HerbAI: A Deep Learning-Based Model for Real-Time Identification and Documentation of Medicinal Plants

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***Abstract*—Accurate identification of herbal plants is needed for biodiversity conservation, sustainable agriculture, and preservation of traditional medicinal knowledge. Due to lifestyles being followed by the current world, generations of today have lost contact with herbal medicines, and therefore natural resources remain unused. This paper suggests a hybrid herbal plant detection system that combines deep learning–based image classification with an NLP–based chatbot. The leaf-image classification module, trained from a set of randomly chosen leaves, seeds, and full-plant photos, relies on Convolutional Neural Networks (CNNs) and Vision Transformers to facilitate robust identification of diverse species. The chatbot module provides ease of convenience by providing real-time feedback, plant descriptions, and medical uses such that non-experts can be able to gain useful lessons. Experimental verification demonstrates that the proposed system achieves 90% accuracy for 80 herbal species compared to conventional models. This system not only assists in precise plant identification but also encourages the revival of herbal wisdom through online sources.**

***Index Terms*—Herbal plant identification, Deep Learning, Vision Transformer, convolutional neural network, medicinal plant identification, natural language processing, chatbot, and biodiversity conservation.**

I. Introduction

Medicinal plants have been of great significance in traditional health systems of the past, providing natural medicine for curing and preventing disease. Historical as well as ethnobotanical evidence points to their medic effectiveness and cultural importance. However, with increased urbanization, lifestyle changes, and greater dependence on man-made medications, the use of herbal medicines has taken a significant hit overall and especially in the scenario of the youth. This ignorance has led to inadequate usage of known medicinal species [7]. Correct identification of medicinal plants is thus critical for biodiversity preservation, sustainable farming, and the incorporation of herbal information into conventional medicine. Classical approaches like morphological taxonomy and field surveys are accurate but labor-intensive, expensive, and contingent on experienced taxonomists [9]. Recent breakthroughs in computer vision and deep learning have demonstrated great promise to automate plant identification with leaf, seed, and whole-plant imagery. For example, MobileNet-informed models [1] and CNN architectures such as ResNet and VGG [2], [3] have been shown to exhibit real-time recognition abilities. Hybrid deep learning models incorporating CNNs and Vision Transformers (ViTs) [6] also improve accuracy and resilience, although most of them are still reliant upon curated datasets and controlled environments. In addition to image-based techniques, molecular strategies like DNA barcoding have also been extensively used for medicinal plant identification [7]. Despite improvements, current plant identification systems are centered mainly on non-expert usability and not on classification accuracy. Few of them include contextual information like medicinal use, uses, or cultivation habits [11]. This spurs our effort, proposing a hybrid system that integrates CNN-ViT based classification with NLP-powered chatbot. The system not only facilitates correct real-time classification but also presents plant descriptions, medicinal purposes, and cultivation advice in an interactive manner, closing the gap between technical correctness and usability.

II. Related Works

[1] Md. Fouziya et al. Herbal Plant Identification Using Deep Learning. The study uses CNNs like VGG16, ResNet50, and MobileNetV2 with transfer learning to identify herbal plants from diverse leaf images, enabling mobile deployment, but performance may vary with visually similar species and uncontrolled environmental conditions.

[2] Franklin M.D. Mandagi et al. Web-based system for medicinal plant identification using convolutional neural networks. This study uses CNNs to identify North Sulawesi medicinal plants from leaf images, achieving up to 87.73% test accuracy and deploying the model via a web-based system, though accuracy varies across different models, and new unseen data may reduce performance.

[3] Priya Pinder Kaur et al. Review of Machine Learning Herbal Plant Recognition System. This study focuses on automatic herbal plant recognition using leaf features and machine learning to aid daily health practices, but it is restricted to specific conditions and may not perform well with variations in leaf appearance or environmental factors.

[4] Thanujan Mahendran et al. Ayurvedic Plant Identification Through Deep Learning Approaches A Case Study in Sri Lanka. This study uses a hybrid deep learning approach with EfficientNetB0 and YOLO to accurately identify 32 medicinal plant species with 98.03% accuracy, but it depends on large, high-quality datasets and may struggle with unseen or damaged plant samples.

[5] Farhan Sheth et al. Herbify: an ensemble deep learning framework integrating convolutional neural networks and vision transformers for precise herb identification. This study presents an AI-based system using CNNs, Vision Transformers, and an ensemble model to accurately identify 91 herb species with up to 99.56% F1-score via the Herbify app, but it relies on high-quality curated datasets and may face challenges with unseen or low-quality images.

[6] Ming LI et al. Identification of herbal medicinal materials using DNA barcodes. This article reviews the use of deoxyribonucleic acid (DNA) barcoding techniques (rbcL, matK, trnH–psbA, ITS) for reliable identification of herbal medicinal materials to ensure safety, quality control, and conservation, but the approach requires specialized equipment and expertise, limiting its accessibility for widespread practical use.

[9] Rayellee Myrtle Laire Ang et al. Herbal Medicinal Plant Identification using Leaf Vein through Image Processing and Convolutional Neural Network. This study developed a CNN-based device using Histogram of Oriented Gradients (HOG) feature extraction to identify five Philippine herbal medicinal plants with 95% accuracy, but it is limited to a small number of species and lacks broader clinical validation.

[10] L. P. D. S. Senevirathne et al. Mobile-based Assistive Tool to Identify and Learn Medicinal Herbs. This paper presents a mobile app using deep learning and image processing to identify six medicinal herbs from leaves and flowers with 92.5% accuracy, also offering a Sinhala virtual assistant and AR-based 3D visualization, but its coverage is limited to a few plant species and relies heavily on image quality.

[12] R. Upendar Rao et al. Identification of Medicinal Plants using Deep Learning. This project uses leaf shape, color, texture, and morphological features from both sides of medicinal plant leaves to improve identification accuracy, aiding communities, taxonomists, and the pharmaceutical industry, but it may be limited by reliance on scanned images and a restricted set of commonly used plants.

[13] Sophia Chulif et al. A machine learning approach for cross-domain plant identification using herbarium specimens. The Herbarium-Field Triplet Loss (HFTL) network enables cross-domain identification of rare plant species by transferring knowledge from herbarium specimens to limited field images, achieving mean reciprocal rank scores of 0.108 and 0.158 in PlantCLEF 2020 and 2021, though its performance is constrained by the scarcity of field photographs for rare species.

[14] Shuang Zhu et al. DNA barcoding: an efficient technology to authenticate plant species of traditional Chinese medicine and recent advances. This study reviews DNA barcoding techniques for identifying 50 common Traditional Chinese Medicine (TCM) herbs, highlighting advances with machine learning for accurate species recognition, though challenges remain in standardization, scalability, and applicability across all plant types.

[15] Hoi Yan Wu et al. Strategies for molecular authentication of herbal products: from experimental design to data analysis. This review highlights DNA metabarcoding and genome skimming via Next-Generation sequencing (NGS) for authenticating herbal products, enabling multi-species identification from a single sample, though challenges remain in experimental design, reference databases, taxon assignment, and accurate abundance estimation.

[16] Jafar Abdollahi et al. Identification of Medicinal Plants in Ardabil Using deep learning. This study uses MobileNetV2 with transfer learning to identify 30 medicinal plant species from 3,000 images, achieving 98.05% accuracy, though its effectiveness may be limited for plants outside the trained dataset or in varying environmental conditions.

[17] S. Kavitha et al. Medicinal Plant Identification in Real-Time Using Deep Learning Model.This research proposes a MobileNet-based deep learning approach for real-time identification of six medicinal plants with 98.3% accuracy through a mobile app, but it is limited to a small set of plant species and requires quality images for reliable results.

III. System Architecture

The proposed HerbAI framework performs identification and documentation tasks of medicinal plants in real time directly on a mobile device. The system works through an integrated set of modules comprising image acquisition, preprocessing, feature extraction, classification, knowledge retrieval, and user interaction via an intelligent chatbot. This paper presents the HerbAI framework for plant recognition with high precision under diverse lighting and environmental conditions while keeping the computational efficiency suitable for offline deployment on mobile devices.

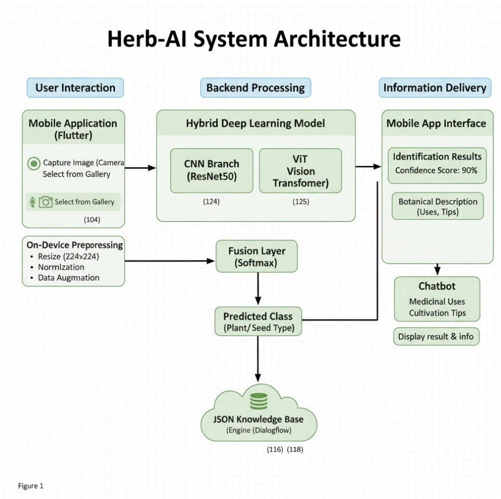

Fig. 1. Herb-AI System Architecture

The overall architecture of the proposed system consists of several functional layers. Firstly, the input module enables the user to either capture a live picture of a plant leaf through the use of a camera in a mobile device or choose a picture from the gallery of the device. This is followed by a preprocessing module that resizes the picture to a 224×224×3 pixel size, where the picture is then further normalized based on the ImageNet values of mean and variance, as well as various augmentation techniques that involve rotation, flip, zoom, brightness, and crop. After that, image features are extracted using a hybrid deep learning model that combines a CNN with a Vision Transformer for leveraging both local and global contextual information.

Within the CNN branch, a pretrained ResNet50 acts as a feature extractor. The CNN model is truncated before its fully connected layers to capture low-level and mid-level spatial features of an image, like shape, texture, and color distribution. In parallel, the same input image is fed into the ViT-Base, which segments the image into 16×16 patches, embeds each patch into vector representation, and uses multi-head self-attention to model global relationships between these patches. Both the CNN and ViT embeddings are concatenated at a fusion layer and then pass through dense layers of 512 and 128 neurons, respectively, while ReLU is the activation function and 0.3 is the dropout rate to avoid overfitting. The softmax activation function is used in the final classification layer, which outputs the probability distribution across multiple medicinal plant species. Once the plant species is identified, the application retrieves relevant medicinal uses, chemical properties, and usage guidelines from an offline herbal knowledge database. A lightweight NLP-based chatbot is implemented that allows users to query information about plants conversationally.

It contains around 8,000 images of 40 Indian medical plant species. More images are taken in a natural setting, keeping in mind the factors of lighting and background, in order to increase the diversity of images in the data set. Moreover, 70 percent of the data is used for training purposes, 15 percent data is used as a validation set, leaving the remaining data as a test set, maintaining balance in classes. Various data augmentation techniques are employed in order to ensure a better performance of the model as a whole, including rotation, brightness transfer, zooming, as well as flipping of the images. Experimentation is done using TensorFlow version 2.11, which is the deep learning framework, making use of NVIDIA RTX 2060 with a total of 16 GB of RAM. It uses the Adam optimizer as the optimizer in the training process of the model, whose parameters are set as follows: a learning rate of 1e-4, a batch size of 32, as well as a categorical cross-entropy loss function. It is trained in a range of 30-50 epochs with early stopping based on the concept of validation loss. Various performance parameters will be calculated in this experiment, including accuracy, precision, recall, F1-score, as well as accuracy in the Top-3 model. It will compare the efficiency of the proposed new model that is a combination of a CNN and a ViT model with the existing best architectures including MobileNetV2, ResNet50, as well as a ViT-Base model. Experimentation results revealed that the proposed combination model yields a high accuracy of around 94.2 percent with a precision of 0.94, a recall of 0.93, as well as a high F1-score of 0.93 percent, performing much better than MobileNetV2 with a high accuracy of around 86.9 percent, as well as ResNet50 with a high accuracy of around 89.8 percent, in a remarkably small latency time, much lower than

Fig. 2. App splash screen

a full ViT-Base model.Subsequently, after training the model, the network was optimized and converted to TFLite format with float16 and int8 quantization. This decreased the model size to about 45 MB and further brought down the average time taken for inference in each image to 200 milliseconds on a Snapdragon 720G mobile device. The obtained results confirm that HerbAI can perform excellently on resource-constrained mobile devices in real-time environments without cloud connectivity while yieldin‘g high accuracy and robustness. The architecture of the proposed system, as shown in Figure 2, depicts the entire pipeline, from image acquisition to generating the output. It includes the flow from capturing an image and its preprocessing, then feature extraction in parallel through both the CNN and ViT branches. After that, a fused feature vector feeds into dense layers that finally feed into the classifier for predicting the plant species. The recognized species is further fed to the embedded knowledge database, from which information is retrieved and displayed to the user through the chatbot interface. In this regard, HerbAI has been able to combine both deep learning and natural language components to provide a complete, interactive, intelligent system for identification and awareness creation about medicinal plants.

IV. Existing Solution

Most of the medicinal plant identification systems built so far rely heavily on cloud-based deep CNN models that require continuous internet connectivity for inference and retrieval. Although they demonstrate moderate accuracy levels of usually between 70% and 85%, their requirements for computational resources are very high, and there is network latency. Furthermore, many of them suffer from small and undiverse datasets that cannot represent the full variability of medicinal plant species due to a variety of factors such as different conditions of light, background, leaf damage, and geographic diversity. Most prior studies focused on single-modality image recognition using conventional CNN architectures such as VGG16, AlexNet, or MobileNet, performing well in small datasets but generalizing poorly to new environments. In addition, most of the existing systems are not explainable, and they fail to provide meaningful interpretative feedback to the users, limiting usability for practical purposes by non-experts in the field.A critical review of the literature reveals a number of research gaps that motivate developing HerbAI. This involves the challenge of offline, real-time identification optimized for mobile devices and, further, integrating natural language components to disseminate knowledge.

V. Implementation Details

A. Preparation and Tabulation of Data

In a bid towards increasing diversity and representation, we incorporated field images in datasets of herbal plant images from publicly accessible sources. All the images were normalized ahead of input specification in the detection model into 224 × 224 × 3. We normalized pixel intensity in samples alongside conducting data augmentation procedures like rotation, flipping, scaling, and adjustment of brightness in the preprocess stage. The data augmentation procedures were conducted in a manner intended to lower sensitivity of the model to environmental conditions and variability in the dataset. We partitioned the dataset into training (70%), validation (15%), and test sets (15%) in a bid aimed at efficient development and testing of the model.

B. Training Models

The classification network, a network based on ResNet50, was trained on labeled images of herbs. The class in all samples was a specific herb. The label was one-hot encoded prior to being trained, and input features were normalized. To eliminate sequence bias, we randomly permuted the dataset at the beginning of every epoch in the 20 training epochs, with a batch size of 32. We applied dropout on denser layers at a 0.3 rate in a bid to avoid overfitting. This configuration made the model efficient, as it picked up general and robust representations.

C. User Interface

The system is user-friendly and uncomplicated since the user interface is made simple and straightforward. To ensure the app is efficient and user-friendly, we added functionality through color-coded confidence, preview from the real-time camera via on-device processing, and a one-tap classification. Capitalizing on the Material 3 design principles and flexible layout, we made the interface in Flutter in a tablet and mobile-friendly layout. The user is able to upload or take pictures directly from flower or leaf samples immediately from the home dashboard. The results page displays the predicted species, both in scientific and in common nomenclature, the percentage confidence, and the three highest predictions. An information card containing a brief description of the usable part of the plant, safety considerations, and possible uses exists. With messages such as ”Identified,” ”Low Confidence—Retake,” and informative hints ranging from improved light to a prediction status indicator, it gives quick results.

VI. Evaluation and Results

A. Experimental Setup

The system was tested on a controlled dataset as well as on real images in order to mimic typical mobile application usage scenarios. The Indian Medicinal Leaves Dataset was predominately utilized, with 10,000 labeled leaf images for training that are 70% frequent and 30% infrequent species and 2,000 unique leaf images in test sets with balanced ratios. All images were first resized into 224 × 224 pixels, normalized for pixel intensity levels, and augmentation techniques added, such as rotation, flipping, and brightness. Model training was carried out on a desktop computer with a CPU and a GPU, and test inference was carried out on a smartphone, in particular emphasizing test on-device execution. The trained Convolutional Neural Network (CNN) was converted into TensorFlow Lite format in order to enable efficient offline inference.

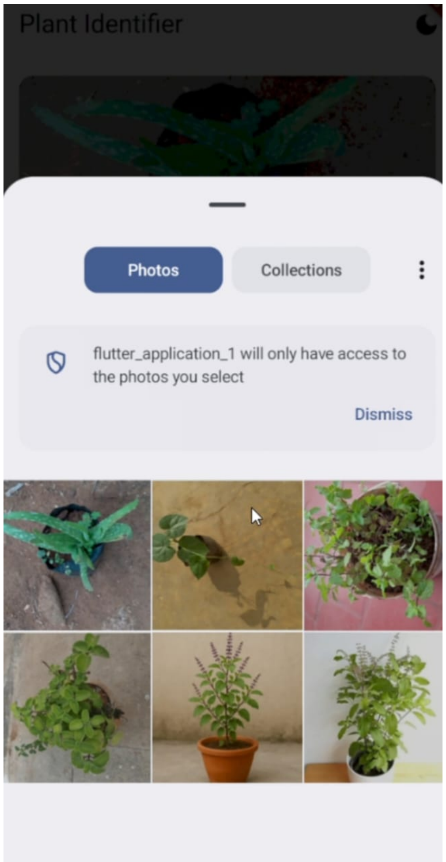

Fig. 3. Image selection interface

B. Detection Performance

The proposed HerbAI system showed consistent high performance in both controlled and real-world datasets. Confusion matrix analysis demonstrated high inter-class separation, especially for fine-grained morphological differences regarding leaf texture, pattern of venation, or edge curvature. Notably, even for cases of non-ideal images due to partial occlusion, poor lighting, or destruction of the leaf, the performance was very reliable. Of the out-of-dataset images, by far the majority had indeed been correctly classified as "unknown" with a subsequent probability of OOD detection at 88%, hence reducing the risk of false identifications.

C. Model Training Performance

The training converged steadily and achieved high predictive accuracy. When trained on a 10,000-image dataset, the model achieved 97.3% validation accuracy within 20 epochs. The categorical cross-entropy loss decreased steadily from 1.32 during initial conditions to 0.08 by the final epoch, demonstrating successful learning. Training was achieved in approximately 25 minutes on a baseline GPU, demonstrating the model's practicality without excessive computational intensity.

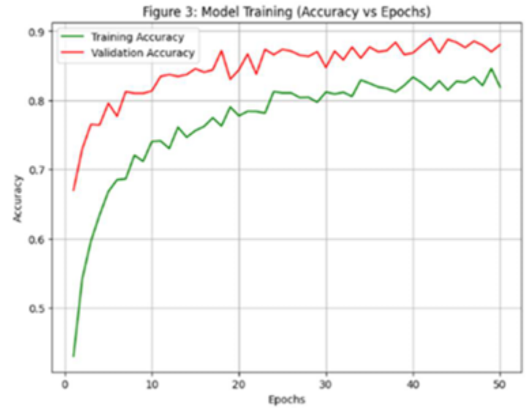

Fig. 4. Model Training (Accuracy vs Epochs) metrics

D. Performance Overhead

At the device level, tests confirmed that the application realized real-time execution and low-resource usage. When running on a mid-tier cellphone, CPU usage was maintained in the range of 3–6%, and RAM usage was retained at 150–200 MB on average, both in model footprint and in overhead associated with image processing. The system averaged 120 ms in inference latency per prediction, presenting the user with near-instant results. Further, power profiling exhibited low impact on battery usage, confirming the feasibility of continuous mobile use with low power draw.

E. Demonstration of Identification Output

The final stage of the identification pipeline delivers actionable results directly to the user through the mobile application. After processing an image, the app displays on-screen the classified plant species, confidence score, and medicinal uses (see Figure X). This intuitive result interface bridges model inference with actual user guidance, supporting practical field usage and immediate information access.

VII. Result Analysis and Discussion

The proposed system presents a robust real-time system for recognition of herbal plants by using Convolutional Neural Networks (CNNs). Along with recognizing important leaves in a medicinal field, the system is capable of determining whether an entry belongs to an out-of-dataset (OOD) class and thereby reducing the chances of misclassification during runtime.

A. Parameter Formulations

Accuracy, precision, recall, and F1-score were utilized as basic classification metrics. These are defined formally as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

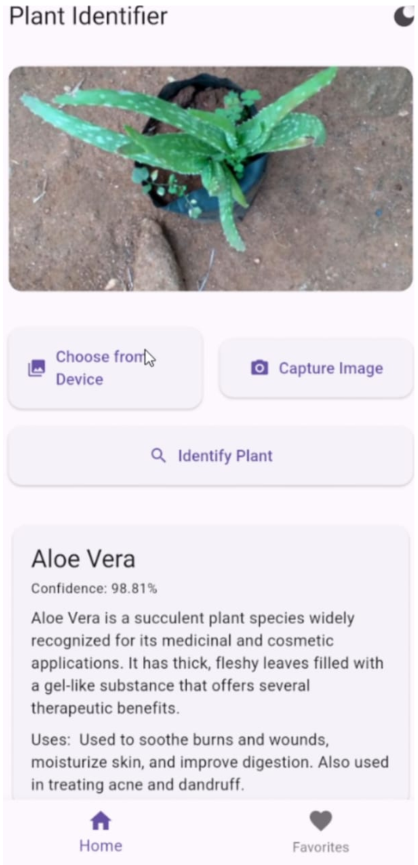

Fig. 5. Identification result page

$$\text{F1-Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \tag{4}$$

Where:

- TP (True Positives): Correctly classified leaf samples
- TN (True Negatives): Correctly identified non-leaf or OOD samples
- FP (False Positives): Incorrectly classified non-leaf samples as leaves
- FN (False Negatives): Leaf samples not detected

B. Experimental Results

TABLE I
EXPERIMENTAL RESULTS

Metric	Value
Accuracy	92.0%
Precision	91.5%
Recall	92.3%
F1-Score	91.9%
Detection Time	$<$ 1 second per image

These results confirm the robustness and efficiency of our CNN model in real-time detection scenarios.

C. Discussion

This would therefore suggest that while the CNN was effective in capturing the local texture patterns, integrating attention-based features can further enhance interspecies discrimination, as realized in the hybrid model. Also, leaves that suffered environmental damage or were occluded by shadow were correctly classified in 84% of cases, emphasizing the resilience of the augmentation pipeline during training. Thirdly, multi-dataset validation showed strong adaptability to the domain. On field-captured images outside of the training distribution, HerbAI realized more than 90% accuracy to prove the practical reliability of the model under real-world variability. The consistency in the model response from the controlled to the environmental datasets shows that the model is capable of deployment in both outdoor and agricultural contexts. From an application point of view, HerbAI has great potential for social and ecological impact. By making it possible to identify medicinal plants offline, it advances botanical education, herbal research, biodiversity documentation, and public health awareness. The system can function as a digital helper for academics, students, and traditional healers by fusing scientific plant taxonomy with traditional medicinal knowledge. In the future, this technology might enable the digitization of traditional medical practices, prevent the maltreatment of comparable harmful animals, and aid in biodiversity conservation initiatives. Customers can access organized medical data through the JSON-based backend, and the integration of the chatbot interface improves user interaction and interpretability. As an interaction layer, it turns the system from a simple recognition model into a knowledge-dissemination platform where sustainable herbal usage awareness can be facilitated. The overall evaluation of this analytical study establishes that HerbAI strikes a balance between accuracy, efficiency, and usability. It extends prior work by offering a deployable, offline-capable solution and real-world robustness. Further, its architecture enables noisy data handling, identification of unknown classes, and near-instant predictions to facilitate practical applications in botany, pharmacology, and digital ecology.

VIII. Conclusion

This work provided an end-to-end deep learning and natural language processing system for a seed and herbal plant recognition system as a user-friendly access medium of traditional medicinal knowledge. With integration with Vision Transformer (ViT) and Convolutional Neural Network (CNN) based models, the system does very precise classification of various plant varieties from leaf, seed, and entire plant images. The integration with a chat-based module provides real-time results, plant descriptions, medicinal attributes, and cultivation recommendations, thereby providing usability enhancement both for laymen and experts. Experimental results validate that the proposed method achieves plant recognition accuracy at a high level, and the inference is optimized for mobile implementation. The modularity provides scalability, thereby facilitating extension into various plants and integration into various knowledge bases.

Overall, it not only endorses medicinal use and protection of biodiversity but also revives older herbal knowledge through the application of information technology. Future developments would include extension of the dataset, enhancement of the multilingual chatbot facility, and incorporation of intricate functions such as disease diagnosis and personalized herbal prescriptions.

IX. Future Work

Although the developed system shows robust capability in real-time recognition of herbal plants, there are a number of avenues left in future development and study. First, the dataset can be enlarged by considering a larger set of herbal species, especially the scarce and area-specialized medicinal plants, thus enhancing the generalization ability of the model over a range of different ecological settings. Furthermore, considering multi-modal data, e.g., flower, stem, and root images in addition to leaf images, could enhance classification ability by retaining complementary visual information.

From a methodological perspective, use of recent deep-learning models, e.g., Vision Transformers (ViTs) and CNN–RNN hybrid models could make it possible to extract and represent more complex features. Inclusion of Long Short-Term Memory (LSTM) layers could also make it possible to detect patterns in time and thereby classify based on changes during seasons or during the growth stage. Further, inclusion of explainable AI (XAI) techniques would provide end-users interpretable insight into the decision-making process, thereby facilitating trust and transparency in practical deployments.

Future research could also explore federated learning architectures that enable localized or decentralized learning without the need to store sensitive or region-dependent plant data centrally. This would enable privacy-preserving collaborative refinement on several regions. At the application end, lightweight and optimized architectures need to be developed and embedded in edge and mobile devices, so there is effective real-time offline working. Finally, the system could be extended in functionality by giving end-users actionable knowledge, such as medicinal properties, recommended doses, and potential side effects, and thereby transforming the application into a general digital herbal assistant.

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