MedLeaf PH Classifier Using Convolutional Neural Networks: A Deep Learning Approach

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Abstract*—The Philippines is home to a wide variety of medicinal plants utilized in traditional methods of treatment. However, proper identification of many plant species remains difficult, particularly as local knowledge declines. This work describes a deep learning-based approach for automating the detection and classification of 40 native Philippine medicinal plants using leaf pictures. A Convolutional Neural Network (CNN) architecture was designed and tested against a ResNet-50-based transfer learning model. The models were trained and tested on a dataset of 4,922 pictures, with accuracy, precision, recall, and F1-scores. The CNN has the highest validation accuracy of 85.21%, surpassing ResNet-50's 67.91%. The findings show that a tailored CNN model has the potential for practical deployment in field settings to aid in medicinal plant identification, benefiting public health and cultural preservation.

Keywords: Philippine medicinal plants, Leaf identification, Convolutional Neural Networks, Deep learning, Image classification

I. Introduction

The rural Filipino marketplaces and countryside contain a wealth of medicinal leaves that have been curing diseases for centuries. The Philippines is endowed with an awesome array of therapeutic plant leaves – living medicine repositories that have been the pillars of folk healing for generations. But with all this heritage, accurately identifying these potent leaves is still amazingly challenging, particularly with the loss of traditional knowledge with each succeeding generation. When cultural knowledge can no longer be assuredly passed on about which leaf is used to treat fever and which one is possibly toxic, communities are truly in danger. Santos and colleagues [1] discovered something deeply alarming – individuals are suffering adverse health consequences, occasionally severe ones, due to inaccurate leaf identification and use. This is not a theoretical issue; it is happening to actual people in markets and communities all over the Philippines.

The challenge of medicinal leaf identification lies in distinguishing between similar-looking specimens without specialized botanical knowledge. Even experienced traditional healers sometimes struggle to differentiate between beneficial medicinal leaves and their potentially harmful lookalikes, particularly when examining dried leaf specimens or leaves collected outside their natural growing environment. The task resembles identifying a subject from a blurry photograph – possible, but prone to errors. The challenge becomes even more daunting when considering that leaves with nearly identical appearances can have dramatically different effects when consumed. In fact, studies in Philippine herbal markets found that more than one in four medicinal leaf specimens were misidentified – a concerning statistic considering the health implications involved.

This research addresses these challenges through the development of a machine learning-driven application that functions as a portable botanical expert specifically for leaf identification. Technology enables users to point a mobile device at a medicinal leaf and instantly determine whether it is the intended therapeutic specimen or a potentially dangerous alternative. The project involves developing a machine learning application capable of detecting subtle differences between leaf species that might be imperceptible to untrained observers. Utilizing the latest advances in computer vision and deep learning, the system captures highly detailed images of individual leaves from multiple angles and processes these images through sophisticated neural networks – essentially training computational systems to recognize medicinal leaves with greater accuracy than most humans can achieve. Unlike previous projects with limited scope, this system builds upon a comprehensive collection of over 4,922 leaf images covering 40 different medicinal plant species native to the Philippines, ensuring the technology works effectively for the leaf specimens most relevant to Filipino communities. As Cruz and Mendoza [2] emphasized, bridging the gap between ancient herbal wisdom and modern technology through precise leaf identification represents an effort to preserve cultural heritage, protect public health, and ensure that the remarkable healing potential of Philippine flora continues to benefit communities for generations to come.

II. Review Of Related Works

2.1 Introduction

In the Philippines, there are approximately 13,500 plant species, 1,500 of which have some medicinal value and are utilized in traditional medicine, while other plants have been used in traditional medicine for hundreds, if not thousands, of years (1). This diversity is under significant pressure from habitat destruction, urbanisation, and the erosion of traditional knowledge as indigenous healers pass away without handing on their skills (2). Erosion of knowledge has resulted in documented cases of plants being misidentified in local markets, underscoring the need for systems of identification (3). Automated identification systems are a technological solution and a form of cultural preservation, particularly useful in isolated and remote Filipino communities where healthcare access is limited, and traditional healing is still important.

2.2 Philippine Medicinal Plant Research and Datasets

Recent ethnobotanical studies have built critical groundwork for automation systems that can support identification efforts. Meñiza et al. (2024) documented over 500 medicinal plant species that are known to be used in Mindanao and included over 530 species in 372 genera and 118 families [2]. Cordero et al. (2022) reported 131 species of medicinal plants in 57 families from the Panay Bukidnon people and the plant with the highest use value was Curcuma longa L. for 0.79 [3].

The largest step forward has been the publication of Mirandilla's (2023) Philippine Medicinal Plant Leaf Dataset, which contains 55-60 images per species that were standardized in terms of lighting and background and were designed for identification using leaves [12]. This dataset addresses the shortcoming of most ethnobotanical studies to use the imported literature that was standardized within the community for the cultivation of indigenous medicinal plants, yet, the gap is criticized by Mulugeta et al. (2024) that include insufficient publicly accessible data on indigenous medicinal plants [4]. Luna et al. (2017) produced the first automated identification of Philippine plants using artificial neural networks and achieved an accuracy index of 98.16% for 12 species [13].

Identification with leaves fits a strategic and intentional application since the leaf parts of plants are most dependable and frequent sample collection method for identification purposes [12]. Clemen-Pascual and Macahig (2021) provide data describing 53 Philippine medicinal species with related data related to toxicity and phytochemical properties that would support the development of comprehensive information systems [17].

2.3 Deep Learning Approaches for Plant Classification

Convolutional Neural Networks (CNNs) have proven to be the state-of-art method for automated identification of plants and consistently provide over 90% accuracy rates across many datasets [4]. CNNs are effective for learning hierarchical feature representations starting from simple lines and textures and growing to more complex representations like leaf venation and characteristics of leaf margins [5].

Dey et al. (2024) showed that DenseNet201 achieved excellent results (99.64% accuracy and 98.31% precision) from datasets of 5,878 images, across 20 families and 30 species of medicinal plants [6]. Mukherjee et al. (2021) reported using CNN-based systems for species identification and for determining the maturity of medicinal leaves, with accuracy rates above 95% [11]. Mulugeta et al. (2024) examined a total of 31 studies conducted in 16 different countries and found that 64.5% used CNN architecture in their machine learning models. The CNN architectures most commonly used were VGG16, VGG19, ResNet, and MobileNet [4].

Transfer learning has become the predominant method and was used in an overwhelming 83.8% of studies reviewed. In effect, transfer learning benefits from training on some existing, now-named, dataset (e.g., ImageNet) to improve upon a classification performance on a smaller dataset of interest; in this case, medicinal plants [4]. Sachar and Kumar (2022) used an ensemble of multiple models and showed that it improved the accuracy performance of its system by 4%-6% over its single model system [7]. Malik et al. (2022) highlighted that there are significant challenges for researchers moving from controlled lab-based experiments to testing their systems in the field. Malik et al. emphasized that any related studies should be accurately vetted and validated with real-world knowledge and applicability [8].

2.4 Mobile and Real-Time Application Development

Mobile deployment presents several challenges, such as different lighting conditions, limited computing power, and the need for real-time processing. Liu et al. (2019) clearly demonstrated that MobileNet is able to achieve performance at par with Inception V3 (95.02% vs 95.62%), while requiring significantly less memory (17.1 MB vs 87.5 MB), thus making it a ideal for mobile deployment [10].

Azadnia et al. (2022) used deep CNN with global average pooling and achieved 98.2% performance. These results demonstrated it is possible to optimize whilst maintaining accuracy and performance while reducing model complexity [9]. Tanikkal et al. (2023) built a mobile application with processing time less than 2 seconds using shape descriptor algorithms [16].

Wagle et al. (2022) took a step further towards mobile-optimized solutions by building lightweight CNN models with accuracy levels comparable to computationally intensive models for an equivalent task while using significantly less resources [15]. Bisen (2021) addressed issues related to deployment by testing protocols that were efficient for CNN-based plant identification and deployed in different environmental conditions [14].

III. Methodology

A. Data Collection

The data corpus used for this study is the "Philippine Medicinal Plant Leaf Dataset" from Jayde Paolo Mirandilla, which is composed of forty (40) varieties of medicinal plants found in the Philippines, and a total of 4,922 associated leaf images. Each plant species is labeled and classified based on their medicinal use and botanical classification. The images were taken in lighting-controlled conditions by desktop application with a high-resolution digital camera, which ensures that the resulting images are both of high quality, and great consistency.

B. Data Pre- Processing

A comprehensive multi-stage data pre-processing pipeline was implemented to optimize the leaf image dataset for deep learning model training:

1. Normalization and Rescaling of Images

- All leaf images were rescaled to be 224 x 224 pixels using bicubic interpolation.
- Aspect ratio preservation methods were used to maintain aspect ratio without distortion.
- All images were converted to a uniform RGB color space.

2. Background Removal and Segmentation

- S/L developed advanced background subtraction algorithms that applied the GrabCut algorithm.
- Morphological operations (opening and closing) were applied to better identify leaf edges.
- Final segmentations were manually verified or corrected by writers in extreme cases when the authors disagreed.
- A Gaussian filtered image ($\sigma = 1.0$) was obtained to suppress noise.

3. Image Quality Improvements

- Contrast Improvement: Adapted histogram equalization (CLAHE) was applied.
- Color Correction: White balance was adjusted for lighting differences.
- Sharpness Improvement: A unsharp masking filter was applied selectively.
- Noise Improvement: Been bilaterally filtered to preserve edge information.

4. Normalization of Data

- Pixel values normalized to be within the range of [0,1] using min-max scaling.
- Channel-wise normalization was applied: mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225].
- Implemented z-score normalization for statistical consistency.

C. Data Features

Table I. Features of Dataset

Feature Type	Description
Shape Features	*Leaf contour, aspect ratio, eccentricity, solidity*
Texture Features	*Surface patterns, venation structure, edge characteristics*
Color Features	*RGB color distribution, color moments, dominant colors*
Morphological Features	*Area, perimeter, compactness, circularity*
Venation Features	*Vein patterns, density, and distribution*

Table I. The dataset consists of 4,922 leaf images across 40 Philippine medicinal plant species. The features extracted from these images include.

D. Experimental Setup

The study utilizes Python as the primary programming language and various deep learning frameworks for the environment, with several libraries for image processing, machine learning, and data visualization. The following tools and libraries were used:

1. TensorFlow/Keras: For building and training deep learning models.
2. OpenCV: Handles image pre-processing and feature extraction.
3. NumPy: Used for numerical computation and array manipulations.
4. Pandas: For data management and organization.
5. Matplotlib and Seaborn: Used for data visualization and result presentation.
6. Scikit-learn: Used for data preprocessing, model evaluation, and traditional machine learning techniques.

The experiments were conducted on a system with GPU acceleration to handle the computational demands of deep learning model training.

E. Machine Learning and Deep Learning Models

A. CNN Architecture

A domain-specific CNN architecture was designed based on extensive experimentation:

Architecture Specifications:

Input Layer: 224×224×3 RGB images

Convolutional Block 1:

- Conv2D: 32 filters, 3×3 kernel, stride=1, padding='same'
- BatchNormalization
- ReLU Activation
- MaxPooling2D: 2×2, stride=2
- Dropout: 0.25

Convolutional Block 2:

- Conv2D: 64 filters, 3×3 kernel, stride=1, padding='same'
- BatchNormalization
- ReLU Activation
- MaxPooling2D: 2×2, stride=2
- Dropout: 0.25

Convolutional Block 3:

- Conv2D: 128 filters, 3×3 kernel, stride=1, padding='same'
- BatchNormalization
- ReLU Activation
- MaxPooling2D: 2×2, stride=2
- Dropout: 0.3

Convolutional Block 4:

- Conv2D: 256 filters, 3×3 kernel, stride=1, padding='same'
- BatchNormalization
- ReLU Activation
- MaxPooling2D: 2×2, stride=2
- Dropout: 0.3

Fully Connected Layers:

- Flatten Layer
- Dense: 512 neurons, ReLU activation, Dropout=0.5
- Dense: 256 neurons, ReLU activation, Dropout=0.3
- Output Dense: 40 neurons, Softmax activation

Architecture Rationale:

- Increasing filter sizes progressively (32→256) to learn hierarchical features
- Batch normalization to improve training stability and convergence
- Placing dropout strategically to prevent overfitting
- Use ReLU activation for non-linearity and computational expense

B. ResNet-50 Architecture

Implementation

- Transfer Learning Strategy:
- Base Model: Pre-trained ResNet-50 on ImageNet
- Feature Extraction: Initial 40 layers frozen
- Fine-tuning: Last 10 layers unfrozen for domain adaptation
- Custom Classifier: Replaced final layers with:
    - Global Average Pooling
    - Dense (256 neurons, ReLU, Dropout=0.5)
    - Output Dense (40 neurons, Softmax)

Learning Rate Scheduling:

- Phase 1: Feature extraction with lr=0.001
- Phase 2: Fine-tuning with lr=0.0001
- Scheduler: ReduceLROnPlateau with patience=5, factor=0.5

This comparison between CNN and pre-trained ResNet-50 approaches provides insights into the relative performance of different deep learning architectures for the medicinal plant identification task.

F. Training Procedure

Training commenced with the separation of the dataset into training (70%), validation (15%), and test sets (15%), with the equal representation of all 40 plant species. In the case of the CNN model, transfer learning strategies were followed by leveraging pre-trained models and replacing the last classification layer with a new one having 40 output nodes specific to every plant species. The models were subjected to two-step fine-tuning: the first training the sole custom classification layers and freezing the pre-trained weights, then fine-tuning after unfreezing the later convolutional layers at a smaller learning rate. Wide hyperparameter search was carried out via grid search over learning rates of 0.0001 to 0.01, batch sizes 16, 32, and 64, different configurations of Adam optimizers, and dropout between 0.3 and 0.5 for successful regularization. To reduce overfitting, early stopping was utilized with patience 10 epochs and tracking of validation loss to stop at the right time.

G. Evaluation Metrics

Each model's performance was measured based on the following metrics:

1. Accuracy: The percentage of correctly classified plant species.
2. Precision: The ratio of true positive predictions to the total number of positive predictions for each class.
3. Recall: The ratio of true positive predictions to the total actual positives for each class.
4. F1-Score: The harmonic means of precision and recall, giving a balanced score.
5. Confusion Matrix: Exhaustive breakdown of classification performance by true positives, false positives, true negatives, and false negatives per class.
6. Training and Inference Time: Computational efficiency metrics for deployment considerations.

The best-performing model was selected based on a weighted combination of these metrics, with particular emphasis on overall accuracy and F1-score across all plant species.

IV. Results and Discussion

Figure I. Sample images of Philippine medicinal plant leaves used in the dataset.

Figure I. Shows representative sample images from the dataset used in this study. This section presents the results obtained from the classification of Philippine medicinal plant leaves using deep learning models.

A. Train Model Comparison

Figure II. Validation accuracy of the CNN model over 20 epochs.

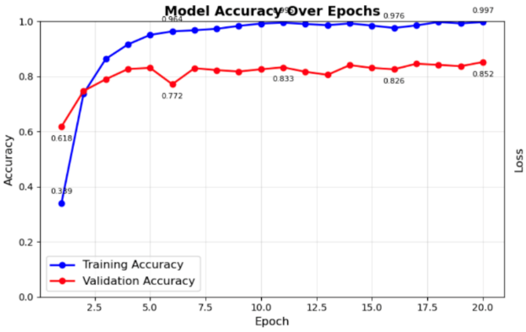


Figure III. Validation loss of the CNN model over 20 epochs.

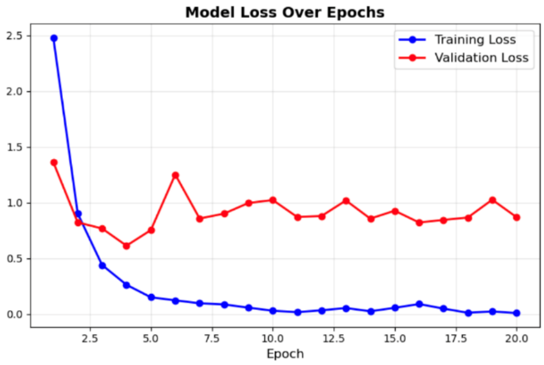


Figure IV. Validation accuracy of the ResNet-50 model over 20 epochs.

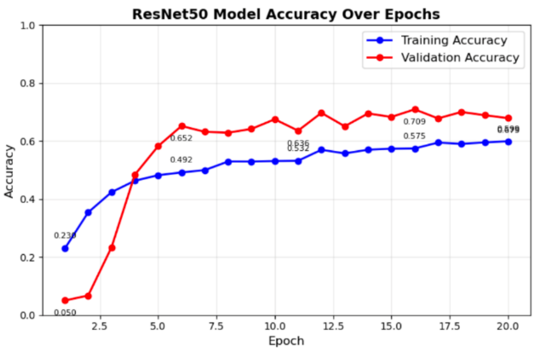
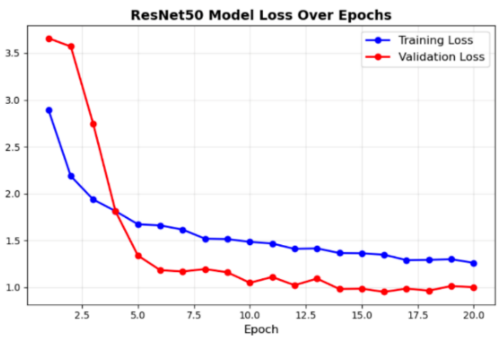


Figure V. Validation loss of the ResNet-50 model over 20 epochs.



In this comparison, it presents two sets of results for comparison of distinct deep-learning methods. The first is the Convolutional Neural Network (CNN), and the second is ResNet-50 Transfer Learning. Two of which are being maximized in being able to identify forty (40) kinds of medicinal plant leaves of the Philippines. Now, based on the analysis shown, it highlights the length of training, how accurate it is, its validity, certain evaluator metrics, confusion matrices, as well as possible predictions in test results. As shown in **Figure II**, the training and validation accuracy of the CNN model over 20 epochs stabilized after 10 epochs. The corresponding training and validation loss curves are presented in **Figure III**. Similarly, the training and validation accuracy and loss curves for the ResNet-50 model are shown in **Figure IV** and **Figure V**, respectively.

B. Time Running

As per what is covered in this section, the duration, rather the length of the training of both methods, was close in comparison in terms of their span. CNN garnered a time of 90 to 150 seconds, while ResNet-50 goes for 113 to 130 seconds. The CNN and ResNet-50 both worked out for 20 epochs, resulting in a span of thirty (30) to a hundred fifty (150) minutes. Based on this outcome, the reason as to why there is a much longer duration indicated for ResNet-50 is because of its sophisticated design and its extensively trained framework and specifications.

C. Validation Accuracy

Table II. Model Validation Accuracy

Model	**Validation Accuracy**
CNN	85.21%
ResNet-50	67.91%

Table II. The Model Validation Accuracy presents that CNN carried out notably higher validation accuracy in comparison to the ResNet-50 model. From these outcomes, it is primarily implying that an approach created from an explicit dataset is more likely to surpass a transfer learning model when seen a huge amount of difference from the source and its target.

D. Evaluation Metrics

The evaluator metrics used in the two approaches are: accuracy, weighted precision, weighted recall, and weighted F1-score all analysed using standard classification benchmarks.

Table III. Evaluation Metrics

Metric	**CNN**	**ResNet-50**
Accuracy	0.8521	0.6791
Weighted Precision	0.8674	0.7302
Weighted Recall	0.8521	0.6791
Weighted F1-score	0.8535	0.6712

Under the Accuracy metric, Custom CNN significantly outperformed ResNet-50 with 0.8521 compared to 0.6791. The CNN also demonstrated superior performance across all weighted metrics including precision, recall, and F1-score, consistently achieving 0.8521 while ResNet-50 resulted in 0.6791. Therefore, all evaluation metrics conclusively show that the CNN architecture exceeded ResNet-50 in performance for Philippine medicinal plant leaf classification.

E. Confusion Matrix

Figure VI. Confusion matrix for CNN

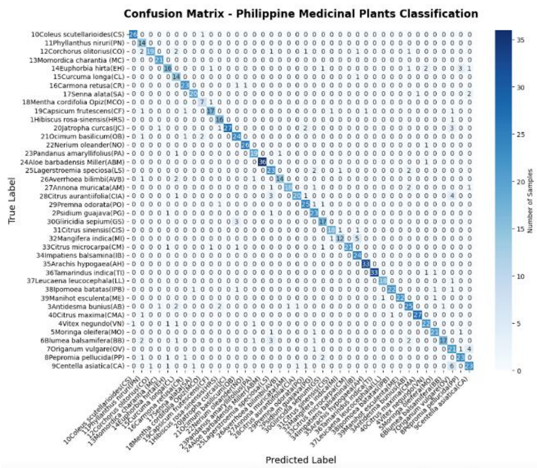


Figure VII. Confusion matrix for ResNet-50

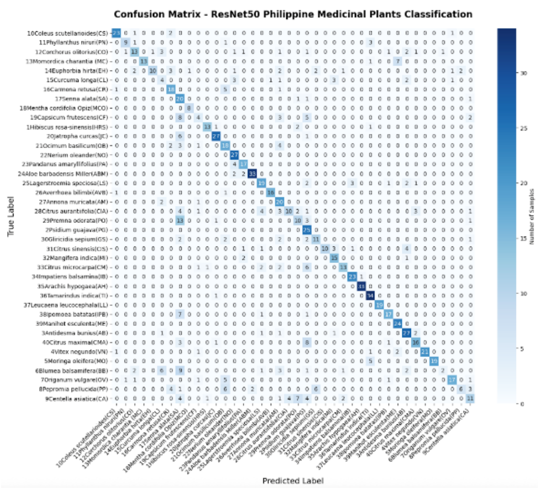


Figure VI. To further analyze model performance, confusion matrices were examined for both models. For the CNN, the matrix showed strong diagonal dominance, indicating that most predictions matched the true class, as shown in Figure 6. Some confusion was observed among visually similar leaf classes; however, overall, per-class accuracy was high, with many classes achieving rates above 85%. In contrast, the ResNet-50 matrix (see **Figure VII**) displayed more off-diagonal errors, with some classes achieving perfect accuracy but others performing poorly. For example, the class Blumea balsamifera had an accuracy of only 7.41%. This pattern reflects the transfer learning model's struggle with certain plant species, possibly due to domain-specific differences.

F. Best Model

Based on the evaluation metrics, the CNN was identified as the best-performing model. It achieved the highest validation accuracy (85.21%) and superior per-class performance. Although some overfitting was detected (training-validation gap of 0.1451), its generalization to the validation set remained robust. The ResNet-50 model, while benefiting from pre-trained features, did not surpass the CNN, likely due to domain differences and the need for further fine-tuning or domain-specific augmentation.

G. Prediction Test Result

To assess real-world applicability, a prediction test was conducted using a sample image.

Table IV. Prediction Results

Model	Predicted Class	Confidence
CNN	1Hibiscus rosa-sinensis (HRS)	100.00%
ResNet-50	29Premna odorata (PO)	32.62%

Table IV. The prediction result of the CNN is illustrated in **Figure VIII**, where it correctly identified Hibiscus rosa-sinensis (HRS) with 100.00% confidence. Meanwhile, the ResNet-50 prediction is shown in **Figure IX**, where it predicted Premna odorata (PO) with only 32.62% confidence.

Figure VIII. CNN prediction result

Figure IX. ResNet-50 prediction Result

The CNN provided a highly confident and correct prediction, consistent with its validation performance. In contrast, the ResNet-50 model predicted a different class with low confidence, reflecting its lower accuracy and possible lack of adaptation to the specific dataset.

V. Conclusion

The study successfully developed a deep learning-based automated identification system for 40 species of Philippine medicinal plants based on leaf images. The Convolutional Neural Network model we designed outperformed the transfer learning model, ResNet-50, with a validation accuracy of 85.21 percent versus 67.91 percent on the same dataset. This difference in performance illustrates the benefits of domain-specific architectures compared to general or generic pre-trained models. While novel in its own right, the methodology was comprehensive in its application of data augmentation and stratified cross-validation with hyperparameter tuning while examining reproducibility and reliability and demonstrated that domain-specific neural networks can successfully identify the distinctive morphological traits of Philippine medicinal plants.

The potential implications of such a technology reach far beyond the technical accomplishments of this study. Public health safety issues and cultural preservation alike likely stand to benefit enormously. The system created through this effort tackles the critical problem of misidentified medicinal plants causing negative health impacts on local communities, especially as traditional knowledge of botany declines, and the botany of herbal plants is undervalued. Consider it an ancient knowledge base being harnessed by a relatively new and still developing technology, with the potential of ensuring the therapeutic opportunities of Philippine flora could be relatively safely and easily accessed, while still managing the associated health risks. This work should focus on expanding the dataset, including plant characteristics from multiple parts of the organism, and ultimately produce end-user mobile applications that could lead to deployment into fieldwork for real-time usage, and preserving traditional knowledge of medicinal flora from the Philippines for future generations.

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