

Medicinal Plant Leaf Classification: From Hand-Crafted Features to Real-Time Mobile Deep Learning

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Abstract

Medicinal plant leaves are central to traditional healthcare in biodiversity-rich countries such as Indonesia, yet high visual similarity between species makes manual identification error-prone. Classification methods for medicinal and herbal leaves have shifted from hand-crafted feature classifiers to deep convolutional and attention-based architectures, and more recently to real-time, on-device deployment. This narrative review traces that progression and identifies open gaps. Twenty primary studies published between 2016 and 2026 were identified through Scopus, Google Scholar, ScienceDirect, and Springer and grouped into five categories: hand-crafted features, CNN transfer learning, attention-based fusion, YOLO-based detection, and mobile/edge deployment. Unlike earlier reviews, each study is also coded for whether its model was validated on physical mobile or embedded hardware. The review finds a clear shift toward deep transfer learning models, many reporting accuracies above 90%, and toward architectures designed for on-device use. However, only three of the nine medicinal-leaf-specific studies tested their models on real hardware; these rarely report standardized latency or frame-rate figures, and public benchmark datasets for Indonesian species remain scarce. These gaps motivate work that evaluates classification accuracy and on-device inference performance together.

Keywords *Medicinal Plant Leaf Classification; Deep Learning; Convolutional Neural Network; Mobile Deployment; Literature Review*

INTRODUCTION

Indonesia is a megadiverse country with as many as 7,500 medicinal plant species (Cahyaningsih et al., 2021), and leaves are among the most widely used parts of these plants in traditional and community-based herbal medicine. Many medicinal species share similar leaf shape, texture, and color, so non-experts often misidentify them (Mulugeta et al., 2024; Yao et al., 2024). A mistaken substitution can compromise a herbal remedy's safety or efficacy. Automated image-based identification has therefore attracted sustained research interest as a way to make accurate species identification accessible without specialist botanical knowledge (Wäldchen & Mäder, 2018; Mulugeta et al., 2024).

This paper is a literature review, not an empirical study: it synthesizes published work on classification methods for medicinal and herbal plant leaves and reports no new experiments. The review is guided by three questions: (1) what classification methods have been applied to medicinal/herbal leaf identification, and how have they evolved; (2) to what extent has the field engaged with real-time, on-device (mobile) deployment rather than offline, server-side evaluation; and (3) what gaps remain open. The remainder of the paper is organized as follows. Section 2 describes the review methodology; Section 3 reviews the literature by method category; Section 4

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synthesizes the findings and discusses gaps; Section 5 presents the conclusion; and Section 6 states the limitations of the review and further research recommendations.

RESEARCH METHOD

This section describes how we identified, selected, and analyzed the literature. Searches were run between June 2025 and March 2026 in Scopus, Google Scholar, ScienceDirect, and Springer using combinations of the keywords "medicinal leaf classification," "herbal plant deep learning," "plant leaf convolutional neural network," "YOLO mobile classification," and "TensorFlow Lite image classification." Results were restricted to 2016–2026 to capture both the foundational CNN transfer-learning era and the recent shift toward real-time, on-device deployment.

Papers were included if they (a) proposed or evaluated a method for classifying plant or leaf images, preferring medicinal/herbal species where available, or (b) addressed a supporting technique, namely model compression or mobile/edge deployment, applied to image classification. Papers were excluded if the classification method or evaluation protocol could not be determined.

Record counts at each screening stage were not logged, so a full PRISMA flow cannot be reported (see Section 5). The final corpus comprises 20 primary studies. One study published after this window ([Nufus et al., 2026](#)) was added before submission because it bears directly on the deployment question. Two earlier reviews ([Mulugeta et al., 2024](#); [Yao et al., 2024](#)) were retained as context rather than as primary studies. Of the 20 included studies, nine address medicinal or herbal leaves directly; the other 11 are cross-domain studies retained because they inform the deployment question.

For each included study, the reviewer recorded the method category, architecture, dataset (size, number of classes, and whether public or self-collected), the headline evaluation metric, and whether the model was tested on physical mobile or embedded hardware. Values were extracted from the full text where it was accessible; figures that could be taken only from the published abstract or publisher record are marked in Table 1. Studies were then grouped into the five method categories used in the prior section of the literature review.

LITERATURE REVIEW

Nine of the 20 studies below concern medicinal or herbal leaves; the other 11 are cross-domain. The sources vary in editorial standing, from Scopus-indexed journals to national journals and one undergraduate thesis ([Wijaya, 2023](#)). Where a single study anchors a category, its findings should be read as indicative rather than conclusive.

Hand-Crafted Feature-Based Classical Machine Learning

Early approaches to herbal leaf classification combined hand-crafted visual features with classical classifiers. [Herdiansah et al. \(2022\)](#) extracted shape features (metric and eccentricity) from herbal leaf images and classified them with a backpropagation neural network, reporting 88.75% accuracy. [Rumandan et al. \(2022\)](#) applied an Extreme Learning Machine to morphological features of medicinal leaves and reported 90% accuracy. These studies showed feasibility but used small, controlled datasets and ignored deployment efficiency.

CNN-Based Classification and Transfer Learning

As deep learning matured, convolutional neural networks (CNNs) replaced hand-crafted features. An early example, [Haryono et al. \(2020\)](#), embedded a CNN on a Raspberry Pi to authenticate seven herbal leaf species. They reported 93.62% accuracy offline and 91.04% when testing on the device, an early bridge to resource-constrained deployment. Transfer learning with pretrained backbones then became the dominant approach. [Purwanto and Sumardi \(2022\)](#) fine-

tuned EfficientNet on seven herbal species photographed with a smartphone and deployed it as a quantized TensorFlow Lite Android app, but reported no accuracy figure. [Kasim et al. \(2025\)](#) trained a CNN on 6,200 smartphone images of 31 herbal species and reported 92.74% accuracy. [Nufus et al. \(2026\)](#) compared MobileNetV2, EfficientNetV2B0, NASNetMobile, and InceptionV3 on a 10-class herbal leaf dataset. All four exceeded 98% validation accuracy, but on a separate 200-image test set, accuracy fell to between 85.5% (NASNetMobile) and 97% (InceptionV3). The authors still recommended MobileNetV2 (93% test accuracy) for mobile use as the best accuracy-efficiency balance. Outside the medicinal domain, [Kulsum and Cherid \(2023\)](#) applied ResNet50 to healthy and diseased apple leaves and reported 91% accuracy.

[Malik et al. \(2022\)](#) trained EfficientNet-B1 on PlantCLEF 2015 combined with a 106-species Borneo botanical garden dataset. Notably, they also tested the model in a field Android application. Real-time Top-1 accuracy was 78.5% and Top-5 accuracy 82.6%, below the 84–87% offline test accuracy. Together with the smaller drop reported by [Haryono et al. \(2020\)](#) and the validation-to-test drop in [Nufus et al. \(2026\)](#), this is one of the few documented gaps between offline and on-device accuracy in the reviewed literature. It underlines the value of field-level evaluation.

Attention-Based Local-Global Feature Fusion

A more recent direction addresses a limitation noted across several CNN studies. Convolutional backbones alone may not jointly capture fine local texture and holistic global shape, both of which matter for separating visually similar species ([Yao et al., 2024](#)). [Sharma and Vardhan \(2025\)](#) proposed AELGNet, a dual-path network that applies residual spatial and channel attention to local image patches and to global features. Evaluated on an Indian medicinal plant and leaf dataset, it reported 99.71% accuracy. This fusion directly targets a limitation that earlier approaches leave unaddressed, although it rests on a single study here.

YOLO-Based Real-Time Detection-Classification

Outside the medicinal-plant domain, YOLO-family detectors have been widely adapted for real-time, often mobile, tasks, including vehicle detection under varying conditions ([Marcelleno et al., 2025](#)), obstacle detection ahead of vehicles ([Aufiqurrahman et al., 2024](#)), warehouse box recognition ([Alif et al., 2024](#)), urban traffic data collection on a mobile app ([Charef et al., 2025](#)), and fabric-pattern classification on a mobile app ([Tri et al., 2024](#)).

Within the medicinal-leaf domain, [Dsouza et al. \(2026\)](#) presented "Herbal-i," a two-stage mobile pipeline. YOLOv5 first detects and localizes the leaf, and MobileNetV2 then classifies the cropped leaf among 40 medicinal species. Trained on 4,988 field images, it reached 98.22% detection precision (recall 75.88%, mAP@0.5 77.46%) and 95.11% classification test accuracy. It is the clearest YOLO-based pipeline built specifically for medicinal leaves, yet remains isolated from the transfer-learning studies in Subsection CNN-Based Classification and Transfer Learning.

Mobile and Edge Deployment Techniques

A complementary line of work makes trained models efficient enough for mobile or embedded hardware. [Han et al. \(2016\)](#) established foundational compression techniques, namely pruning, quantization, and Huffman coding, that shrink deep networks without a proportional loss of accuracy. Using runtimes such as TensorFlow Lite, Indonesian studies have deployed image classifiers for other problems: fingerprint recognition ([Nurfita & Ariyanto, 2018](#)), wetland fish identification ([Wiranda et al., 2020](#)), coffee bean defect detection on Android ([Wijaya, 2023](#)), and river garbage recognition on an ESP32 microcontroller ([Giri et al., 2023](#)). These studies generally report workable on-device accuracy, supporting TensorFlow Lite as a target for leaf classifiers, although none addresses leaves.

FINDINGS AND DISCUSSION

Table 1 compares the five method categories, including whether each study was validated on physical hardware; Table 2 and Figure 1 summarize study counts and timing.

Table 1. Comparative summary of medicinal/herbal leaf classification method categories

Method Category	Representative Studies	Approach	Reported Accuracy	On-Device Tested?
Hand-crafted features + classical ML	Herdiansah et al. (2022) ; Rumandan et al. (2022)	Shape/morphological feature extraction + BPNN or ELM classifiers	88.75% (Herdiansah et al.)†; 90% (Rumandan et al.)†	No
CNN-based classification and transfer learning	Haryono et al. (2020) ; Purwanto and Sumardi (2022) ; Malik et al. (2022) ; Kasim et al. (2025) ; Nufus et al. (2026) ; cross-domain: Kulsum and Cherid (2023)	Custom CNNs and pretrained backbones (EfficientNet, MobileNetV2, ResNet50, InceptionV3, NASNetMobile) fine-tuned on leaf images	93.62% offline / 91.04% on device (Haryono et al.)†; 92.74% (Kasim et al.)†; >98% validation, 85.5–97% test (Nufus et al.); 84–87% offline / 78.5% Top-1 in field app (Malik et al.); 91% apple leaves (Kulsum & Cherid)†; not reported (Purwanto & Sumardi)	Partial: Haryono et al. (Raspberry Pi); Malik et al. (Android)
Attention-based local-global fusion	Sharma and Vardhan (2025)	Dual-path attention over local patches and global features	99.71% on an Indian medicinal plant dataset†	No
YOLO-based real-time detection-classification	Dsouza et al. (2026) ; cross-domain: Marcelleno et al. (2025) , Aufiqurrahman et al. (2024) , Alif et al. (2024) , Charef et al. (2025) , Tri et al. (2024)	Two-stage YOLO detection + lightweight CNN classification (medicinal case); YOLOv8 in other real-time domains	YOLOv5 mAP@0.5 77.46%, MobileNetV2 95.11% (Dsouza et al.)	Yes (Dsouza et al. ; mobile app)
Mobile/edge deployment and compression	Han et al. (2016) ; Nurfita and Ariyanto (2018) ; Wiranda et al. (2020) ; Wijaya (2023) ; Giri et al.	Pruning/quantization and TensorFlow Lite conversion on non-leaf image tasks	Domain-specific; not comparable with leaf classification	Yes, in non-leaf domains (Android, ESP32)

Method Category	Representative Studies	Approach	Reported Accuracy	On-Device Tested?
	(2023)			

† Figure taken from the published abstract or publisher record; not yet cross-checked against the full text.

Table 2. Distribution of the 20 included studies by method category

Method Category	Studies	Medicinal-leaf-specific	Cross-domain	Years	Medicinal studies tested on hardware
Hand-crafted + classical ML	2	2	0	2022	0
CNN / transfer learning	6	5	1	2020–2026	2
Attention-based fusion	1	1	0	2025	0
YOLO-based detection	6	1	5	2024–2026	1
Mobile/edge deployment	5	0	5	2016–2023	–
Total	20	9	11	2016–2026	3

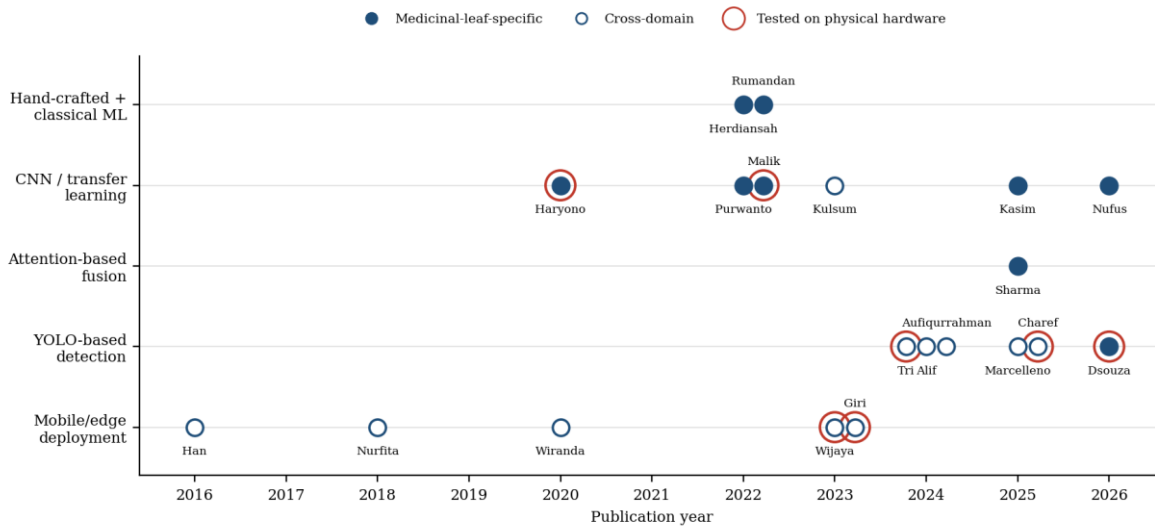


Figure 1. Timeline of the 20 reviewed studies by method category. Filled markers denote medicinal-leaf-specific studies, hollow markers denote cross-domain studies, and a red ring marks studies tested on physical hardware.

The counts show three patterns. Medicinal-leaf-specific work is concentrated in the CNN category (five of nine studies), while the YOLO and deployment categories draw almost entirely on other domains. Twelve of the 20 studies were published in 2023 or later, reflecting the recent growth of the field. Dataset provenance is mostly local and small. Five medicinal-leaf studies used self-collected images (Haryono et al., 2020; Rumandan et al., 2022; Purwanto & Sumardi, 2022; Kasim et al., 2025; Dsouza et al., 2026), two used public datasets (Sharma & Vardhan, 2025; Nufus et al., 2026), and one combined both (Malik et al., 2022); the source for Herdiansah et al. (2022)

could not be confirmed.

The trajectory from hand-crafted classifiers to transfer learning, then to attention-based and detection-plus-classification pipelines, mirrors the pattern documented by [Mulugeta et al. \(2024\)](#) in their systematic review of 31 medicinal-plant deep learning studies published between 2018 and 2022. In that corpus, 64.5% of studies used a CNN-based classifier, 83.8% relied on transfer learning, and 96.7% focused on the leaf organ.

Three gaps stand out. First, despite frequent claims that models are "mobile-friendly" or "lightweight," only three of the nine medicinal-leaf studies validated their models on physical hardware. Two did so on smartphones ([Malik et al., 2022](#); [Dsouza et al., 2026](#)) and one on a Raspberry Pi ([Haryono et al., 2020](#)); [Purwanto and Sumardi \(2022\)](#) built an Android app but reported no accuracy, and the ESP32 deployment by [Giri et al. \(2023\)](#) concerns a non-leaf task. These studies rarely report standardized on-device latency or frame rate alongside accuracy, so the accuracy-efficiency trade-off central to mobile deployment is seldom made explicit. Second, dataset availability remains a constraint. [Mulugeta et al. \(2024\)](#) found that 67.7% of the studies they reviewed used private datasets, a pattern also visible here, which limits cross-study comparison and reproducibility. Public Indonesian collections such as IndoHerb ([Musyaffa et al., 2024](#)) exist, but none of the reviewed studies used one, and field-condition benchmarks remain scarce. Third, YOLO-based detection-plus-classification pipelines have proven real-time viability in other mobile domains ([Marcelleno et al., 2025](#); [Charef et al., 2025](#); [Tri et al., 2024](#)). Yet they remain underexplored for medicinal leaves, with [Dsouza et al. \(2026\)](#) the only example identified.

This review extends [Mulugeta et al. \(2024\)](#) in three ways: it codes every study for on-device validation, exposing how rarely mobile suitability is tested; it covers work to 2026, including attention-based and YOLO pipelines; and it includes Indonesian studies, bringing the dataset gap for Indonesian species into view.

CONCLUSIONS

On the first research question, medicinal leaf classification has moved from hand-crafted features with classical classifiers (88.75–90% accuracy), through CNN transfer learning that commonly exceeds 90%, to attention-based fusion and two-stage YOLO pipelines. On the second, engagement with real deployment is thin: only three of nine medicinal-leaf studies tested their models on physical hardware, and on-device latency is rarely reported. On the third, key gaps remain: joint accuracy-efficiency evaluation, public benchmarks for Indonesian species, and YOLO-based pipelines designed for medicinal leaves.

This review contributes an on-device validation lens applied across five method categories. Its practical implication is that offline accuracy alone is a weak guide to field performance, as the drop observed by [Malik et al. \(2022\)](#) shows. Practitioners choosing a model for a mobile herbal-identification app should look for on-device accuracy and latency figures rather than offline benchmarks alone, and researchers should report both.

LIMITATIONS & FURTHER RESEARCH

Six limitations bound the conclusions of this review. First, the search was narrative rather than fully systematic and covered four English- and Indonesian-language databases. Record counts per screening stage were not logged, which prevents a PRISMA flow and limits reproducibility. Relevant studies may also have been missed, so the counts in Table 2 are indicative.

Second, extraction depth was uneven: some figures come from abstracts or publisher records rather than full texts (marked † in Table 1). These values may omit test conditions, so cross-row comparisons need caution. Third, no formal quality appraisal was applied, so studies from venues of different standing were weighted equally. Fourth, 11 of the 20 studies are cross-domain;

their deployment results suggest, but do not demonstrate, feasibility for leaves.

Fifth, reported metrics are heterogeneous (validation, test, and Top-1 accuracy on different datasets) and should not be read as a ranking of methods. Sixth, a single reviewer screened and extracted data without an inter-rater check, so selection and coding errors cannot be ruled out.

Future work should evaluate real-time classifiers under actual mobile conditions and report accuracy, latency, and frame rate together on named hardware. It should also build public, well-documented datasets of Indonesian medicinal leaves captured in field conditions, and compare YOLO-based detection-plus-classification pipelines against strong transfer-learning baselines on the same data.

DECLARATION OF INTEREST

The authors are conducting related work on real-time medicinal leaf classification for mobile devices. This review was prepared independently of that work's results.

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