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Herbal Leaf Identification for Balinese Lontar Usada Knowledge Preservation Using YOLOv8 Object Detection

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Abstract: Indonesia is a megabiodiversity country with more than 30,000 documented medicinal plant species. Much of this ethnobotanical knowledge is preserved in the *Lontar Usada Bali*, a traditional Balinese manuscript that records the medicinal uses of plants. However, preserving this knowledge is challenging due to the declining number of traditional practitioners and the difficulty of identifying medicinal plants in natural habitats. This study proposes a deep learning-based medicinal plant detection system using the YOLOv8 architecture to identify 12 classes of medicinal plant leaves in Taman Usada Bali. A total of 1,344 images containing 3,230 annotated leaf objects were collected under diverse lighting and background conditions. To improve model generalization, horizontal flipping, vertical flipping, rotation, Mosaic, and MixUp augmentations were applied. Five YOLOv8 variants (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x) were evaluated using Precision, Recall, F1-score, mAP50, and mAP50–95 metrics. Experimental results showed that all models achieved high detection performance, with YOLOv8m obtaining the highest mAP50–95 score of 0.8676. However, Cost Benefit Analysis (CBA) using the Weighted Sum Model (WSM) identified YOLOv8n as the optimal model. Although YOLOv8m achieved the highest accuracy, YOLOv8n obtained the highest WSM score (2.6400) by balancing detection performance (mAP50–95 of 0.8464) and computational efficiency. With a 6 MB model size, 2.7 ms inference time, and 1.559 hours of training, YOLOv8n is suitable for real-time mobile and edge-computing applications. The novelty of this study lies in integrating *Lontar Usada Bali* taxonomy into a structured dataset, applying WSM for model selection, and enhancing detection robustness through Mosaic and MixUp augmentation.

Keywords: Cost-Benefit Analysis; Deep Learning; Medicinal Plant Image Detection; Ethnobotany of Balinese Usada Lontar; YOLOv8

INTRODUCTION

Indonesia is a megabiodiversity country with approximately 30,000 species of medicinal plants, 67% of which are documented in the ancient manuscript Lontar Usada Bali (Tarigan & Stevani, 2021; Saputra et al., 2022). This manuscript describes the use of medicinal plants to treat various diseases and holds strategic value for the preservation of ethnobotanical knowledge (Suardiana & Suryawan, 2019). However, this knowledge faces a serious threat of extinction, as indicated by the generational gap in understanding the morphology of medicinal plants and the decreasing number of traditional practitioners proficient in the taxonomy documented in Lontar Usada Bali. Manual identification of medicinal plants is further challenged by the visual similarities among species and the complexity of environmental contexts, which may lead to fatal risks in therapeutic applications. These challenges highlight the urgency of digitizing ethnobotanical knowledge as an effort to preserve cultural heritage and modernize access to healthcare.

Digitization through Computer Vision technology offers a promising technological breakthrough for preserving the knowledge contained in Lontar Usada Bali. Previous studies have established a strong foundation for the development of deep learning algorithms across various strategic domains, including ship movement pattern identification (Widyantara et al., 2022), road damage detection (Arianta et al., 2025), Virtual Reality (VR)-

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based learning activity classification (Sindu et al., 2024), and speech recognition (Wirdiani et al., 2024). In the domains of cultural preservation and object detection, prior research has successfully implemented You Only Look Once version 5 (YOLOv5) for hand object classification (Rusjayanthi et al., 2025), recognition of Balinese script characters on lontar media, and medical detection in facial images (I et al., 2023). This body of prior research provides a solid foundation for the successful application of deep learning algorithms in this study.

Despite these advancements, a significant research gap remains unaddressed in the existing literature. First, while works by Sindu et al. (2024) and Rusjayanthi et al. (2025) successfully utilized deep learning, their focuses were heavily restricted to standard image classification or basic object tasks, which fail to handle the complex multi-instance object detection required to isolate overlapping leaves in natural, cluttered backgrounds. Second, although I et al. (2023) explored cultural preservation through Balinese script recognition on lontar media, there is currently a complete absence of computer vision studies that utilize a specialized dataset of Balinese herbal plants directly mapped to the ethnobotanical taxonomy of Lontar Usada Bali. Finally, previous deep learning implementations typically evaluate and select models based purely on isolated accuracy metrics, completely overlooking deployment trade-offs. None of the aforementioned studies have integrated a multi-criteria optimization framework to balance detection accuracy against computational costs, such as training and inference time, which is a critical requirement for practical deployment on resource-constrained mobile and edge devices.

To bridge these gaps, this study proposes the implementation of deep learning using the YOLOv8 architecture for the multi-class identification of medicinal plant species in Taman Usada Bali. The novelty of this research is explicitly realized through three strategic contributions embedded within the system development. First, this study establishes a direct linkage between the visual characteristics of herbal plant leaves and the traditional taxonomy documented in the Lontar Usada Bali into a single structured dataset. Second, it applies the Weighted Sum Model (WSM) method within a Cost and Benefit Analysis (CBA) framework to select the optimal YOLOv8 variant, ensuring a precise balance between medically relevant precision and computational efficiency in terms of training time and inference speed. Third, the model's ecological validity is significantly enhanced through the implementation of Mosaic and MixUp data augmentation techniques on natural-background images to effectively resolve complex environmental occlusions and real-world background noise. By systematically addressing these technical and cultural dimensions, this research not only advances real-time object detection on mobile and edge devices but also introduces a sustainable paradigm for the digital preservation of Balinese ethnobotanical heritage.

LITERATURE REVIEW

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) have been the dominant deep learning architecture for processing large-scale visual data over the past decade. Unlike earlier approaches that relied on manual feature extraction, modern CNNs automatically integrate feature extraction and classification within a single end-to-end learning framework (Alzubaidi et al., 2021).

A CNN architecture generally consists of three main layers:

1. **Convolutional Layer:** This layer applies a set of learnable filters to extract important features from images, such as edges, textures, and complex shape patterns. In medicinal plant leaf classification, these features may include leaf contours, venation structures, and texture variations.
2. **Pooling Layer:** This layer reduces the spatial dimensions of the extracted feature maps, thereby decreasing computational complexity, reducing memory consumption, and mitigating the risk of overfitting while preserving the most relevant information.
3. **Fully Connected Layer:** Located at the end of the network, this layer transforms the extracted features into a one-dimensional vector and performs the final classification by assigning the input image to the most probable target class.

Recent advancements in CNN architectures have focused on improving parameter efficiency, enabling deeper networks to learn high-level semantic representations while maintaining manageable computational and memory requirements (Aslan et al., 2022).

The YOLO Family (You Only Look Once)

In recent years, the object detection paradigm has increasingly shifted toward one-stage detectors to meet the growing demand for real-time computing applications. Among these approaches, the YOLO (You Only Look Once) family of architectures has become one of the most influential object detection frameworks. Unlike traditional multi-stage detection methods, YOLO formulates object detection as a single regression task, enabling the simultaneous prediction of bounding box coordinates and class probabilities in a single forward (Ali & Zhang, 2024).

The evolution of YOLO has demonstrated significant advancements in both detection accuracy and computational efficiency:

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1. **2021–2022:** The introduction of YOLOv6 and YOLOv7 improved backbone network design, feature extraction capabilities, and training optimization strategies, resulting in enhanced detection performance and inference speed.
2. **2023–2025:** Recent developments in the YOLO family, particularly YOLOv8 and its successors, have focused on anchor-free detection architectures and computational efficiency to facilitate deployment on resource-constrained edge devices (Ali & Zhang, 2024).

The primary objective of recent YOLO developments is to balance detection accuracy and computational efficiency while maintaining robust performance in complex environments.

YOLOv8 Architecture

Released by Ultralytics in 2023, YOLOv8 sets a new standard for architectural flexibility in simultaneous object detection, instance segmentation, and image classification (Jocher et al., 2023). YOLOv8's cutting-edge design introduces radical structural changes from its predecessors:

1. Anchor-Free Paradigm: YOLOv8 abandons the anchor-based approach and instead predicts object centers directly. This approach accelerates model convergence and reduces the computational complexity of post-processing steps such as Non-Maximum Suppression (NMS).
2. C2f Structure Block: Replacing the old C3 module, the C2f block (Cross-Stage Partial Bottleneck with two convolutions) is designed to facilitate richer inter-layer information flow, enabling the retention of complex leaf features without increasing the model file size.
3. Decoupled Head: Uses separate network heads to handle classification and localization (bounding box regression) computations independently. This task separation has been shown to significantly boost Mean Average Precision (mAP) scores on overlapping objects.

Although numerous studies have proposed architectural modifications to YOLO-based detectors, such as attention mechanisms, lightweight convolution modules, and customized backbone networks, these approaches often increase model complexity and reduce deployment flexibility. Recent studies have demonstrated that the baseline YOLOv8 architecture already provides strong feature extraction and localization capabilities across various object detection tasks. Therefore, instead of introducing additional architectural components, this study focuses on evaluating the effectiveness of vanilla YOLOv8 variants for medicinal plant leaf detection under natural environmental conditions. This approach enables a fair assessment of the trade-off between detection accuracy and computational efficiency while maintaining compatibility with mobile and edge-computing platforms.

Object Detection in Ethnobotanical and Agricultural Applications

The application of object detection algorithms in the fields of ethnobotany and agriculture has experienced rapid growth due to advances in deep learning techniques and the increasing availability of modern computational resources. However, detecting medicinal plant leaves in natural environments remains a challenging task compared to detection in controlled laboratory settings. According to a recent survey by Tang et al. (2023), the primary challenges include severe occlusion caused by overlapping leaves, variations in natural lighting conditions, and complex background noise that often shares similar visual characteristics with the target objects.

In addition to environmental factors, the high degree of visual similarity among medicinal plant species requires object detection models to possess strong feature extraction capabilities and high discriminative sensitivity. Subtle differences in leaf morphology, texture, and color patterns must be accurately captured to ensure reliable species identification.

To overcome the limitations associated with natural data variability, advanced data augmentation techniques have been widely adopted. Spatial augmentation methods such as Mosaic and MixUp have been empirically shown to improve model robustness and generalization performance. These techniques increase data diversity, reduce background dependency, mitigate overfitting, and enhance the model's ability to detect objects under complex real-world conditions. Consequently, the application of Mosaic and MixUp contributes to improving the ecological validity of object detection systems deployed in natural environments (Wang et al., 2022).

Cost–Benefit Analysis (CBA) in Model Selection

In contemporary applied artificial intelligence research, selecting the most suitable model should not rely solely on predictive performance metrics such as Mean Average Precision (mAP). Instead, model evaluation should simultaneously consider predictive performance and computational efficiency to support practical deployment on resource-constrained platforms, including mobile devices and edge-computing systems. Such a cost–benefit perspective has become increasingly important as edge AI applications require an appropriate balance between detection accuracy and computational resource consumption (Cao et al., 2024a; Ayan et al., 2023).

In this study, a Cost–Benefit Analysis (CBA) perspective is adopted by categorizing the evaluation criteria into benefit and cost groups. The benefit criteria represent predictive performance and include Precision, Recall, F1-score, mAP50, and mAP50–95. The cost criteria represent computational requirements, including training time,

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inference time, and model size. This evaluation strategy enables a balanced assessment between detection accuracy and computational efficiency when selecting the most appropriate YOLOv8 variant.

To systematically evaluate these multiple criteria, the Weighted Sum Model (WSM) is employed as the multi-criteria decision-making method within the proposed evaluation framework. WSM aggregates normalized criterion values using predefined weights to compute a composite score for each alternative, thereby enabling objective comparison among competing models. The model with the highest overall score is considered the optimal model because it provides the best trade-off between predictive performance and computational efficiency (Sorooshian & Parsia, 2019). The weighted criteria are then aggregated to produce a comprehensive performance score for each model. Through the normalization and weighting processes of the WSM decision matrix, model variants can be evaluated not only based on predictive performance but also on computational efficiency. Consequently, lightweight architectures such as YOLOv8n may be identified as the optimal choice because they provide a more balanced trade-off between detection accuracy and resource requirements, even when their accuracy is slightly lower than that of larger model variants.

Table 1 State of the Art

No.	Research Title	Research Description and Comparison
1	A Deep Learning-Based Recognition Technique for Plant Leaf Classification (Kanda et al., 2021)	This approach combines Conditional Generative Adversarial Network (CGAN) technology for synthetic leaf data augmentation, feature extraction using ResNet-50, and classification using a Logistic Regression model. It was tested on 7 different datasets, achieving an average accuracy of 96.1%.
2	Classification of Medicinal Plants Based on Leaf Images Using a CNN Algorithm (Sinaga & Sembiring, 2025)	Using a CNN (MobileNetV2) with transfer learning to classify 10 types of medicinal plant leaves with 98.43% accuracy. This model focuses on single-image classification rather than object detection in complex real-world environments.
3	Herbal Leaves Classification Based on Leaf Image Using CNN Architecture Model VGG16 (Mardiana et al., 2023)	Exploring the use of a VGG16-based transfer learning method with optimized ImageDataGenerator to reduce overfitting. Classifying 10 classes of centered single-leaf herbal images and achieving an accuracy rate of 97%
4	Classification of Herbal Plants for Skin and Hair Health Based on Leaf Images Using a CNN Algorithm with an Inceptionv3 Architecture (Melati et al., 2025)	Using an InceptionV3 CNN to classify 10 specific herbal plants used in skin and hair care. With a focus on ease of deployment, the trained model was efficiently converted to the TensorFlow Lite format for use in offline smartphone applications.
5	Classification of Herbal Plant Leaf Types Based on the Usada Taru Pramana Palm-leaf Manuscript Using CNN (Dewi et al., 2023, 2024)	Using the Lontar Usada Taru Pramana manuscript as a basis for classifying 50 types of herbal leaves using the TPHerbleaf dataset. Comparing three architectures (MobileNet, Inception ResNet V2, EfficientNet B2), with MobileNet yielding the best results (82% accuracy).
6	Tomato detection in natural environment based on improved YOLOv8 network (Dong et al., 2025)	Optimizing the YOLOv8 algorithm by replacing the backbone with MobileNetV3, incorporating CBAM attention, and using the SIoU loss function for tomato ripeness detection. The model was designed to remain lightweight when handling leaves and branches that obscure one another (occlusion).
7	TPH-YOLOv5: Improved YOLOv5 Based on Transformer Prediction Head for Object Detection on Drone-captured Scenarios (Zhu et al., 2021),	Modifying YOLOv5 with a Transformer Prediction Head (TPH) and a Convolutional Block Attention Module (CBAM) to detect objects with high density and varying scales in drone footage. Demonstrating strong localization capabilities for micro-scale objects across large areas.

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8	DC-YOLOv8: Small-Size Object Detection Algorithm Based on Camera Sensor (Lou et al., 2023)	Redesigning the YOLOv8 architecture to address weaknesses in the detection of small-size objects. Proposing a new downsampling method and a DC network (a combined module of standard convolutions and depth-wise separable convolutions) to preserve the richness of spatial contextual information in the image.
9	LAYN: Lightweight Multi-Scale Attention YOLOv8 Network for Small Object Detection (Ma et al., 2024).	Introducing the "LAYN" framework by using GhostNet as the primary backbone, combined with YOLOv8, Multi-Scale attention techniques, and the Soft-NMS algorithm. This approach significantly reduces the number of parameters (by 48.66%) to make it suitable for edge devices with limited computational resources.
10	Small Pests Detection in Field Crops Using Deep Learning Object Detection (Khalid et al., 2023)	A historical comparison of the performance of the YOLO family of models (YOLOv3, v4, v6, and v8) in detecting extremely small plant pests. The results demonstrate that the YOLOv8 algorithm achieves the highest mAP (84.7%) in real-time agricultural management.
11	A Lightweight YOLOv8 Tomato Detection Algorithm Combining Feature Enhancement and Attention (Yang et al., 2023)	Developing a more lightweight YOLOv8s by implementing Depthwise Separable Convolution (DSConv), Dual-Path Attention Gate (DPAG), and a Feature Enhancement Module (FEM). This successfully boosted the mAP to 93.4% while reducing the model size to just 16 MB.
12	Machine Vision-Based Crop-Load Estimation Using YOLOv8 (Ahmed et al., 2023).	Developing a machine vision system based on YOLOv8 instance segmentation combined with Principal Component Analysis (PCA) to detect the 3D architecture of apple tree branches and trunks during the dormant season, in order to automatically estimate harvest load capacity.

Current research on medicinal plant identification has employed methods such as Convolutional Neural Networks (CNN) (Kanda et al., 2021; Sinaga & Sembiring, 2025; Mardiana et al., 2023), InceptionV3 (Melati et al., 2025), and specialized datasets such as TPHerblEAF (Dewi et al., 2023, 2024). However, these studies are generally limited to single-image classification and do not support object detection capabilities. In contrast, object detection algorithms such as YOLOv8 demonstrate superior real-time detection performance in natural environments (Dong et al., 2025), supported by various architectural modifications, including TPH-YOLOv5 with Transformer integration (Zhu et al., 2021), DC-YOLOv8 for small object detection (Lou et al., 2023), and multi-scale algorithms (Ma et al., 2024). In the agricultural domain, YOLOv8 has proven effective for pest identification (Khalid et al., 2023), fruit detection (Yang et al., 2023), and harvest yield estimation (Ahmed et al., 2023).

A fundamental limitation of previous studies is the reliance on small-scale, non-standardized datasets and image acquisition conducted in controlled environments. This study introduces a novel application of YOLOv8 as an integrated model for identifying medicinal plants in the Usada Bali Garden, with the following specific advantages: Smart Ethnobotany Integration Directly linking visual objects to the taxonomy documented in the Lontar Usada Bali within a single structured dataset, CBA-WSM Optimization Applying the Weighted Sum Model (WSM) method to select the most suitable YOLOv8 variant based on the trade-off between medical precision and computational efficiency, Ecological Validity Implementing Mosaic and MixUp data augmentation techniques on natural-background image data to address species occlusion in native environmental conditions.

METHOD

This study was conducted through a series of systematic steps to achieve the intended objectives in a structured manner. The overall research process is illustrated in Figure 1.

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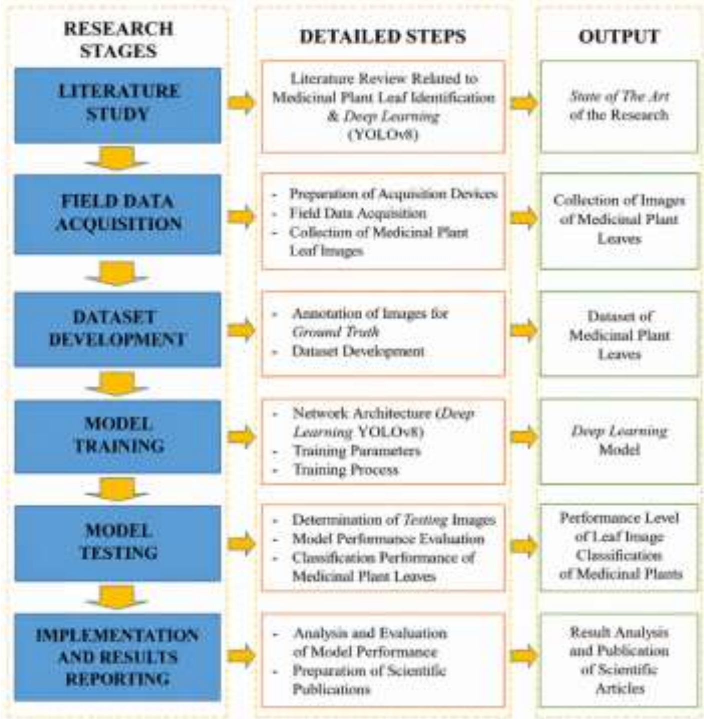

Fig. 1 The Research Process Flow

This section presents the experimental results of five YOLOv8 variants and a comprehensive Cost–Benefit Analysis (CBA) based on the Weighted Sum Model (WSM). The evaluation includes model performance, convergence characteristics, and computational efficiency, which are systematically analyzed using quantitative metrics, comparative tables, and graphical visualizations. The details of the activities in each research phase are outlined as follows:

1. **Literature Review**
   Process: Conducting an in-depth analysis of the literature related to medicinal plant species identification, deep learning, and YOLOv8.
   Output: A comprehensive literature review document.
   Performance Indicator: A thorough understanding of the application of deep learning models for the automatic identification of medicinal plant species.
2. **Field Data Acquisition**
   Process: Capturing images of 12 medicinal plant species at Taman Usada Bali using natural backgrounds under varying lighting conditions and shooting angles.
   Output: A dataset of medicinal plant species images.
   Performance Indicator: A dataset consisting of 12 classes of medicinal plant leaves with representative variations in environmental conditions.
3. **Dataset Creation**
   Process: Annotating leaf images by adding labels and bounding boxes using annotation tools, followed by resizing and splitting the dataset into training, validation, and testing sets.
   Output: An annotated and structured dataset of medicinal plant leaf images.
   Performance Indicator: A dataset that is ready for training the YOLOv8 model and meets scientific dataset standards.
4. **Model Training**
   Process: Training the model using all YOLOv8 variants (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x) with uniform hyperparameter settings. The Weighted Sum Model (WSM) method is applied to ensure the reliability of botanical identification.
   Output: Trained YOLOv8 models with optimized weights for each variant.
   Performance Indicator: The model is capable of automatically detecting and classifying medicinal plant leaves.
5. **Model Testing**
   Process: Testing is conducted on all YOLOv8 variants and evaluated using accuracy, precision, recall, mAP, and Explainable AI visualization metrics, as well as inference speed measurements to assess

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computational efficiency. The test results are compared to determine the impact of model complexity on detection performance.
Output: Quantitative evaluation results for the performance of each YOLOv8 variant.
Performance Indicator: Identification of a model with an optimal balance between accuracy and computational efficiency.

6. **Implementation and Reporting of Results**
Process: The research findings are systematically analyzed to interpret model performance and its alignment with the research objectives. Technical documentation of the dataset, model architecture, and evaluation results is then compiled into a research report and a scientific article for the targeted journal.
Output: A reference dataset, the best-performing model, and a scientific article.
Performance Indicator: Publication of a scientific article and contribution to the development of an image-based medicinal plant recognition system.

As an initial foundation for the research, several stages have already been completed, including the design of the research framework, the determination of the acquisition and annotation schemes for medicinal plant image data, and the development of a YOLOv8-based classification and detection workflow. These initial achievements demonstrate the methodological readiness and technical feasibility of the research to be conducted and completed according to the proposed timeline. The architecture of the developed YOLOv8 framework is shown in Figure 2.

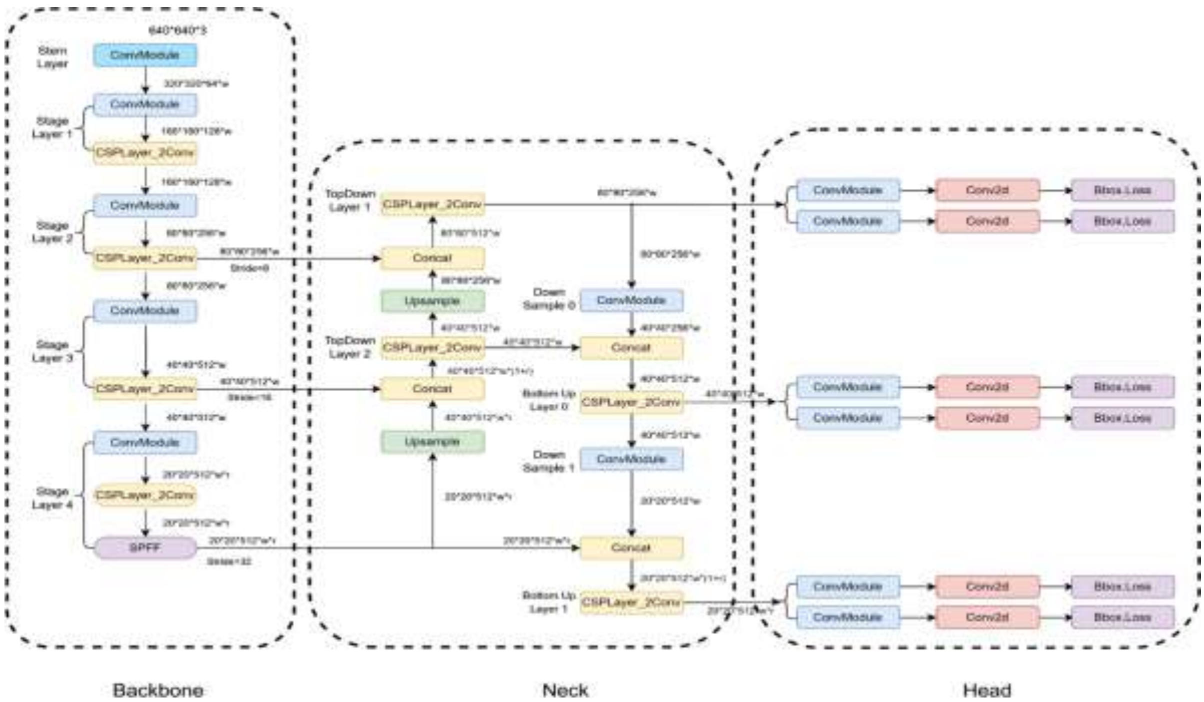

Fig. 2 YOLOv8 Architecture

As shown in Figure 2, the YOLOv8 architecture consists of three main components: the backbone, the neck, and the head. The backbone extracts essential visual features from the input image such as the shapes, textures, and patterns of medicinal plant leaves through a series of efficient convolutional layers. These features are then integrated in the neck using the Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) mechanisms to combine multi-scale information, enabling the detection of objects with varying sizes and orientations in natural backgrounds. Subsequently, the head performs the final prediction by generating bounding box coordinates, confidence scores, and object class labels in an anchor-free manner, which simplifies the training process and improves detection accuracy. The prediction results are then filtered using Non-Maximum Suppression (NMS) to eliminate duplicate bounding boxes. With its lightweight, efficient, and accurate architecture, YOLOv8 is highly suitable for the real-time identification and classification of medicinal plant species in real-world environments.

This study has completed the design phase of a workflow for an image-based medicinal plant species identification system. To evaluate the reliability of the developed model, a testing scenario was designed to represent the conditions of capturing medicinal plant images in the natural environment of Taman Usada Bali.

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This scenario is illustrated through examples of the detection and classification results of medicinal plant objects, as shown in Figure 3.

The workflow for training the YOLOv8 identification model is illustrated in Figure 4, with the following detailed description:

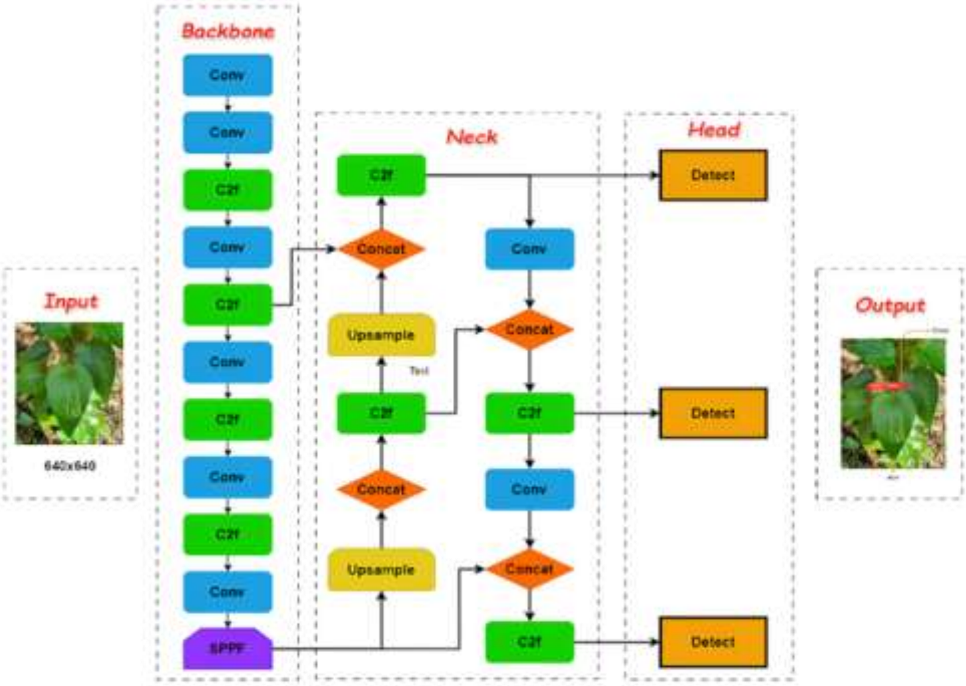

Fig. 3 Illustration of Medicinal Plant Image Identification Using YOLOv8

1. **Model Training** The training process was conducted using the deep learning-based YOLOv8 architecture, utilizing medicinal plant leaf images as training data. The outcome of this stage is a YOLOv8 model with trained weights capable of recognizing and distinguishing 12 types of medicinal plant leaves with visually similar characteristics.
2. **Selection and Configuration of Model Variants** This study employs five YOLOv8 variants YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x to compare their performance. Parameter and hyperparameter tuning were systematically applied to optimize model performance during the training, validation, and inference stages.
3. **Detection and Classification Process** Input images with a resolution of 640 × 640 pixels were normalized and processed by the YOLOv8 model through the stages of feature extraction (backbone), multi-scale feature fusion (neck), and object prediction (head). The model generated outputs in the form of medicinal plant leaf classes, confidence scores, and bounding box coordinates. Subsequently, the Non-Maximum Suppression (NMS) technique was applied to eliminate duplicate detections, resulting in final images with the most accurate bounding boxes and class labels.

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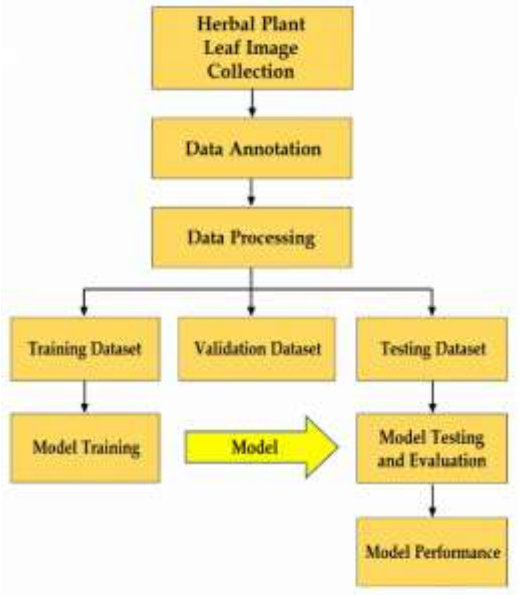

Fig. 4 YOLOv8 Detection Training Flowchart

Hardware Specifications

The YOLOv8 model training process was conducted in a cloud-based computing environment using Google Colab Pro to ensure computational efficiency and training stability. This platform was selected because it provides priority access to high-performance GPUs, enabling faster model convergence and reduced training time. In addition, Google Colab Pro offers seamless compatibility with the PyTorch ecosystem and supports High-Memory Instances, which are well suited for handling large-scale datasets and computationally intensive deep learning workloads. The hardware specifications utilized in this study are presented in the following table:

Table 2 Google Cloud Service Specifications

Nama Layanan Cloud	Google Colab Pro
Tipe Mesin	Tesla T4
GPU	NVIDIA Tesla T4 (16GB VRAM)
CPU	Intel(R) Xeon(R) CPU @ 2.20GHz
RAM	52GB
Storage	200 GB
Sistem Operasi	Linux (Ubuntu 20.04 LTS)

Model Training Hyperparameter Configuration

In this study, the YOLOv8 training process was configured using a set of parameters and hyperparameters that play a crucial role in determining the performance of herbal plant leaf detection. All training scenarios employed an input image size of 640 × 640 pixels, which was selected to achieve a balance between feature extraction capability and computational efficiency. This resolution is one of the most commonly used configurations in YOLOv8 because it preserves object details while maintaining efficient processing during both training and inference stages. Model optimization was performed using the Stochastic Gradient Descent (SGD) optimizer. SGD was selected due to its ability to provide strong generalization performance in object detection tasks, particularly when applied to relatively large datasets. Furthermore, SGD requires less memory than adaptive optimization algorithms such as Adam and AdamW and can achieve a more stable convergence process when combined with appropriate learning rate and momentum settings. As a result, SGD offers an effective balance between training efficiency, model stability, and detection performance.

The learning rate was configured using the default settings of the Ultralytics YOLOv8 framework for the SGD optimizer, with an initial learning rate (lr0) of 0.01 and a final learning rate factor (lrf) of 0.01. These parameters regulate the magnitude of weight updates during each training iteration, ensuring that the optimization process remains effective and stable throughout model training.

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During the inference stage, the model employed a confidence threshold of 0.25, which corresponds to the default setting in YOLOv8. This parameter defines the minimum confidence score required for a prediction to be considered a valid detection. Predictions with confidence scores below this threshold are discarded, thereby reducing the likelihood of false detections and improving the reliability of the detection results. The Intersection over Union (IoU) threshold used in the Non-Maximum Suppression (NMS) process was set to the default YOLOv8 value of 0.70. This parameter is used to remove redundant detections by retaining only the bounding box with the highest confidence score when multiple bounding boxes overlap. It is important to note that the IoU threshold applied during NMS differs from the IoU thresholds used for model performance evaluation. In this study, model performance was evaluated using mAP50, which applies an IoU threshold of 0.50, and mAP50-95, which measures the average detection performance across IoU thresholds ranging from 0.50 to 0.95. These evaluation metrics provide a comprehensive assessment of the model's localization accuracy and object detection performance under varying levels of overlap strictness.

Table 3 Hyperparameter

Paramater	Value	Description
Learning rate (lr0)	0,01	The default value for the SGD optimizer in YOLOv8.
Final learning rate factor (lrf)	0,01	The default value for the SGD optimizer in YOLOv8.
Image Size	640 × 640 pixels	The resolution of the input images used during training.
Optimizer	SGD (Stochastic Gradient Descent)	Used in all training scenarios.
Batch Size	16	Number of images processed per iteration.
Epoch	100	Maximum number of training cycles.
Early Stopping (Patience)	15	Early stopping was applied, and training was terminated if no improvement was observed for 15 consecutive epochs.
Confidence Threshold	0,25	Default values for YOLOv8 during the inference stage.
IoU Threshold	0,70	Used to eliminate duplicate detections.
IoU Evaluation (mAP50)	0,50	Used for model performance evaluation.
IoU Evaluation (mAP50-95)	0,50-0,95	Evaluation of object overlap at various levels.

Cost and Benefit Analysis (CBA)

Cost and Benefit Analysis (CBA) was employed in this study to determine the best-performing model among the five YOLOv8 variants evaluated. This method provides a balanced assessment by considering model performance as the benefit and computational efficiency as the cost. Specifically, testing accuracy was used as the benefit criterion, while training time and inference time were used as cost criteria. Accuracy measures the model’s ability to correctly detect objects in images, whereas training time and inference time reflect the computational resources and execution time required for model training and deployment.

To identify the optimal model, mAP50–95 was selected as the primary benefit metric because it evaluates detection performance across multiple Intersection over Union (IoU) thresholds ranging from 0.50 to 0.95, providing a more comprehensive assessment of model accuracy. Meanwhile, training time and inference time were chosen as cost metrics since longer processing times generally require greater computational resources and may increase operational costs.

To rank the evaluated models, a normalization technique was applied to the performance metrics prior to the ranking process. The normalization method used in this study is presented in Equation (1).

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{Max_i(x_{ij})}, & \text{If } x_{ij} \text{ is } \mathit{benefit} \\ \dfrac{Min_i(x_{ij})}{x_{ij}}, & \text{If } x_{ij} \text{ is } \mathit{cost} \end{cases} \tag{1}$$

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In this study, WSM was employed to determine the best-performing YOLOv8 model among the five variants evaluated by simultaneously considering multiple performance criteria. The benefit criterion was represented by the mAP50–95 value, while the cost criteria consisted of training time and inference time. Before the evaluation process, all criterion values were normalized to ensure comparability across different scales using Equation (1). In this equation, x_{ij} represents the original value of the benefit or cost criterion, r_{ij} denotes the normalized criterion value, i represents the alternative, and j represents the criterion.

After the normalization process, the weighted summation was performed using Equation (2) by aggregating all normalized criteria for each alternative. The normalized values were multiplied by their corresponding weights and then summed to obtain the final score of each model. The model with the highest WSM score was selected as the optimal model, as it provides the best trade-off between detection accuracy and computational efficiency.

$$W\ S\ M_i = \sum_{j=1}^{n} W_j r_{ij} \quad (2)$$

In Equation (2), $W\ S\ M_i$ denotes the final weighted score of alternative i , whereas W_j represents the weight of criterion j. Following previous studies, all criteria were assigned an equal weight of **1**, implying that each criterion contributed equally to the overall evaluation and ranking process.

Table 4 Cost-Benefit Analysis Parameter Details

Cost	Benefit	Rank
- Box Loss - Class Loss - **Training Time** - Model Size - **Inference Time**	- Precision - Recall - F1-Score - mAP50 - **mAP50-95**	Sorted by the highest sum of normalized costs and benefits.

RESULTS

This chapter presents the research findings based on three main aspects. First, it describes the collection of medicinal plant leaf images, including *sirih*, *pule*, *binahong*, *kumis kucing*, *dadap*, *girang*, *salam*, *pranajiwa*, *mint*, *sembung gunung*, *kunyit*, and *jahe*, covering the image acquisition process and dataset construction. Second, it explains the implementation of a Deep Learning-based detection and classification system using the YOLOv8 architecture, including data preprocessing and model training stages. Finally, this chapter evaluates the performance of the YOLOv8 model in image classification and compares the results of different YOLOv8 variants to identify the most suitable model for medicinal plant detection tasks.

Medicinal Plant Leaf Image Acquisition Process

The image acquisition process was the initial stage of this study and was conducted using a Samsung S25FE Android smartphone, producing images in .jpg format. Data collection was carried out at Taman Usada Bali to obtain diverse visual characteristics of medicinal plant leaves and strengthen the dataset. Image acquisition was performed once a week over a one-month period to capture variations in leaf morphology.

Natural backgrounds from the Taman Usada Bali environment were used to ensure realistic image conditions. Images were captured at a distance of approximately 10–15 cm from the object under varying lighting conditions, including morning and afternoon sessions. Through this process, a total of 1,344 medicinal plant leaf images were successfully acquired, with an image resolution of 3024 × 4032 pixels.

Fig. 5 Sample image data of herbal plant leaves that were acquired

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Dataset Construction

Dataset construction is a critical stage in this study to ensure the availability of representative data for training the YOLOv8 model. The dataset consists of 12 classes of medicinal plant leaf images, namely *sirih*, *pule*, *binahong*, *kumis kucing*, *dadap*, *girang*, *salam*, *pranajiwa*, *mint*, *sembung gunung*, *kunyit*, and *jahe*, which were directly obtained through field image acquisition. 1) Data Annotation, the first stage of dataset construction was data annotation, which aimed to provide accurate labels for each medicinal plant object in the images. Annotation was performed using the web-based labeling tool Roboflow by assigning bounding boxes to each leaf object as ground truth for training and evaluation. From the 1,344 originally acquired images, a total of 3,230 images were generated after applying data augmentation techniques. 2) Dataset Splitting, the annotated dataset was divided into training, validation, and testing sets to support effective model development and evaluation. The dataset distribution consisted of 88% training data (2,829 images), 8% validation data (267 images), and 4% testing data (134 images). This division enables the YOLOv8 model to learn image patterns, reduce overfitting through validation, and evaluate model performance objectively using unseen test data. Dataset Augmentation, data augmentation was applied to improve dataset diversity, strengthen model generalization, and reduce the risk of overfitting. Several augmentation techniques were implemented, including horizontal flip, vertical flip, 90° rotation (clockwise, counterclockwise, and upside down), and Mosaic MixUp augmentation. These techniques enabled the YOLOv8 model to recognize medicinal plant leaves under more complex and realistic conditions, such as varying angles, lighting, and noise. Augmentation was applied only to the training dataset, while the validation and testing datasets remained unchanged to maintain objective evaluation results.

Table 5 The Number of Images Per Class

No.	Class	Number of Images
1	*Sirih*	106 Images
2	*Pule*	103 Images
3	*Binahong*	125 Images
4	*Kumis Kucing*	110 Images
5	*Dadap*	111 Images
6	*Girang*	130 Images
7	*Salam*	110 Images
8	*Pranajiwa*	103 Images
9	*Mint*	108 Images
10	*Sembung Gunung*	113 Images
11	*Kunyit*	117 Images
12	*Jahe*	108 Images
Total		**1,344 Images**

Figure 6 illustrates the augmented dataset used in this study. Following the augmentation process, the dataset increased to a total of 3,230 images, which were subsequently divided into 2,829 training images (88%), 267 validation images (8%), and 134 testing images (4%). All images underwent preprocessing steps, including auto-orientation and resizing to 640 × 640 pixels. Furthermore, the applied augmentation techniques consisted of horizontal flipping, vertical flipping, 90° rotation (clockwise, counterclockwise, and upside down), and mosaic mix up augmentation. These augmentation techniques were employed to increase the diversity of the training data, reduce the risk of overfitting, and enhance the model's generalization capability in recognizing herbal leaf objects under various orientations and image acquisition conditions.

Fig. 6 Dataset Distribution, Preprocessing, and Augmentation Configuration

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Figure 7 presents an example of the bounding box annotations applied to the herbal leaf dataset used in this study. Each leaf object was manually annotated and assigned to its corresponding class using a bounding box. These annotations serve as ground-truth labels during the YOLOv8 training process, enabling the model to learn both the location and class of each object. Accurate annotation is essential for improving the model's detection and classification performance.

Fig. 7 Example of bounding box annotations in the herbal leaf dataset

Implementation of the YOLOv8-Based Medicinal Plant Leaf Classification Model

After the dataset was successfully constructed, the next stage involved implementing the YOLOv8-based image detection model. This process included hyperparameter configuration, model training, experimental training scenarios, and visualization of the training results to evaluate the performance of each YOLOv8 variant in detecting and classifying medicinal plant leaf images. The YOLOv8 training process was conducted using five experimental scenarios representing five YOLOv8 model variants. Table 1 presents the detailed hyperparameter configurations used in each training scenario.

Table 6 Model Training Scenario Hyperparameter Configuration Details

No.	Skenario	Model	*Optimizer*	Batch Size	Epoch
1	N	YOLOv8n	SGD	16	100 Epoch (*Early stop patience=15*)
2	S	YOLOv8s	SGD		
3	M	YOLOv8m	SGD		
4	L	YOLOv8l	SGD		
5	X	YOLOv8x	SGD		

Visualization of the Model Training Process

The YOLOv8 training process utilized five model variants: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, all trained using the SGD optimizer. Consistent hyperparameter settings were applied across all scenarios, including a batch size of 16, 100 epochs, and early stopping with a patience value of 15. SGD was selected due to its strong generalization capability, stable convergence, and computational efficiency in object detection tasks. The best model was determined based on evaluation metrics to achieve optimal medicinal plant leaf classification performance.

The training results of all YOLOv8 variants (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x) demonstrated stable convergence and high detection performance for medicinal plant leaf classification. Overall, the training and validation loss values consistently decreased, indicating effective feature learning and good model generalization. Evaluation metrics such as precision, recall, mAP50, and mAP50-95 increased significantly during the early training stages before stabilizing at high values.

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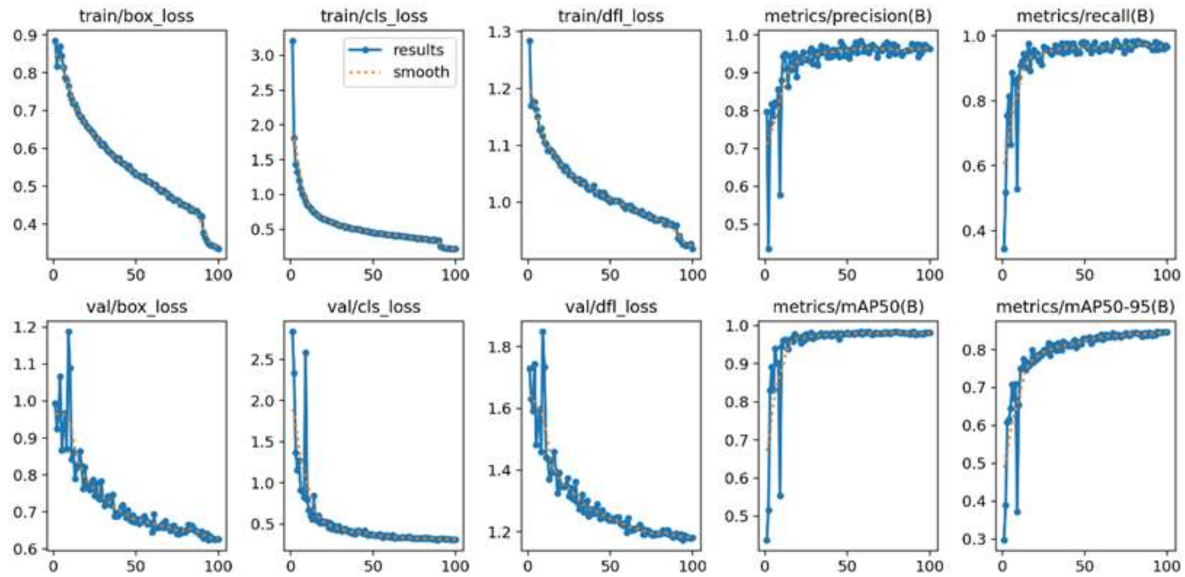

Fig. 8 Loss Curves and Evaluation Metrics for the YOLOv8n Model

The YOLOv8n model achieved stable convergence with mAP50 approaching 0.98 and mAP50-95 around 0.85, showing strong detection capability with efficient computational performance. YOLOv8s demonstrated highly efficient convergence within 60 epochs, with mAP50 close to 0.99 and stable validation performance without significant overfitting. YOLOv8m achieved the best overall accuracy among all variants, with mAP50 nearing 0.99 and mAP50-95 around 0.88, indicating excellent precision in both classification and object localization. Meanwhile, YOLOv8l also showed strong and stable performance, maintaining precision and recall values above 0.95 with highly accurate object detection results. Finally, YOLOv8x produced very high detection accuracy with mAP50 close to 0.99 and mAP50-95 around 0.86, although minor validation fluctuations and slight overfitting indications were observed during later training stages. Table 5.2 presents the performance results of the five YOLOv8 variants (n, s, m, l, and x) trained using the SGD optimizer. Model performance was evaluated using precision, recall, F1-score, mAP50, and mAP50-95 metrics to assess the effectiveness of medicinal plant leaf detection and classification.

Table 7 Summary of Results from 5 Model Training Scenarios

No.	Model	*Epoch*	*Train time (h)*	*Size (mb)*	*Precision*	*Recall*	*F1-Score*	mAP 50	mAP50-95
1	Yolov8n	100	1.559	6	0.9638	0.9671	0.9655	0.9813	0.8464
2	Yolov8s	57	1.036	21,5	0.9764	0.9739	0.9751	0.9863	0.8388
3	Yolov8m	100	2.174	49,6	0.9811	0.9795	0.9803	0.9906	0.8676
4	Yolov8l	100	4.838	83,6	0.9866	0.9639	0.9751	0.9849	0.8632
5	Yolov8x	75	4.937	130,4	0.9809	0.9653	0.9730	0.9880	0.8605

Determine the best model using Cost and Benefit Analysis (CBA)

To determine the best YOLOv8 model configuration for medicinal plant leaf classification, this study applied the Cost and Benefit Analysis (CBA) method. The mAP50-95 metric was used as the main benefit criterion because it provides a comprehensive evaluation across multiple Intersection over Union (IoU) thresholds, while training time was used as the primary cost criterion to represent computational efficiency and resource consumption.

The CBA method enabled an objective comparison between models by considering both detection performance and computational efficiency. Before analysis, all benefit and cost metrics were normalized to a range between 0 and 1. For benefit criteria, the highest value received a score of 1, whereas for cost criteria, the lowest value received a score of 1. This normalization process ensures that all criteria are placed on a comparable scale, eliminating bias caused by different measurement units and magnitudes.

After the normalization process, the final score of each model configuration was computed using the Weighted Sum Model (WSM) as defined in Equation (2). In this step, each normalized criterion was multiplied by its

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corresponding weight, and the results were aggregated to obtain a single composite score for each YOLOv8 configuration. Mathematically, the final score is expressed as a weighted summation of all normalized criteria. This approach ensures a balanced decision-making process by integrating both detection accuracy and computational efficiency into a unified evaluation framework, allowing the selection of the most optimal model for real-world deployment scenarios

Table 8 Cost-Benefit Analysis of 5 Training Model Configuration Scenarios

No	Model	Benefit	Cost		Size (mb)	Benefit Norm.	Cost Norm.		Summation (WSM_i)	Rank
		mAP50-95	Train Time (h)/ (Epoch)	Inference Time (ms)			Train Time (h)	Inference Time (ms)		
1	**Yolov8-n**	**0.8464**	**1.559 (100/100)**	**2,7**	**6**	**0.9755**	**0.6645**	**1.000**	**2.6400**	**1**
2	Yolov8-s	0.8388	1.036 (57/100)	5,4	21,5	0.9668	1.000	0.5000	2.4668	2
3	Yolov8-m	0.8676	2.174 (100/100)	8,6	49,6	1.0000	0.4765	0.3140	1.7905	3
4	Yolov8-l	0.8632	4.838 (100/100)	19,7	83,6	0.9949	0.2141	0.1371	1.3461	4
5	Yolov8-x	0.8605	4.937 (75/100)	27,0	130,4	0.9917	0.2098	0.1000	1.3015	5

The results indicate that the selected hyperparameter configurations significantly influenced the performance of the YOLOv8 models, as demonstrated through the Cost and Benefit Analysis (CBA) ranking. Based on the combined evaluation of mAP50-95 as the benefit criterion and training and inference time as the cost criteria, YOLOv8n achieved the highest overall score of 2.640, making it the best-performing model configuration. YOLOv8n emerged as the best-performing model in the CBA evaluation, achieving an mAP50–95 score of 0.8464 while maintaining superior computational efficiency. With a training time of only 1.559 hours, the fastest inference speed of 2.7 ms, and a compact model size of 6.0 MB, YOLOv8n offers the best balance between detection accuracy and computational cost among the evaluated YOLOv8 variants.

These results indicate that YOLOv8n provides the optimal balance between detection accuracy and computational efficiency, making it highly suitable for real-time medicinal plant detection applications, particularly on mobile and edge computing devices. Although YOLOv8m achieved slightly higher accuracy (mAP50-95 of 0.8676), its higher training and inference costs resulted in lower overall efficiency. Therefore, YOLOv8n was selected as the most optimal model for medicinal plant detection in this study.

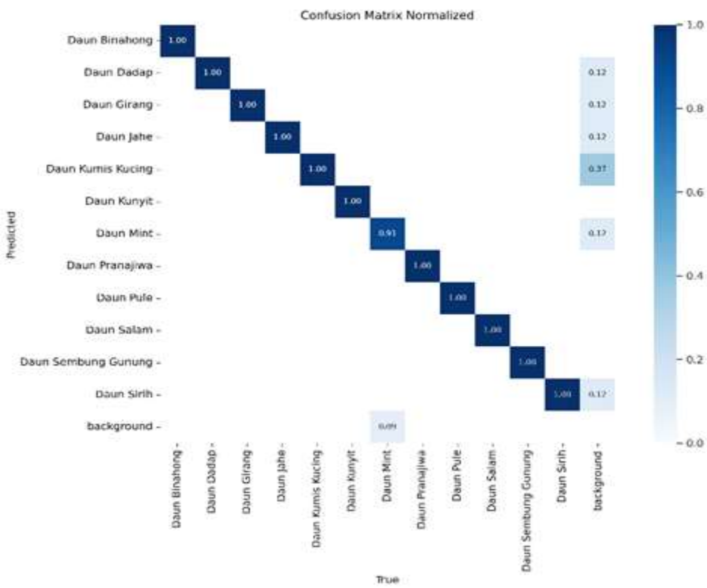

Fig. 9 Confusion Matrix from Yolov8n Model Testing

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Testing the best model

The confusion matrix and detection visualization results demonstrate that YOLOv8n achieved excellent performance in detecting and classifying medicinal plant leaves under natural environmental conditions. Testing was conducted using 134 images from 12 medicinal plant classes, and the model consistently produced high confidence scores ranging from 0.84 to 0.96. Despite being the lightweight nano variant, YOLOv8n successfully extracted leaf morphological features accurately under varying lighting conditions and complex backgrounds. The Normalized Confusion Matrix showed high classification precision across all classes, with several classes achieving perfect accuracy (1.00) and the remaining classes maintaining True Positive Rates above 0.96. Most errors were caused by background interference rather than misclassification between plant species, indicating strong generalization capability for real-world medicinal plant detection applications.

Fig. 10 Visualization of YOLOv8n Detection Results on Images of Herbal Plant Leaves

DISCUSSIONS

The implementation of YOLOv8 demonstrated strong effectiveness in detecting medicinal plant leaves under natural in-situ conditions. Among the evaluated variants, YOLOv8m achieved the highest detection accuracy, with an mAP50–95 score of 0.8676, owing to its deeper architecture and enhanced feature extraction capability. However, this superior performance required greater computational resources, with an inference time of 8.6 ms and a training time of 2.174 hours.

To determine the most suitable model for practical deployment, a Cost–Benefit Analysis (CBA) based on the Weighted Sum Model (WSM) was conducted. The results identified YOLOv8n as the optimal variant, achieving the highest WSM score of 2.6400. Although its mAP50–95 score (0.8464) was slightly lower than that of YOLOv8m, YOLOv8n provided the best balance between detection accuracy and computational efficiency, offering a compact model size of 6.0 MB, a training time of 1.559 hours, and an inference time of 2.7 ms. These characteristics make YOLOv8n highly suitable for real-time deployment on mobile and edge-computing devices.

Although no architectural modifications were introduced, the baseline YOLOv8 architecture achieved strong detection performance under complex natural conditions. Therefore, the primary contribution of this study lies not in architectural innovation but in the development of a structured medicinal plant dataset derived from the *Lontar Usada Bali* and the implementation of a CBA–WSM framework for systematic model selection. Furthermore, the proposed system supports the preservation of ethnobotanical knowledge by enabling reliable medicinal plant identification under varying illumination, occlusion, and cluttered background conditions. The application of Mosaic and MixUp augmentation techniques further improved model robustness and reduced the risk of misidentification in real-world environments

The scientific contribution and novelty of this study are further strengthened through comparison with recent international studies. The achieved mAP50–95 score of 0.8676 demonstrates competitive performance compared with recent deep learning–based medicinal plant identification systems, such as the study by Tan et al. (2024),

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which reported high recognition accuracy for medicinal plant identification. Unlike previous studies that primarily focused on image classification, the proposed approach performs real-time object detection under natural (*in-situ*) conditions, enabling simultaneous localization and classification of medicinal plant leaves in complex environments characterized by varying illumination, occlusion, and background clutter. The effectiveness of the applied augmentation techniques in handling leaf occlusion is consistent with the findings of Cao et al. (2024b), who highlighted the importance of accurate localization for biologically complex objects using the Pyramid-YOLOv8 architecture. Furthermore, the selection of the lightweight YOLOv8n variant is supported by the studies of Shahriar Zaman Abid et al. (2024) and Dwi Satoto et al. (2025), which emphasize computational efficiency and inference speed as critical factors for real-time vision applications. Finally, the model's ability to distinguish overlapping leaf features supports the findings of Solimani et al. (2024), demonstrating the effectiveness of YOLOv8's Decoupled Head architecture in independently optimizing classification and localization tasks within complex vegetation environments.

CONCLUSION

This study successfully implemented the YOLOv8 architecture for medicinal plant leaf detection and classification in the natural environment of Taman Usada Bali. The main contributions of this research are threefold: (1) the development of a structured medicinal plant dataset based on the ethnobotanical taxonomy documented in the *Lontar Usada Bali*; (2) the validation of YOLOv8 for detecting medicinal plant leaves under challenging natural conditions involving varying illumination, occlusion, and cluttered backgrounds; and (3) the introduction of a Cost–Benefit Analysis (CBA) framework combined with the Weighted Sum Model (WSM) for selecting the most suitable model based on both predictive performance and computational efficiency.

Experimental results showed that all YOLOv8 variants achieved strong detection performance across 12 medicinal plant classes. Mosaic and MixUp augmentation techniques improved model generalization and reduced overfitting. While YOLOv8m achieved the highest detection accuracy (mAP50–95 = 0.8676), the CBA–WSM evaluation identified YOLOv8n as the optimal model due to its superior balance between accuracy (mAP50–95 = 0.8464) and computational cost. With a compact model size of only 6 MB, the shortest training time (1.559 hours), and the fastest inference time (2.7 ms) among all evaluated variants, YOLOv8n is highly suitable for deployment on mobile and edge-computing devices.

Beyond its technical contributions, this study demonstrates the potential of computer vision technology to support the preservation and dissemination of ethnobotanical knowledge contained in the *Lontar Usada Bali*. However, several limitations should be acknowledged. The dataset includes only 12 medicinal plant classes, all images were collected exclusively in Taman Usada Bali, and the proposed model has not yet been evaluated within a real-world mobile application environment. Future research should expand the dataset to include a larger number of medicinal plant species, collect data from diverse geographical locations and environmental conditions across Bali, and integrate YOLOv8n into a mobile-based application for real-time field evaluation. Further developments may also incorporate multilingual ethnobotanical information, cloud-based medicinal plant databases, and explainable artificial intelligence (XAI) techniques to improve usability, transparency, and knowledge accessibility.

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