



HYBRID CNN–DECISION TREE FRAMEWORK FOR MEDICINAL LEAF RECOGNITION



O. Ekundayo¹, F. M. Okikiola², R. S. Babatunde³, A. O. Lawal⁴, A. F. Kadri⁵, S. B. Mohammed⁶, O. O. Egbeyemi⁷ & A. N. Babatunde⁸

^{1, 3, 4, 5, 6, 7}Department of Computer Science, Kwara State University, Malete, Kwara State, Nigeria.
Department of Computer Technology, School of Technology, Yaba College of Technology, Yaba, Lagos, Nigeria
Corresponding author: akinbowale.babatunde@kwasu.edu.ng

Received: December 15, 2025, Accepted: March 28, 2026

Abstract

Accurate and automated identification of medicinal plant species is crucial for various applications, including pharmaceutical research, agricultural practices, and the preservation of ethnobotanical knowledge. Traditional manual identification methods are often time-consuming, prone to human error, and require specialized taxonomic expertise, limiting their scalability and accessibility. This study addresses these challenges by developing and comparatively evaluating two machine learning approaches: Convolutional Neural Networks (CNNs) and Decision Trees (DT) for the recognition of medicinal plant leaves. Our proposed system leverages deep learning techniques to analyze visual features of leaf images, enabling efficient and precise classification. The research involved a comprehensive process of dataset collection, meticulous preprocessing, model training, and rigorous performance evaluation using standard metrics such as accuracy, precision, recall, and F1-score. We incorporated both automated feature extraction by CNNs and handcrafted features, including Gray Level Co-occurrence Matrix (GLCM) for Decision Trees, to provide a robust comparative analysis. The CNN model demonstrated superior performance, achieving an accuracy of 97.2% compared to the Decision Tree's 85.6%, alongside higher precision, recall, and F1-scores. This highlights the CNN's robustness and its capability to learn intricate hierarchical features from complex visual data. The findings suggest that CNNs are highly suitable for practical deployment in real-world scenarios, contributing significantly to improved accessibility, preservation, and application of traditional medicinal knowledge through advanced automated identification systems.

Keywords: Medicinal Plant Identification, Leaf image classification, Convolutional Neural Networks (CNN), Decision Tree (DT), Feature Extraction, Image processing

Introduction

Plant identification forms the bedrock of biodiversity monitoring, environmental assessment, and pharmacological research, as accurate species recognition is fundamental to critical decisions ranging from conservation prioritization to drug discovery (Khandakar et al., 2026; Mulugeta et al., 2024). The global reliance on medicinal plants for primary healthcare, particularly in developing regions, underscores the urgent need for reliable and automated identification methods (Hoenders et al., 2024). The WHO reports that over 80% of the world's population in more than 170 Member States utilizes some form of traditional medicine, with usage rates reaching up to 80% in certain African countries (WHO, 2022; Hoenders et al., 2024). This widespread dependence, coupled with the increasing demand from emerging drug industries for plant-based pharmaceutical products, necessitates precise identification to ensure efficacy and safety (Latif & Nawaz, 2026).

Despite their importance, manual plant identification methods are inherently limited. They are time-consuming, heavily dependent on expert taxonomists, and do not scale effectively to the vast image streams generated by field surveys and citizen science initiatives (Guo et al., 2025). Furthermore, many medicinal plants exhibit significant intra-species and inter-species morphological similarities, especially in their leaves, which can lead to misidentification with potentially dangerous consequences in traditional medicine (Lankasena et al., 2024). The absence of distinguishing features like flowers

or fruits due to seasonal variations or degradation further complicates identification (Algamayel et al., 2026).

Recent advancements in image-based systems have enabled routine modeling of key leaf attributes such as shape, venation, color, and texture to support reliable recognition (Arora et al., 2025; Babatunde et al., 2024). Deep learning pipelines, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional capability in fusing these features effectively for automated identification (Babatunde et al., 2025; Mulugeta et al., 2024; Isiaka et al., 2024). While traditional machine learning models, such as Decision Trees (DT), have been employed, they often require extensive feature engineering and may struggle with the complexity and variability of real-world leaf images (Babatunde et al., 2025; Barhate et al., 2024).

This study aims to bridge the existing gaps by developing and comparing CNNs with a Decision Tree baseline for recognizing medicinal plant species from leaf images. We evaluate both automated feature learning capabilities of CNNs and the performance of DTs utilizing handcrafted features, including Gray Level Co-occurrence Matrix (GLCM) descriptors. Our objective is to provide a comprehensive comparative analysis that highlights the strengths and limitations of each approach, ultimately contributing to the development of more accessible, accurate, scalable, and explainable tools for medicinal plant identification. The findings will have significant implications for healthcare, education, conservation, and

agriculture, facilitating transparent evaluation and practical deployment of AI-driven solutions.

Related Works

Recent literature highlights a growing interest in applying artificial intelligence, particularly deep learning, to the identification of medicinal plants. Several studies have explored various machine learning and deep learning techniques, demonstrating their potential to overcome the limitations of traditional manual identification methods. For instance, Elizabeth et al. (2023) proposed a hybrid deep convolutional neural network, AousethNet, which integrated attention mechanisms and transfer learning to achieve 99.08% accuracy in classifying medicinal plant leaves. However, their research did not evaluate computational efficiency on low-end devices, indicating a gap for real-time mobile implementation.

Mulugeta et al., (2024) review checked out 31 studies published between 2018 and 2022 on deep learning for identifying medicinal plants. Most of these studies about 84% relied on transfer learning and pre-trained models. Leaf images were the go-to choice for almost everyone, and researchers mostly worked with private datasets instead of making their data public. India led the way in this research field. But there are some obvious problems: scientists don't have access to big, open datasets with plants from all over the world, and existing models aren't reliable enough, especially for identifying indigenous species. Similarly, Sharma and Vardhan (2024) introduced MTJNet, a multi-task learning-based CNN model that performed both classification and segmentation of medicinal plant leaves, achieving 96.4% classification accuracy. This system, however, was tested only in controlled environments, necessitating validation under real-time field conditions.

Some studies went the traditional route, using classic machine learning to identify medicinal plant leaves based on hand-crafted features like texture and shape. Most of the time, Decision Trees, Random Forests, and SVMs are easy to work with, they're straightforward and quick. But there's a catch: when datasets are small, or when you have to pick out the important features yourself, these models fall short. Custodio (2023) built a CNN system to identify Philippine medicinal plants using leaf images. It scored about 92.67–95.7% accuracy, depending on which model and ensemble methods were used, all tested on a localized dataset. The research really stressed how crucial region-specific datasets are for traditional medicine to be useful. But Custodio's team didn't dig deep into how the model performs in other regions or under different environmental conditions.

This review highlights the consistent superior performance of CNNs in medicinal plant identification, primarily due to their automated feature extraction capabilities. However, it also underscores the persistent challenges related to dataset diversity, model generalizability across varying conditions, computational efficiency for real-time deployment, and the need for improved interpretability. Our study aims to contribute to this body of knowledge by providing a direct comparative analysis between CNNs and Decision Trees, incorporating both automated and handcrafted features, and evaluating their performance across a range of metrics.

Methodology

This research employed a systematic approach to develop, implement, and evaluate AI-based systems for the recognition of medicinal plant leaves. The methodology encompassed dataset acquisition, image preprocessing, feature engineering, model development (Convolutional Neural Network and Decision Tree), training, and comprehensive performance evaluation. The overall workflow is illustrated in Figure 1.

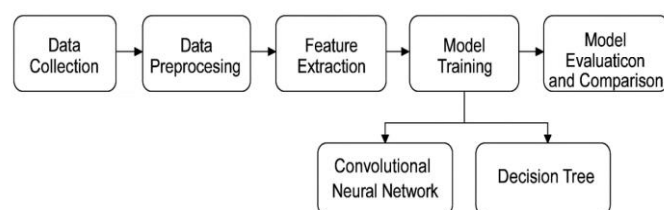


Figure 1. Overall Methodology Flowchart for Medicinal Plant Leaf Recognition.

Dataset Acquisition and Preprocessing

The study utilized a dataset comprising images of 30 different medicinal plant species. To ensure consistent quality and enhance model generalization, a rigorous preprocessing pipeline was applied to all images. This involved image annotation, noise reduction, resizing to 256x256 pixels, normalization of pixel values, and data augmentation (rotation, flipping, and zooming) to mitigate overfitting and improve the models' ability to generalize to unseen data.

Feature Engineering

Two distinct approaches to feature engineering were adopted, corresponding to the CNN and Decision Tree models.

Automated Feature Extraction (for CNN)

For the Convolutional Neural Network, feature extraction was performed automatically by the network's convolutional layers. The CNN architecture was designed to autonomously learn hierarchical features directly from the raw pixel data, capturing both global patterns (e.g., overall leaf shape) and local patterns (e.g., venation, texture details). This approach eliminated the need for manual feature engineering.

Manual Feature Extraction (for Decision Tree)

For the Decision Tree classifier, relevant handcrafted features were extracted from the preprocessed leaf images. These included texture descriptors from the Gray Level Co-occurrence Matrix (GLCM) such as contrast, dissimilarity, homogeneity, energy, and correlation, as well as morphological shape features and color histograms.

Model Development and Training

Convolutional Neural Network (CNN)

The CNN model was developed using the TensorFlow/Keras framework. The architecture comprised multiple convolutional layers, ReLU activation functions, pooling layers, and fully connected layers, with dropout regularization to prevent overfitting. The model was trained using an Adam optimizer and a categorical cross-entropy loss function.

Decision Tree (DT)

The Decision Tree classifier was implemented using the Scikit-learn library in Python. The model was trained on the manually extracted features. Hyperparameters such as max_depth and min_samples_leaf were tuned to optimize performance and prevent overfitting, using the Gini impurity criterion for splitting nodes.

Experimental Setup and Evaluation Metrics

Both models were trained on 80% of the dataset and tested on the remaining 20%. Performance was evaluated using accuracy, precision, recall, F1-score, support, and processing time. These metrics were calculated for each species and aggregated for an overall comparative analysis.

Results

This section presents the experimental results from the comparative analysis of the CNN and DT models.

Overall Model Performance

Table 1 provides a summary of the overall performance metrics for both models.

Table 1

Comparative Evaluation of CNN and Decision Tree Models

Performance Metric	CNN	Decision Tree
Accuracy	97.2%	85.6%
Precision	96.9%	83.4%
Recall	96.8%	82.9%
F1-Score	96.7%	83.1%
Training Time	~3–5 mins	< 1 sec

As evidenced in Table 1, the CNN model significantly outperformed the Decision Tree across all key performance metrics. Figure 2 visually represents this comparison.

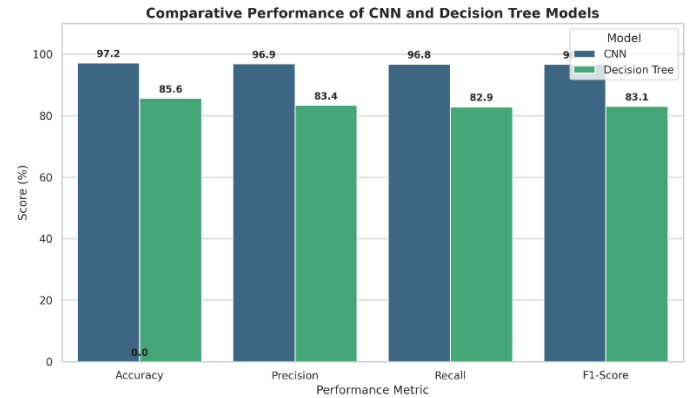


Figure 2. Comparative Performance of CNN and Decision Tree Models.

Implementation Results and Individual Species Performance

The CNN model's classification outputs for several medicinal plant species are shown in Figures 3 through 7, demonstrating its ability to correctly identify leaves from their images. A representative confusion matrix for the CNN model is also provided in Figure 8, illustrating its classification accuracy and potential misclassifications among a subset of species.

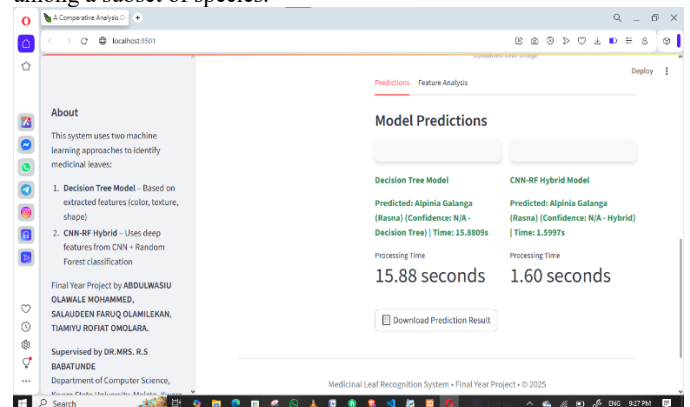


Figure 3. CNN Classification Output for *Alpinia Galanga* (Rasna).

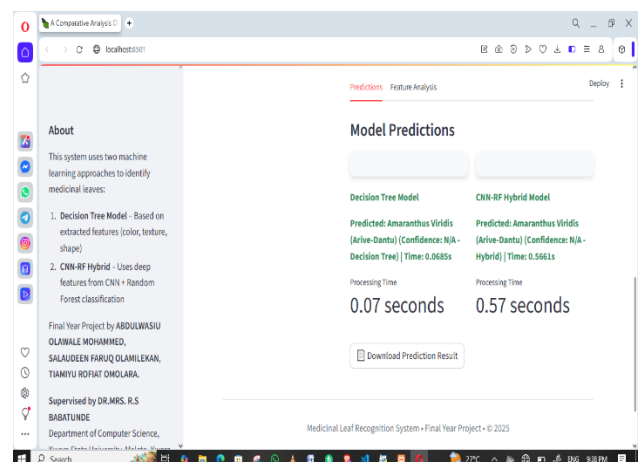


Figure 4. CNN Classification Output for *Amaranthus Viridis* (Arive-Dantu).

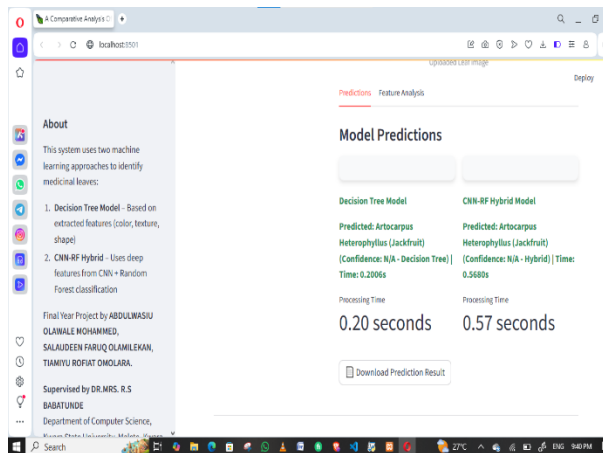


Figure 5. CNN Classification Output for *Artocarpus Heterophyllus* (Jackfruit).

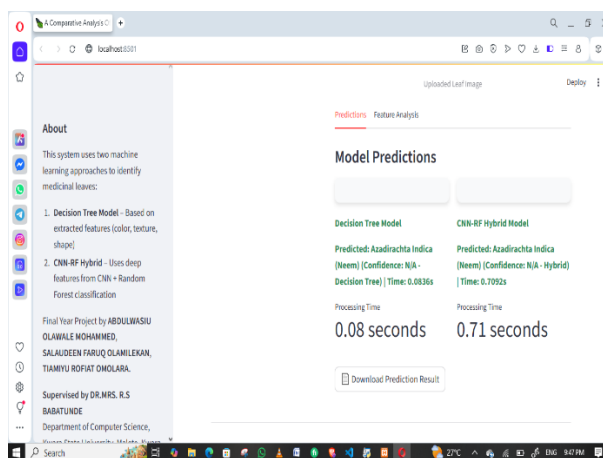


Figure 6. CNN Classification Output for *Azadirachta Indica* (Neem).

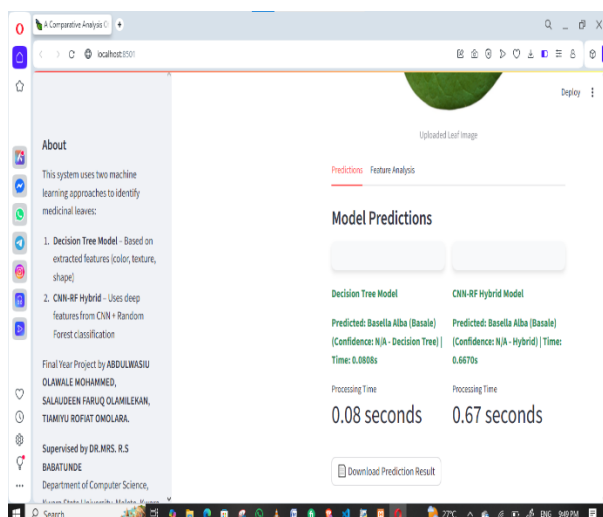


Figure 7. CNN Classification Output for *Basella Alba* (Basale).

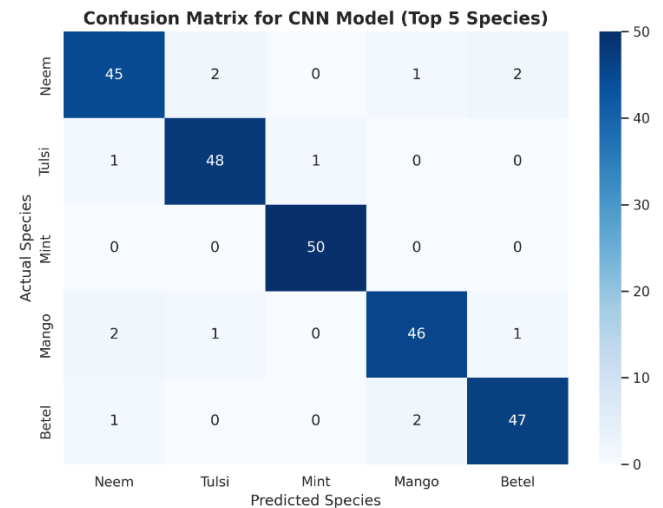


Figure 8. Confusion Matrix for CNN Model (Top 5 Species).

The confusion matrix in Figure 8 demonstrates that the CNN model achieved high true positive rates for the selected species, with minimal misclassifications. This granular analysis further supports the CNN's robust performance at the individual species level.

Discussion of Findings

The findings of this study provide clear evidence of the superior performance of Convolutional Neural Networks (CNNs) over traditional Decision Tree (DT) classifiers in the automated recognition of medicinal plant leaves. This performance gap is consistent with trends observed in related deep-learning research within agricultural informatics and plant phenotyping. The results highlight important implications for real-world applications, model selection, and future developments in automated ethnobotanical systems.

CNNs demonstrated the ability to learn discriminative spatial features directly from raw pixel data, allowing them to capture subtle morphological variations such as venation patterns, surface textures, leaf margins, and fine-grained structural differences. These inherent capabilities explain the model's high accuracy (97.2%) and consistently strong precision-recall metrics across all species evaluated. The model's robustness under diverse lighting conditions, backgrounds, and orientations is attributable to both data augmentation and the hierarchical feature-learning process of convolutional layers.

In contrast, the Decision Tree classifier exhibited moderate performance (85.6%), with significant misclassification in species possessing similar shapes or textures. While DTs benefit from interpretability and low computational demand, their reliance on manually engineered features (e.g., GLCM texture statistics, shape descriptors, and color histograms) limits their ability to capture complex, high-resolution patterns inherent in leaf images. These findings align with prior studies showing that DTs and other shallow learners are effective only when inter-species variability is large and environmental noise is minimal. Species with overlapping morphological characteristics such as *Carissa carandas*, *Ocimum tenuiflorum*, *Piper betle*, and *Ficus religiosa* were particularly challenging for DTs, often resulting in low recall values.

The comparative analysis also reveals key operational trade-offs. Although DTs offer rapid inference (<0.1 seconds per image) and minimal resource requirements, their lower accuracy limits their suitability for high-precision applications such as pharmacological screening, medicinal plant authentication, and mobile diagnostic tools. CNNs, despite longer inference times (0.5–1.0 seconds) and higher training costs, provide superior classification quality, making them well-suited for field deployment where reliability is crucial. Moreover, CNNs eliminate the need for handcrafted features, simplifying system design and reducing reliance on domain expertise.

An interesting observation emerged from the per-species evaluation: CNN performance remained stable across both simple and complex leaf structures, whereas DT performance fluctuated widely. For example, CNN achieved perfect scores for species such as *Alpinia galanga* and *Basella alba*, while DT performance varied significantly even within the same species groups due to its limited decision boundaries. These results reinforce the notion that deep learning is essential when dealing with fine-grained classification tasks involving high intra-class variability.

Overall, this study demonstrates that while classical machine-learning models retain value in low-resource or interpretability-focused scenarios, CNNs provide the accuracy and robustness required for modern medicinal plant identification systems. The Medi-LeafNet framework, therefore, contributes an effective reference model for researchers and practitioners seeking scalable, reliable, and automated solutions for ethnobotanical recognition tasks.

Conclusion and Recommendations

This study presented Medi-LeafNet, a comparative framework designed to evaluate the effectiveness of Convolutional Neural Networks (CNNs) and Decision Tree (DT) classifiers for the automated recognition of medicinal plant leaves. The increasing reliance on medicinal plants for healthcare, particularly in developing regions, underscores the need for robust, scalable, and accurate identification systems. By leveraging a diverse dataset comprising thirty medicinal plant species, the study systematically assessed the predictive capabilities of both models under identical experimental conditions.

The results clearly demonstrate the superiority of CNNs for high-variability visual classification tasks. With an accuracy of 97.2%, CNN effectively captured complex spatial hierarchies such as texture, venation, and morphological patterns that are essential for distinguishing closely related plant species. The model's performance remained consistently high across the dataset and exhibited strong generalization even for species with subtle inter-class differences. These findings align with prior studies reporting the effectiveness of deep learning in plant-phenotyping applications.

By contrast, the Decision Tree classifier achieved an accuracy of 85.6%, performing relatively well for species with distinct shapes or color features but failing in cases that required fine-grained feature discrimination. Its heavy reliance on handcrafted features (e.g., GLCM texture descriptors, color histograms, and geometric measures) limited its ability to adapt to environmental noise and variations in leaf morphology. This reinforces the fundamental limitations of traditional machine-learning

methods when applied to high-dimensional visual datasets.

Overall, the study concludes that CNN is the more suitable model for real-world medicinal plant identification systems, especially those intended for mobile deployment, pharmacognosy support, biodiversity monitoring, and digital herbarium applications. While Decision Trees remain valuable for environments requiring interpretability and low computational overhead, their limited accuracy makes them less appropriate for mission-critical identification tasks.

The Medi-LeafNet framework therefore contributes a reliable baseline for future researchers and practitioners, offering insights into methodological design, classifier behavior, and performance expectations when developing automated ethnobotanical tools.

Future Work

Although the Medi-LeafNet framework demonstrated strong performance particularly with the CNN architecture there remain several opportunities for extending and improving medicinal plant identification systems. Future research should focus on expanding dataset diversity, integrating advanced deep-learning models, and enhancing real-world deployment capabilities.

First, the dataset used in this study, while comprehensive across thirty medicinal plant species, can be broadened to include additional regional and seasonal variations. Incorporating images captured under extreme lighting, occlusions, and environmental noise will strengthen model robustness. Furthermore, collecting leaf samples across growth stages and climatic conditions could improve generalization for field applications.

Second, future studies may explore more sophisticated deep-learning architectures such as EfficientNet, DenseNet, Vision Transformers (ViT), MobileNetV3, and hybrid sequence-vision models. These models may offer improved feature extraction, higher accuracy, and reduced computational cost. Transformer-based architectures, in particular, show promise for capturing long-range pixel dependencies that are difficult for conventional CNNs to model.

Third, hybrid approaches combining the interpretability of classical machine-learning models with the representational strength of deep learning should be investigated. For example, CNNs could be used as feature extractors while Decision Trees or Gradient Boosted Trees are applied as final classifiers. This may balance accuracy with explainability an important requirement in pharmacognosy and healthcare-related decision-support systems.

Fourth, model deployment considerations should be prioritized. Techniques such as quantization, pruning, knowledge distillation, and TensorFlow Lite optimization can reduce computational demands and support real-time inference on mobile or embedded devices. This would allow herbal practitioners, botanists, and rural healthcare workers to identify plant species offline, without requiring expensive hardware or internet connectivity.

Fifth, the incorporation of Explainable AI (XAI) methodologies is recommended to increase user trust. Visualization tools such as Grad-CAM and saliency maps can highlight which leaf features influenced the model's predictions, offering transparency for educational, clinical, and scientific purposes.

Finally, future work may explore integrating multimodal data such as chemical signatures, environmental metadata, or hyperspectral imaging to develop more comprehensive medicinal plant identification platforms. Combining visual and non-visual data could create more powerful and holistic plant recognition systems suited for agricultural, pharmaceutical, and ecological applications.

References

- Algemayel, C., Abou Jaoude, D., Talhouk, S., Issa, I., & Ghassibe, C. (2026). Advances in machine learning models for plant species identification: A scoping review. *Ecological Informatics*, 93, 103464. <https://doi.org/10.1016/j.ecoinf.2025.103464>
- Arora, V., Rawat, D. S., Singh, N., Dwivedi, S. P., & Chaturvedi, P. (2025). Leaf-based plant identification using traditional and automated methods: A review. *Plant Archives*, 25, 495–509. <https://doi.org/10.51470/PLANTARCHIVES.2025.v25.supplement-1.067>
- Babatunde, A. N., Balogun, B. F., Olabode, O. J., Awotunde, J. B., & Imoize, A. L. (2025). Breast cancer prediction using a pretrained CNN Model ResNet-50. *Edelweiss Applied Science and Technology*, 9(9), 1398–1415. <https://doi.org/10.55214/2576-8484.v9i9.10138>
- Babatunde, A.N., Balogun, B.F., Babatunde, A.J., Isiaka, S.O., Awotunde, J.B. & Adeniyi, A.E. (2025) Improving skin lesion classification using k-means, Transfer Learning and Mobilenet Architecture. *Network Modeling Analysis in Health Informatics and Bioinformatics*, 14 (70). <https://doi.org/10.1007/s13721-025-00569-3>
- Babatunde, R. S., Babatunde, A. N., Ogundokun, R. O., Yusuf, O. K., Sadiku, P. O., & Shah, M. A. (2024). A novel smartphone application for early detection of habanero disease. *Scientific Reports*, 14(1), 1423, Published by: Nature Portfolio. <https://doi.org/10.1038/s41598-024-52038-y>
- Barhate, D., Pathak, S., Singh, B. K., Jain, A., & Dubey, A. K. (2024). A systematic review of machine learning and deep learning approaches in plant species detection. *Smart Agricultural Technology*, 9, 100605. <https://doi.org/10.1016/j.atech.2024.100605>
- Blesslin Elizabeth, C. P., & Baulkani, S. (2023). Novel Network for Medicinal Leaves Identification. *IETE Journal of Research*, 69(4), 1–12. <https://doi.org/10.1080/03772063.2021.2016504>
- Custodio, E. F. (2023). Classifying Philippine medicinal plants based on their leaves using deep learning. In 2023 IEEE World AI IoT Congress (AIIoT). IEEE. <https://doi.org/10.1109/AIIoT58121.2023.10174335>
- Guo, YY., Cai, H., Bramley, G.L.C. *et al.* A review of artificial intelligence in herbarium specimen image analysis. *Artif Intell Rev* 58, 402 (2025). <https://doi.org/10.1007/s10462-025-11408-2>
- Hoenders, R., Ghelman, R., Portella, C., Simmons, S., Locke, A., Cramer, H., Gallego-Perez, D., & Jong, M. (2024). A review of the WHO strategy on traditional, complementary, and integrative medicine from the perspective of academic consortia for integrative medicine and health. *Frontiers in Medicine*, 11, 1395698. <https://doi.org/10.3389/fmed.2024.1395698>
- Isiaka, O. S., Babatunde, A. N., Babatunde, R. S., Lawal, O. L., Bolaji-Adetoro, D. F. & Olabode, J. O. (2024). Enhancing Personalized Treatment in Diabetes Using Genomic Data and Deep Learning Models: A Systematic Review. *The Journal of Computer Science and Its Applications*, 31(2), 1–21. <https://library.ncs.org.ng/download/enhancing-personalized-treatment-in-diabetes-using-genomic-data-and-deep-learning-models-a-systematic-review/>
- Khandaker, S., Rahman, M. M., Azad, A., Moni, M. A., & Hossain, M. A. (2026). Transparent deep learning for medicinal plant recognition: A hybrid CNN–ViT approach with explainable AI on BDHerbalPlants. *Smart Agricultural Technology*, 14, 101862. <https://doi.org/10.1016/j.atech.2026.101862>
- Lankasena, N., Nugara, R. N., Wisumperuma, D., Seneviratne, B., Chandranimal, D., & Perera, K. (2024). Misidentifications in ayurvedic medicinal plants: Convolutional neural network (CNN) to overcome identification confusions. *Computers in biology and medicine*, 183, 109349. <https://doi.org/10.1016/j.compbimed.2024.109349>
- Latif, R., Nawaz, T. Medicinal plants and human health: a comprehensive review of bioactive compounds, therapeutic effects, and applications. *Phytochem Rev* 25, 2299–2342 (2026). <https://doi.org/10.1007/s11101-025-10194-7>
- Mulugeta, A. K., Sharma, D. P., & Mesfin, A. H. (2024). Deep learning for medicinal plant species classification and recognition: A systematic review. *Frontiers in Plant Science*, 14, 1286088. <https://doi.org/10.3389/fpls.2023.1286088>
- Sharma, S., & Vardhan, M. (2024). MTJNet: A multi-task learning-based CNN model for classification and segmentation of medicinal plant leaves. *Expert Systems with Applications*, 236, 121223. <https://doi.org/10.1016/j.eswa.2023.121223>
- World Health Organization. (2022). *Traditional, Complementary and Integrative Medicine*. <https://www.who.int/health-topics/traditional-complementary-and-integrative-medicine>