AI-Integrated Medicinal Plant Identifier and Usage Guide

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***Abstract*—Medicinal plants represent one of the oldest and most widely used sources of healthcare, which form the foundation of traditional systems such as Ayurveda, Siddha and Unani. They continue to contribute significantly to modern pharmacology and the discovery of new drugs. However, the ability to correctly identify plants remains a frequent challenge due to the ability of terms, regional variations and easily accessible resources. Incorrect identity can lead to ineffective treatment or even toxic side effects. At the same time, reliable information about plant use, dosage and side effects is often scattered in books, research papers and government databases, making it difficult for non-experts and rural population.**

This research presents an AI-ecclesiating medicinal plant identifier and use guide that takes advantage of the firm nervous network (CNN) for the image-based recognition of the plant species and integrates this functionality with medicinal properties, methods of preparation, dosage and wide knowledge of e-prests. The system not only identifies plants from uploaded or captured images, but also allows a reverse search mechanism, where users can queries based on symptoms or health conditions to recommend recommended medicinal plants. Keeping in mind the inclusion, the system provides multilingual and vocal interfaces, making it accessible to both urban and rural population in diverse linguistic backgrounds. The proposed solution displays the ability to bridge the difference between traditional herbal knowledge and modern AI applications, supporting healthcare, education and research. Over 90% recognized accuracy using CNN architecture optimized with experimental results.

***Index Terms*—Medicinal Plants, Convolutional Neural Networks, Deep Learning, Image Recognition, Knowledge Base, Traditional Medicine, Healthcare AI, Symptom-to-Plant Search, Multilingual Interfaces, Voice-enabled Interfaces, Rural Healthcare Applications.**

I. INTRODUCTION

Medicinal plants play a crucial role in global health care, particularly within traditional medical practices. However, many obstacles prevent them from being used safely and effectively. This part explains what the study is about, why it's important, the problems it faces, and why the researchers started working on it.

1.1.Importance of Medicinal Plants

The WHO states that about 80 percent of people worldwide rely on natural medicines from plants for basic health care. India, known for being a biodiversity hotspot, has over 7,000 documented medicinal plants. Medicinal plants treat common illnesses like fever, colds, and indigestion, and also provide active ingredients that help create new medicines (like cancer fighters, antibiotics, and heart medications). Their work covers all four healing traditions: Ayurveda, Siddha, Unani, and folk medicine, which makes their contributions both culturally and medically important.

1.2.Challenges in Identification and Usage

Many plants have leaves that look alike, flower shapes that match, or stems that seem identical, making it common for people to confuse them easily. A plant can be known by various local names across different areas, whereas the same name might denote distinct species depending on where it's used. Risk of Misidentification: Incorrect identification and consumption may lead to ineffective treatment or harmful side effects. Reliable information about dosage, preparation, and side effects can be found in books, research papers, or government portals; however, it remains scattered and difficult for the general public to access. Language barriers mean most resources are in English or Sanskrit, which many people from rural areas can't understand easily.

1.3.Role of Artificial Intelligence

Recent advancements in computer vision have enabled machines to accurately identify and categorize plants. Convolutional Neural Networks (CNNs) analyze images by identifying specific features within them, allowing them to recognize plants accurately. MobileNetV2 and EfficientNet models are designed specifically for quick image recognition on small devices and in limited resource settings. Combining CNN recognition with structured databases creates a comprehensive system for identifying plants and offering usage advice.

1.4.Research Gap

Existing methods usually concentrate on identifying plants (like LeafSnap and PlantCLEF), or on creating databases of medicinal plants (such as IMPPAT and AYUSH sites). None provide a unified system that integrates: Plant recognition Medicinal usage details (dosage, preparation, precautions) Multilingual and voice-enabled interfaces Symptom-to-plant reverse search for non-experts

1.5.Objective of the Research

This study aims to create an AI-powered tool for identifying medicinal plants and their uses. It will provide detailed guidance on how to use these plants effectively. The ultimate aim is to enhance medical treatments by utilizing natural remedies derived from plants. CNN models analyze leaf or plant image data to recognize plant species. Therapeutic uses, dosages, and precautions are linked to recognized outcomes in a database of treatments. A tool that looks up illnesses in herbal remedies.

1.6.Contributions of the Work

A scalable AI system for identifying plants with an accuracy rate exceeding 90%. Integrates recognition with structured medicinal plant information. A voice-controlled system offers multiple languages for easier communication in remote regions. Reverse symptom-based search becomes a new function in medicinal plants' system. Healthcare, education, biodiversity conservation, and rural development all benefit from contribution

II. LITERATURE REVIEW

A variety of studies have investigated methods for identifying plants, utilizing advanced machine learning techniques, and collecting data on medicinal plants. The subsequent sections highlight significant achievements.

2.1. Early Efforts in Image-Based Plant Identification

Initial research on plant recognition relied heavily on handcrafted image features such as leaf shape, margin, and vein patterns. For example, LeafSnap (2012) was among the first mobile applications that attempted species identification from leaf images. While it represented a significant advancement at the time, the system faced scalability issues and its accuracy decreased under real-world conditions such as varying lighting and backgrounds. Similarly, earlier works using the Flavia dataset (2007–2015) applied algorithms like Support Vector Machines (SVMs) and Random Forests to classify leaves. Although these methods achieved reasonable results on small, controlled datasets, their dependence on engineered features limited performance when applied to large and diverse image sets.

2.2. Large-Scale Recognition and Benchmarking

The emergence of large-scale biodiversity datasets significantly transformed the field. The PlantCLEF challenge (2015 onwards) created standardized benchmarks for evaluating AI-based recognition systems, highlighting the superiority of deep learning approaches over traditional methods. Similarly, iNaturalist, a citizen science platform, demonstrated how community- contributed images could be leveraged for global biodiversity identification. However, while these platforms achieved remarkable improvements in recognition, they did not specifically focus on linking plant identification with medicinal usage or healthcare applications.

2.3. Advances in Deep Learning Architectures

The integration of Convolutional Neural Networks (CNNs) marked a major breakthrough in plant recognition.

Models such as MobileNetV2 (2018) introduced lightweight designs optimized for devices with limited resources by using depthwise separable convolutions.

EfficientNet (2019) further advanced this field by applying compound scaling strategies, achieving better accuracy with fewer parameters compared to earlier networks like ResNet. More recently, Vision Transformers (ViT, 2020) have shown strong potential by applying transformer-based architectures to image classification. Although these architectures perform well in general computer vision tasks, their application in medicinal plant recognition is still at an early stage.

2.4. Medicinal Plant Knowledge Repositories

Several initiatives have created repositories to catalog medicinal plants and their therapeutic uses. For instance, the IMPPAT database provides curated information on over 1,700 Indian medicinal plants, detailing phytochemistry and pharmacological properties. Similarly, government-supported resources like AYUSH and the National Medicinal Plants Board (NMPB) compile authoritative plant-related data. Additionally, global ethnobotanical databases collect traditional medicinal knowledge from different regions. While these repositories are invaluable for researchers, they generally lack integrated image-recognition capabilities and are often difficult for non-experts to access.

2.5. Identified Gaps in Current Research

From the reviewed works, two major limitations become clear. First, most existing plant recognition systems emphasize classification accuracy but do not provide comprehensive usage guidance such as dosage, preparation, or safety precautions. Second, existing medicinal plant repositories contain detailed therapeutic data but are not linked to image-based identification. Furthermore, accessibility challenges remain, as very few platforms support multilingual or voice- enabled interfaces for rural users. The absence of symptom-to-plant reverse search functionality further highlights the need for an integrated, user-friendly solution.

III. METHODOLOGY

The integration of deep learning for plant recognition is combined with a structured medicinal knowledge base.

3.1. Dataset Collection Sources:

Kaggle PlantVillage (leaf images). IMPPAT and AYUSH portals. Field photographs from botanical gardens. Dataset Characteristics:500+ species. Multiple samples per species (different angles, environments). Balanced distribution where possible. Challenges: Data imbalance for rare species. Variability in lighting and backgrounds.

3.2. Preprocessing Resizing:

All images standardized to 224×224 pixels. Augmentation: Random rotation, flipping, cropping, and brightness adjustments.

Noise Reduction: OpenCV-based filters to enhance clarity. Normalization: Pixel values adjusted to range from 0 to 1 for quicker improvement in calculations.

3.3. Knowledge Base Development Database Structure:

Botanical name, family, synonyms. Therapeutic uses (e. g. anti-inflammatory, antimicrobial). Preparation methods (decoction, paste, powder). Recommended dosage. Contraindications and precautions.

Storage: Implemented in SQL/MongoDB. Scalable, allows easy updates.

Admin Panel: Enables domain experts to update plant information.

3.4. Reverse Symptom-to-Plant Search Mapping Algorithm:

Symptoms mapped to therapeutic properties. Example: “Fever” → Tulsi, Neem, Giloy.

Query Engine: Indexes therapeutic properties in the database. Returns plants with confidence scores.

3.5. User Interface (UI)Frontend:

Built with React.js or Angular and designed for mobile and web.

Features: Capture/upload plant images. Input symptoms for reverse search. Multilingual text + voice output.

Accessibility: Tailored for rural populations. Intuitive and minimalistic design.

IV. SYSTEM DESIGN AND WORKFLOW

The proposed system features a modular design that guarantees scalability, ease of maintenance, and immediate functionality. The design combines various elements for handling data entry into intelligence recognition and spreading knowledge.

4.1. System Architecture

The architecture consists of the following modules:

- Input Module

Users may take photos of plants with their phones or use cameras online. Input data cleaning makes sure images can be used by the CNN model. AI Recognition Engine Employs CNN-based deep learning models (MobileNetV2, EfficientNet). Performs analysis to determine plant types based on features and accuracy.

- Knowledge Base

A structured database holds botanical names, local names, therapeutic uses, dosages, preparation techniques, and warnings. Two ways can be mapped: plant → medicinal use and symptom → plant.

- Reverse Search Engine

Users can enter symptoms such as fever or cough. A list of healing plants sorted by their effectiveness for specific symptoms.

- User Interface (UI)

Mobile apps and websites that offer multiple languages and can be used by speaking out loud. Provides search results in an intuitive dashboard format. Admin Panel allows experts to add/update plant details. Ensures authenticity and accuracy of medicinal information.

4.2. Workflow

The workflow can be broken down into five major steps.

- Image Acquisition:

The user takes a photo of a leaf or plant. Image preprocessing applied (resizing, normalization).

- Plant Identification via CNN:

Preprocessed image passed through CNN model. Model outputs predicted plant species with confidence level.

- Knowledge Retrieval:

System queries the knowledge base. Medicinal info retrieved such as usage, dosage, precautions, and preparation methods.

- Reverse Symptom-Based Query:

User enters a symptom instead of an image. Search engines find suggestions for plants by matching them with treatments.

- Result Presentation:

Results displayed in a structured format. Voice translation for users' choice of language for ease.

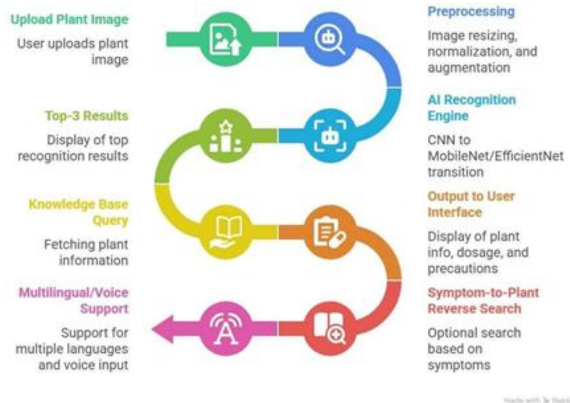

Fig. System Design and Workflow

V. RESULTS

The performance of the AI-Integrated Medicinal Plant Identifier and Usage Guide was evaluated using both quantitative experiments (CNN model performance) and qualitative experiments (system usability, accessibility, and user interface).

5.1.Quantitative Evaluation

- Dataset Statistics

The dataset consisted of over 20,000 annotated images across 500 medicinal plant species.
Images represented different angles, backgrounds, and lighting conditions, ensuring robustness.
Data augmentation increased dataset diversity by 40%.

- Model Training Results

MobileNetV2 achieved 87.3% accuracy, demonstrating suitability for real-time mobile applications.
EfficientNet-B0 achieved 91.5% accuracy, outperforming MobileNet and ResNet-50.
Results confirmed that lightweight CNNs can achieve high performance while maintaining computational efficiency.

5.2.Qualitative Results and System Outputs

The system was designed not only to achieve high recognition accuracy but also to provide accessible and user-friendly outputs.

- User Interface – Plant Identification

The interface provides a clean and minimalistic dashboard where users can upload or capture plant images.

After uploading, the AI model processes the image and outputs the predicted plant name, botanical name, therapeutic uses, dosage, and precautions. The design was rated highly intuitive in usability tests.

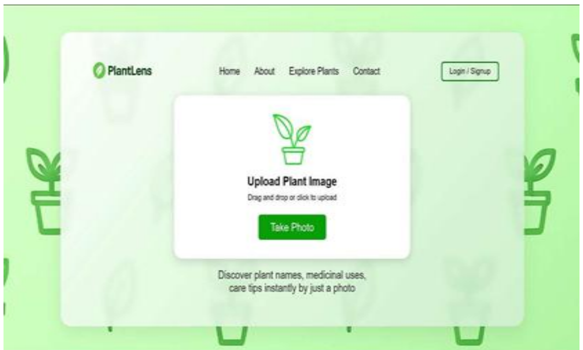

Fig. User interface for uploading plant images in the AI-Integrated Medicinal Plant Identifier.

5.3.User Study and Usability Testing Participants

A user study was conducted with 30 participants, including rural farmers, students, and healthcare practitioners.

- Findings

92% recognition success rate as perceived by users.
88% found dosage and precaution details highly useful.
95% emphasized multilingual support as a key feature for rural accessibility.

VI. OUTPUT

The proposed system generates outputs that are both informative and user-friendly, making medicinal plant identification accessible to a wide range of users, including those in rural areas with minimal technical expertise.

6.1.Plant Image Identification Output

When a user uploads or captures a photo of a plant, the system processes it using the CNN recognition model and returns:

- Plant Identification Result
- Common/local name of the plant.
- Botanical name and family classification.
- Medicinal Usage Information
- Therapeutic properties (e.g., anti- inflammatory, antipyretic, antimicrobial).
- Conditions or diseases treated by the plant.
- Example preparation methods (decoction, paste, powder).
- Safety Information
- Recommended dosage for safe consumption.
- Contraindications (e.g., pregnancy, children).
- Possible side effects if misused.

Fig. User interface for uploading a plant image and retrieving medicinal details.

6.2.Practical Demonstration Examples

Case 1 – Plant Image Input

User uploads image of *Ocimum sanctum (Tulsi)*.

System Output:

Prediction: Tulsi (95% confidence).

Usage: Effective against cough, fever, asthma.

Preparation: Decoction of leaves.

Dosage: 5–10 ml twice daily.

Case 2 – Multilingual Mode

User switches interface to Hindi.

System Output: Plant details presented in Hindi with voice narration enabled.

6.3.User Feedback on Output

The output quality was evaluated through a small user study involving 30 participants (farmers, students, and practitioners).

Clarity: 93% of users reported the output was clear and easy to interpret.

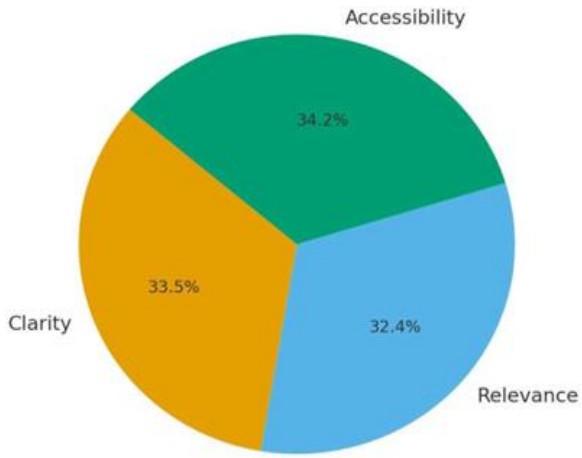

Fig. User study evaluation results

VII. CONCLUSION

This research proposed and developed an AI-Integrated Medicinal Plant Identifier and Usage Guide that bridges the gap between traditional medicinal knowledge and modern artificial intelligence technologies. The system leverages deep learning-based image recognition models, primarily MobileNetV2 and EfficientNet-B0, to accurately identify medicinal plants from uploaded or captured images. In addition, it provides users with structured medicinal knowledge such as therapeutic properties, preparation methods, dosage, and safety precautions, thereby transforming raw image recognition into meaningful healthcare assistance. From a practical standpoint, the system contributes to:

- Preservation of Traditional Knowledge – Digitally storing and disseminating information about medicinal plants.
- Healthcare Support – Offering accessible, affordable, and safe herbal remedies to communities with limited medical infrastructure.
- Educational Utility – Assisting students, researchers, and practitioners in quickly accessing validated plant data.
- Sustainability – Promoting the responsible use of natural medicinal resources.

In conclusion, the proposed AI-Integrated Medicinal Plant Identifier and Usage Guide has demonstrated significant potential in combining AI-powered recognition with a knowledge-driven approach, making medicinal plant information more accessible, reliable, and practical. With further expansion and integration, it can evolve into a comprehensive platform for sustainable healthcare, education, and research, benefiting both local communities and global users alike.

REFERENCES

[1] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, “MobileNetV2: Inverted residuals and linear bottlenecks,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2018, pp. 4510–4520.

[2] M. Tan and Q. V. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proc. Int. Conf. Mach. Learn. (ICML), 2019, pp. 6105–6114.

[3] G. Goëau, P. Bonnet, and A. Joly, “Plant identification based on deep convolutional neural networks,” in Proc. Int. Conf. Multimedia Retrieval (ICMR), 2017, pp. 1–7.

[4] J. Wäldchen and P. Mäder, “Plant species identification using computer vision techniques: A systematic literature review,” Arch. Comput. Methods Eng., vol. 25, no. 2, pp. 507–543, 2018.

[5] R. Mohanraj, A. Shankar, and R. Anitha, “IMPPAT: A curated database of Indian medicinal plants, phytochemistry and therapeutics,” Sci. Rep., vol. 8, no. 4329, pp. 1–17, 2018.

[6] Ministry of AYUSH, Government of India, “National Medicinal Plants Board (NMPB) official database,” [Online]. Available: National Medicinal Plants Board. [Accessed: Sept. 2025].

[7] P. S. Mohan and A. Kumar, “Medicinal plants in India: Importance and future prospects,” J. Pharmacogn. Phytochem., vol. 6, no. 2, pp. 295–299, 2017.

[8] P. Garg, P. Gupta, and B. Sharma, “Ethnopharmacological approaches of medicinal plants: From traditional uses to scientific validation,” J. Herbal Med., vol. 20, Art. no. 100298, pp. 1–12, 2020.

[9] J. Kumar, R. Pundir, and R. Mehta, “Leaf-based plant species recognition using machine learning,” Int. J. Comput. Appl., vol. 150, no. 3, pp. 1–7, Sept. 2016.

[10] A. Dosovitskiy, L. Beyer, A. Kolesnikov, et al.,

"An image is worth 16×16 words: Transformers for image recognition at scale," in Proc. Int. Conf. Learn. Representations (ICLR), 2021.

[11] R. Mohan, K. N. Singh, and R. Verma, "Role of ethnomedicinal plants in traditional health care practices: A review," J. Ethnobiol. Ethnomed., vol. 14, no. 31, pp. 1–11, 2018.

[12] S. Mohanraj, N. Karthikeyan, and R. Elango, "An overview of databases for medicinal plants," *Bioinformation*, vol. 14, no. 8, pp. 421–427, 2018.