* is a widespread weed, especially in tropical and subtropical areas [27]. The active compounds contained in *Ageratum conyzoides* can be used as antibacterials to treat skin infections caused by Staphylococcus epidermidis and Propionibacterium acnes bacteria.
- *Syzygium polyanthum* contains secondary compounds such as flavonoids, alkaloids, tannins, phenols, saponins, and essential oils. The leaves of this plant have antihypertensive, anti-inflammatory, antioxidant, cholesterol-lowering, gout medication, analgesic, and antimicrobial activities [28]. This makes herbal leaves an attractive alternative in natural medicine and a worthy subject for further research. Ten types of herbal leaves as shown in Figure 1 below.

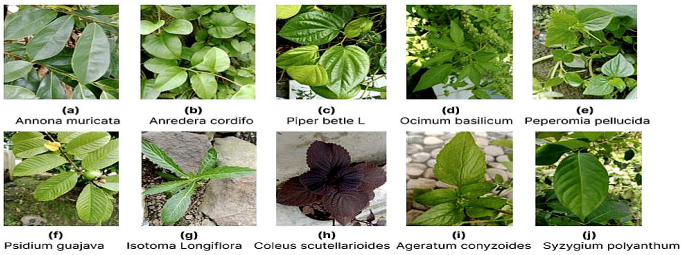


Figure 1. Ten types of herbal leaves. Source: Authors' own work, based on experimental data.

2.3. YOLOv11

YOLO (You Only Look Once) is a real-time object detection algorithm that uses a single neural network to predict bounding box and class probabilities directly from a complete image in a single evaluation [29]. Developed by Ultralytics in 2024 using the PyTorch 2.6.0 framework (PyTorch Foundation, Linux Foundation, San Francisco, CA, USA) and Python 3.12 (Python Software Foundation, Wilmington, NC, USA) programming language, YOLOv11 comes in several variants, including Nano, Small, Medium, Large, and Extra Large, which can be selected according to resource and accuracy requirements. The YOLOv11 architecture optimizes speed and accuracy with new innovations such as the C3K2 block, SPFF module, and C2PSA block that enhance its ability to process spatial information while maintaining high-speed inference. This algorithm operates based on the dataset state provided by Roboflow (Roboflow Inc., Des Moines, IA, USA) [30]. The operation of YOLOv11 consists of three main components, as follows: backbone for feature extraction, neck for feature linking, and head for bounding box and object class prediction, as seen in Figure 2 below:

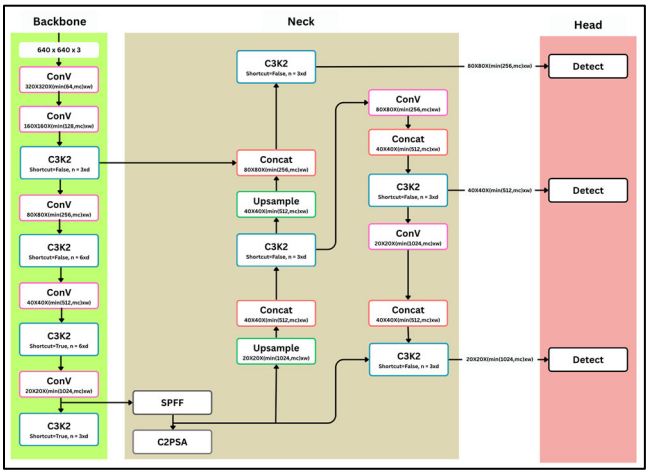


Figure 2. YOLOv11 model architecture.

In simple terms, the YOLOv11 algorithm has an architecture consisting of three main parts, namely the backbone, neck, and head, which are built with a more efficient and optimized approach compared to previous versions. Each part of YOLOv11 has its own function, as shown in Figure 3.

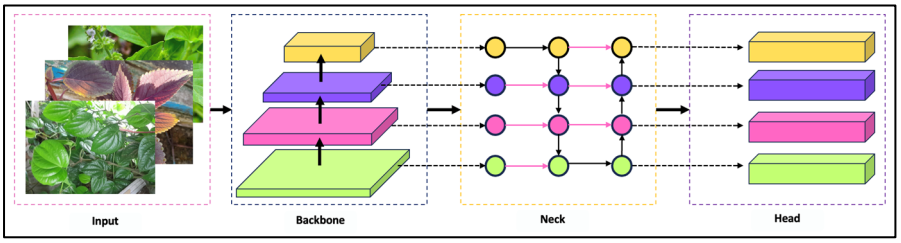


Figure 3. Backbone, neck, and head functions of YOLOv11 [31]. The various colors stand for different stages of feature extraction and processing, while the arrows show how feature maps move.

Figure 3 illustrates that YOLOv11 identifies key visual elements and converts them into features for further processing. Backbone extracts features from the image, while neck combines features from different layers to handle objects of different sizes, using an approach that is more efficient in feature propagation and local accuracy. The head generates bounding boxes, object classes, and detection probabilities. The Yolo model's training process with 10 types of leaves dataset as shown in Figure 4 below.

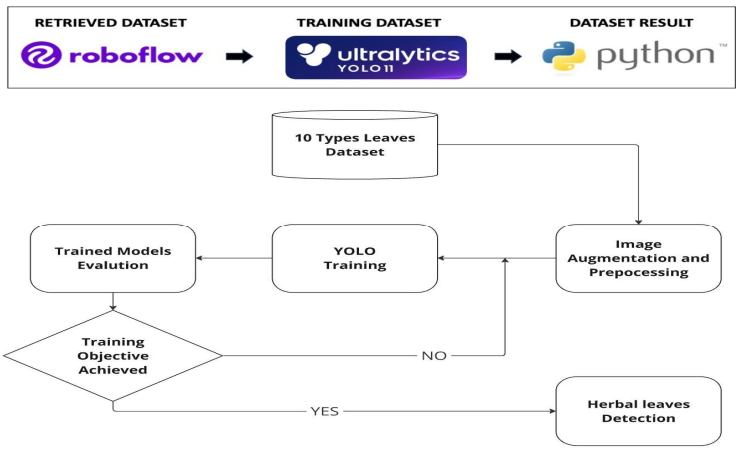


Figure 4. Research flowchart. Source: Authors' own work, based on experimental data.

Figure 4 describes the YOLO model's training process with the 10 Types of Leaves dataset. The process begins with retrieving the dataset from Roboflow, then moves on to data augmentation and preprocessing to improve the dataset's quality. The processed dataset is then used to train the YOLO model. After the training is completed, the model is evaluated to ensure that the training objectives are met. If the training goal is not met, the process repeats the preprocessing and training stages until it is. The final output of a well-trained model is exported using Python 3.12 (Python Software Foundation, Wilmington, NC, USA).

3. Materials and Methods

3.1. Dataset Retrieval

The first step is to obtain herbal leaf data from Roboflow, which offers a computer vision dataset and API. The dataset used in this study consists of 10,000 herbal leaf photos from Roboflow classified into the following ten classes: *Annona muricata*, *Anredera cordifolia*, *Piper betle*, *Ocimum basilicum*, *Peperomia pellucida*, *Psidium guajava*, *Isotoma longiflora*, *Coleus scutellarioides*, *Ageratum conyzoides*, and *Syzygium polyanthum*. Each class contains about 1000 photos with a resolution of 640 × 640 pixels. This dataset covers diverse backgrounds, lighting, and angles to enhance model accuracy in field conditions, as shown in Figure 5.

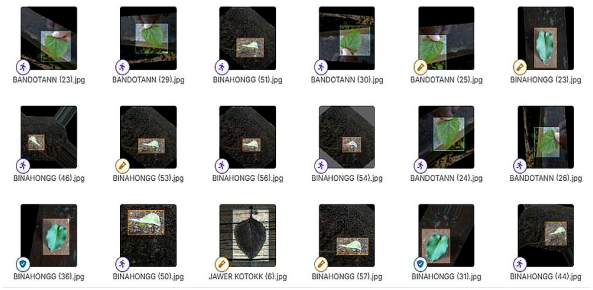


Figure 5. Result of downloading images of herbal leaves on Roboflow.

The next step after image collection is the image labeling process. The object labeling process is carried out using Roboflow, as seen in Figure 6.

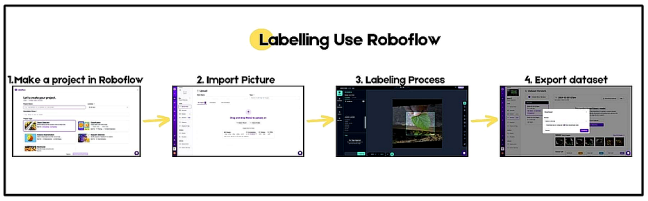


Figure 6. Stages of labeling using Roboflow.

In Figure 6, Roboflow is used for easy image labeling. The process includes importing images, labeling objects, and applying minor changes such as cropping and flipping to artificially enlarge the training dataset without changing the data ID. This approach is effective for enhancing the training model data. Dataset augmentation techniques such as rotation, scaling, and inversion were used to improve the accuracy of herbal leaf detection by increasing the diversity of the data. Data sharing is carried out for research, validation, and model testing. These techniques, as seen in Figure 7, were applied to correct errors in the herbal leaf image data.



Figure 7. Augmentation object.

3.2. Training Data

In this study, the dataset was divided into 70% for training, 20% for validation, and 10% for testing, with a total of 10,000 images from 10 classes. The YOLOv11 model was trained with a batch size of 16, 50 epochs, and an initial learning rate of 0.000714 that decreased by 10% every 50 epochs. After dataset sharing, evaluation techniques are used to calculate metric values such as accuracy (A), recall (R), mAP, and precision (P). The YOLOv11 training of Nano, Small, and Medium types show comparison of different times and RAM as shown in Table 1 below.

Table 1. Training requirements, indicates that YOLOv11 Nano utilized the fewest training resources, while YOLOv11 Medium took the most time and GPU RAM.

Model	Training Time (Hours)	GPU
Yolov11 Nano	2.2	2.56 GB (Tesla T4)
Yolov11 Small	2.6	4.35 GB (Tesla T4)
Yolov11 Medium	4	8.75 GB (Tesla T4)

4. Result and Discussion

Testing was performed on a dataset that had been created using the training process in Google Colab. The dataset consists of 10,000 images divided into 10 classes with 7000 images for training, 2000 for validation, and 1000 for testing, all 640 × 640 pixels in size. Testing was performed with 50 epochs using the following three YOLOv11 models: YOLOv11n, YOLOv11s, and YOLOv11m. The results of the three models will be compared. Testing the dataset using the Yolo v11 model with the Convolutional Neural Network method obtained results as in Table 2 below.

Table 2. Yolov11 training dataset result: (**a**) Nano, (**b**) Small, (**c**) Medium.

Class	img	Instance	Precision	Recall	mAP 50	mAP 50–59
All	2000	2820	0.933	0.921	0.972	0.734
Ageratum conyzoides	199	272	0.856	0.923	0.947	0.778
Annona muricata	208	232	0.921	0.957	0.983	0.647
Anredera cordifolia	220	317	0.963	0.934	0.989	0.869
Coleus scutellarioides	199	307	0.942	0.899	0.972	0.831
Isotoma longiflora	198	282	0.927	0.947	0.964	0.754
Ocimum basilicum	198	218	0.995	0.928	0.993	0.606
Peperomia pellucida	203	505	0.917	0.722	0.914	0.554
Piper betle	179	222	0.893	0.955	0.977	0.88
Psidium guajava	195	265	0.922	0.942	0.982	0.708
Syzygium polyanthum	200	200	0.998	1	0.995	0.708

(**a**)

Class	img	Instance	Precision	Recall	mAP 50	mAP 50–59
All	2000	2820	0.947	0.906	0.973	0.739
Ageratum conyzoides	199	272	0.858	0.912	0.962	0.795
Annona muricata	208	232	0.945	0.957	0.986	0.653
Anredera cordifolia	220	317	0.965	0.927	0.989	0.872
Coleus scutellarioides	199	307	0.964	0.876	0.968	0.845
Isotoma longiflora	198	282	0.942	0.927	0.973	0.754
Ocimum basilicum	198	218	0.988	0.917	0.987	0.6
Peperomia pellucida	203	505	0.928	0.693	0.913	0.556
Piper betle	179	222	0.93	0.95	0.976	0.884
Psidium guajava	195	265	0.952	0.902	0.982	0.711
Syzygium polyanthum	200	200	0.994	1	0.995	0.715

(**b**)

Class	img	Instance	Precision	Recall	mAP 50	mAP 50–59
All	2000	2820	0.932	0.928	0.974	0.743
Ageratum conyzoides	199	272	0.86	0.929	0.964	0.797
Annona muricata	208	232	0.906	0.961	0.98	0.656
Anredera cordifolia	220	317	0.955	0.933	0.989	0.872
Coleus scutellarioides	199	307	0.941	0.883	0.971	0.841
Isotoma longiflora	198	282	0.94	0.95	0.973	0.767
Ocimum basilicum	198	218	0.994	0.94	0.991	0.612
Peperomia pellucida	203	505	0.886	0.787	0.91	0.564
Piper betle	179	222	0.926	0.96	0.981	0.885
Psidium guajava	195	265	0.913	0.936	0.982	0.721
Syzygium polyanthum	200	200	0.997	1	0.995	0.71

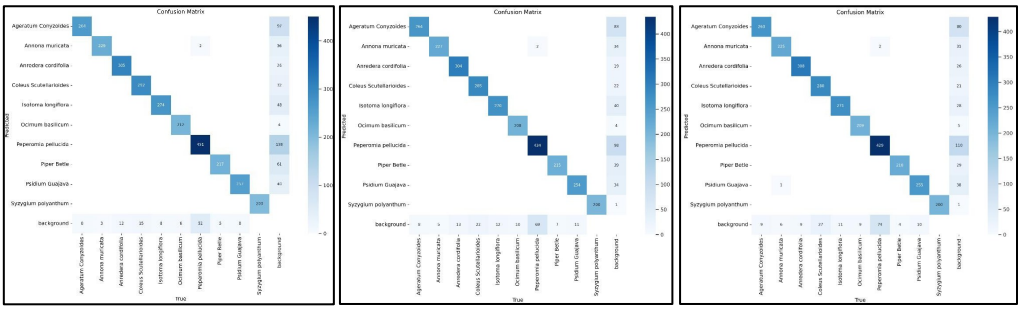
(**c**)

The YOLOv11 Nano model showed a precision value of 0.933 (93.3% relevant positive predictions) and a recall of 0.921 (92.1% successful detections). The model also had an mAP50 of 0.972 and mAP50-95 of 0.734. For further evaluation, a visualization using its Confusion Matrix was performed to assess the performance of the model, displaying the number of correct and incorrect predictions for each herbal leaf class.

In the YOLOv11 Small model, the object detection performance showed a precision of 0.947 (94.7%) and recall of 0.906 (90.6%), which means that this model can detect 90.6% of positive objects in the test data. mAP50 at IoU 0.25 reached 0.973, indicating that this model is better than YOLOv11 Nano in detecting objects at the IoU threshold of 0.25. mAP50-

95 in the IoU range of 0.25 is 0.739, indicating improved performance at more stringent IoU levels.

The YOLOv11 Medium model test results showed precision 0.932, recall 0.928, mAP50 0.974, and mAP50-95 0.743. Precision 0.932 means 93.2% of the herbal leaf detections identified by the model are accurate; although, there is still room for improvement. Recall 0.928 indicates the model successfully identified 92.8% of the herbal leaves in the test dataset. Next, we will visualize it using the Confusion Matrix as in Figure 8 below.

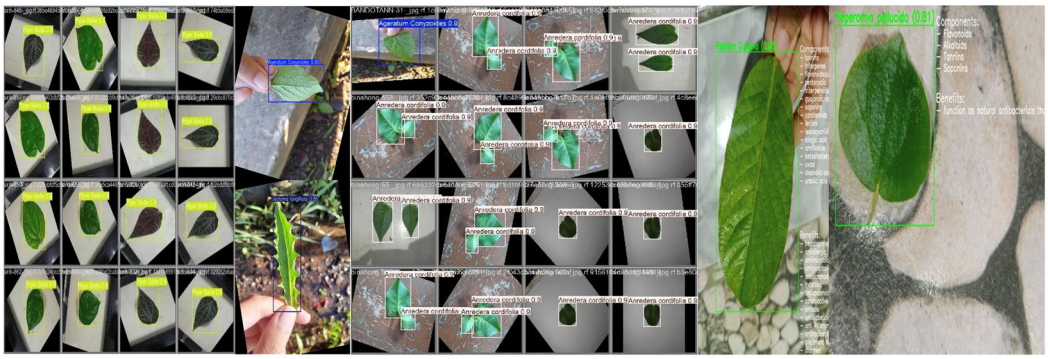


(**a**) (**b**) (**c**)

Figure 8. Confusion Matrix detection of herbal leaves using YOLOv11: (**a**) Nano, (**b**) Small, (**c**) Medium.

To check for error imbalance in counting herbal leaf types, its Confusion Matrix adds a new class representing the background. The number in the last row indicates leaves that were not detected, while the number in the last column indicates leaves that were detected in the wrong location.

Training with the YOLOv11 Nano model still needs improvement, especially in prediction accuracy on bounding box precision. YOLOv11 Small shows a new background class for result consistency, and its classification performance is better than YOLOv11 Nano, especially at a tighter IoU level. The YOLOv11 Medium model is effective in classifying herbal leaves but needs improvement in prediction accuracy and bounding box consistency. These changes will improve the accuracy and precision of the model, as we can see in Figure 9 below.



(**a**) (**b**) (**c**)

Figure 9. Herbal leaf detection results using YOLOv11: (**a**) Nano, (**b**) Small, (**c**) Medium.

5. Conclusions

YOLOv11 Medium showed the best performance in herbal leaf detection and classification with the highest mAP50-95 (0.743), precision 0.932, recall 0.928, and mAP50 0.974, indicating accurate and consistent detection under strict IoU conditions. YOLOv11 Small excels in efficiency with precision 0.947, recall 0.906, mAP50 0.973, and mAP50-95 0.739, while YOLOv11 Nano offers better speed with precision 0.933, recall 0.921, mAP50 0.972,

and mAP50-95 0.734; although, it is less consistent in detection than Medium. YOLOv11 Medium is the best choice for applications that require high accuracy, but YOLOv11 Nano and Small are superior for devices with low specifications. This study has limitations, such as the limited size of the dataset, which may affect the ability of the model to be generalized to various field conditions. Therefore, future research needs to expand the dataset, explore the latest YOLO variants, and optimize the model to be more efficient on devices with low specifications.

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References

1. Rani, D.M.; Wongso, H.; Purwoko, R.Y.; Winarto, N.B.; Shalas, A.F.; Triatmoko, B.; Pratama, A.N.W.; Keller, P.A.; Nugraha, A.S. Anti-cancer bioprospecting on medicinal plants from Indonesia: A review. *Phytochemistry* **2023**, *216*, 113881. [CrossRef]
2. Kaur, A.; Kaur, S.; Singh, H.P.; Datta, A.; Chauhan, B.S.; Ullah, H.; Kohli, R.K.; Batish, D.R. Ecology, Biology, Environmental Impacts, and Management of an Agro-Environmental Weed *Ageratum conyzoides*. *Plants* **2023**, *12*, 2329. [CrossRef]
3. Sura, S.P. The Phytochemical Landscape of Herbal Plants: Insights and Implications. *Int. J. Adv. Res. Sci. Commun. Technol.* **2023**, 916–918. [CrossRef]
4. Basir, H.; Purnamasari, I.; Thalib, M.; Daeng Pine, A.T.; Saldi; Nurka Sari, N.P. Formulasi Dan Uji Stabilitas Fisik Facial Wash Ekstrak Etanol Daun Kitolod (*Isotoma longiflora* L.) Serta Aktivitasnya Terhadap Staphylococcus epidermidis. *J. Kesehat. Yamasi Makassar* **2024**, *8*, 33–45. [CrossRef]
5. Nwafor, C.; Manduna, I.T. Local processing methods for commonly used medicinal plants in South Africa. *Med. Plants-Int. J. Phytomed. Relat. Ind.* **2021**, *13*, 289–301. [CrossRef]
6. Javid, A.; Fatima, M.; Hamad, M.; Ahmed, M. From roots to codes: Applications of computer-aided drug discovery from medicinal plants. *S. Afr. J. Bot.* **2024**, *173*, 159–174. [CrossRef]
7. Purwono, S.; Nisa, U.; Astana, P.; Wijayaningsih, R.; Wicaksono, A.; Wahyuningsih, M.; Kertia, N.; Mustofa, M.; Wahyuono, S.; Fakhrudin, N. Factors Affecting the Perception of Indonesian Medical Doctors on Herbal Medicine Prescription in Healthcare Facilities: Qualitative and Quantitative Studies. *J. Herb. Med.* **2023**, *42*, 100747. [CrossRef]
8. Bajpai, M. YOLO Models for Security and Surveillance Applications. *Int. J. Res. Appl. Sci. Eng. Technol.* **2024**, *12*, 2513–2518. [CrossRef]
9. Musyaffa, M.S.I.; Yudistira, N.; Rahman, M.A.; Basori, A.H.; Mansur, A.B.F.; Batoro, J. IndoHerb: Indonesia medicinal plants recognition using transfer learning and deep learning. *Heliyon* **2024**, *10*, e40606. [CrossRef]
10. Sharma, V.; Kumar, V.; Longchamps, L. Comparative performance of YOLOv8, YOLOv9, YOLOv10, YOLOv11 and Faster R-CNN models for detection of multiple weed species. *Smart Agric. Technol.* **2024**, *9*, 100648. [CrossRef]
11. Siahaan, R.D.; Simbolon, I.N. Enhancing Real-Time Herbal Plant Detection in Agricultural Environments with YOLOv8. *J. ISI* **2024**, *6*, 2491–2507. [CrossRef]
12. Mia, J.; Bijoy, H.I.; Uddin, S.; Raza, D.M. Real-Time Herb Leaves Localization and Classification Using YOLO. In Proceedings of the 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 6–8 July 2021; pp. 1–7. [CrossRef]
13. Susa, J.A.B.; Dellosa, R.M.; Doculan, J.A.D.; Jallorina, R.D.; Evangelista, R.S.; Zapanta, G.S.; Mindoro, J.N. Identification of Philippine Therapeutic Leave Using Deep Learning. In Proceedings of the 2022 International Conference on Emerging Technologies in Electronics, Computing and Communication (ICETECC), Jamshoro, Pakistan, 7–9 December 2022; pp. 1–6. [CrossRef]
14. Meiriyama, M.; Devella, S.; Adelfi, S.M. Klasifikasi Daun Herbal Berdasarkan Fitur Bentuk dan Tekstur Menggunakan KNN. *JATISI* **2022**, *9*, 2573–2584. [CrossRef]
15. Errayes, A.O.; Abdussalam-Mohammed, W.; Darwish, M.O. Review of Phytochemical and Medical Applications of Annona Muricata Fruits. *J. Chem. Rev.* **2020**, *2*, 70–79. [CrossRef]

16. Aruperes, G.Y.; Pangemanan, D.H.C.; Mintjelungan, C.N. Daya Hambat Ekstrak Daun Binahong (*Anredera cordifolia* Steenis) Terhadap Pertumbuhan Bakteri Streptococcus mutans. *e-GiGi* **2021**, *9*, 250. [CrossRef]
17. Alba, T.M.; de Pelegrin, C.M.G.; Sobottka, A.M. Ethnobotany, ecology, pharmacology, and chemistry of *Anredera cordifolia* (Basellaceae): A review. *Rodriguesia* **2020**, *71*, 01042019. [CrossRef]
18. Sadiah, H.H.; Cahyadi, A.I.; Windria, S. Kajian Daun Sirih Hijau (*Piper betle* L) Sebagai Antibakteri. *J. Sain Vet.* **2022**, *40*, 128. [CrossRef]
19. Metasari, D.; Sianipar, B.K.; Arfianti, M. Pemanfaatan pekarangan rumah untuk tanaman daun sirih (piper betle) bahan pembuatan handsanitizer di Panti Asuhan Bumi Raflesia. *J. Indones. RAYA (Pengabdi. Pada Masy. Bid. Sos. Hum. Kesehat. Ekon. Dan Umum)* **2021**, *2*, 69–73. [CrossRef]
20. Kumalasari, M.L.F.; Andiarna, F. Uji Fitokimia Ekstrak Etanol Daun Kemangi (*Ocimum basilicum* L). *Indones. J. Health Sci.* **2020**, *4*, 39. [CrossRef]
21. Tondolambung, A.H.; Edy, H.J.; Lebang, J.S. Uji Efektivitas Antibakteri Sediaan Krim Ekstrak Etanol Daun Kemangi (*Ocimum basilicum* L.) Terhadap *Staphylococcus aureus*. *Pharmacon* **2021**, *10*, 661. [CrossRef]
22. Permadani, A.; Nikmah, H.; Halimatussakdiah, H.; Mastura, M.; Amna, U. Skrining Fitokimia Daun Sirih Cina (*Peperomia pellucida* L.) dari Kecamatan Bireun Bayeun, Aceh Timur. *Quim. J. Kim. Sains Dan Terap.* **2024**, *6*, 6–12. [CrossRef]
23. Rahmawati, R.P.; Anggun, L.; Primandana, A.Z.; Dwiyanti, U. Pengaruh Pemberian Ekstrak Etanol 96% Daun Suruhan (*Peperonia pellucida* (L.) Kunth) terhadap Pertumbuhan Bakteri Propionibacterium acnes dengan Metode Difusi Cakram. *Indones. J. Farm.* **2021**, *6*, 22. [CrossRef]
24. Sravani, S.; Charitha, C.S.; Nadendla, R.R. A Complete Review on *Psidium guajava* Linn (Medicinal Plant). *Int. J. Pharm. Sci. Rev. Res.* **2021**, *67*, 13–17. [CrossRef]
25. Aji, N.P.; Noviyanty, Y.; Fahlevi, R. Skrining Fitokimia dan Profil KLT Metabolit Sekunder dari Ekstrak Etanol Daun Miana (*Coleus scutellarioides* Benth). *J. Farm. Malahayati* **2023**, *6*, 149–157. [CrossRef]
26. Rante, D.; Asmuruf, F.A.; Jannah, L.R.; Nadeak, E.S.M.; Simaremare, E.S. Anticoagulant Activity Test of Ethanol Extract *Coleus scutellarioides* (L.) Benth. *Int. J. Pharm. Bio-Med. Sci.* **2024**, *4*, 351–357. [CrossRef]
27. Baral, D.; Chaudhary, M.; Lamichhane, G.; Pokhrel, B. *Ageratum conyzoides*: A Potential Source for Medicinal and Agricultural Products. *Turkish J. Agric.-Food Sci. Technol.* **2022**, *10*, 2307–2313. [CrossRef]
28. Haryanto, F.K.; Jesica, I.A.; Arafi, A.R.; Pranasti, E.A.; Rosa, D. Review Jurnal: Pemanfaatan Daun Salam (*Syzygium polyanthum* (Wight) Walp.) Sebagai Pengobatan Tradisional di Indonesia. *Pharm. J. Pharmacy, Med. Health Sci.* **2023**, *4*, 20–33. [CrossRef]
29. Sulake, N.R. A Comprehensive Guide to YOLOv11 Object Detection. *Data Science Blogathon*. Available online: https://www.analyticsvidhya.com/blog/2024/10/yolov11-object-detection/ (accessed on 26 December 2024).
30. Jegham, N.; Koh, C.Y.; Abdelatti, M.; Hendawi, A. Evaluating the Evolution of YOLO (You Only Look Once) Models: A Comprehensive Benchmark Study of YOLO11 and Its Predecessors. 2024. Available online: http://arxiv.org/abs/2411.00201 (accessed on 26 December 2024).
31. Wu, M.; Yun, L.; Wang, Y.; Chen, Z.; Cheng, F. Detection algorithm for dense small objects in high altitude image. *Digit. Signal Process.* **2024**, *146*, 104390. [CrossRef]

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