AI-Driven Recognition of Indian Medicinal Flora using Convolutional Neural Networks

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Plants, people, and culture have always been deeply intertwined, each influencing the other in maintaining an equilibrium that has shaped centuries of traditional healing practices. Identifying plants with healing properties requires extensive knowledge and experience, and relies heavily on human perception, which can lead to errors. Leveraging Deep Learning with Convolutional Neural Networks and transfer learning to overcome these limitations, we have worked to develop an integrated system for the identification of medicinal plants native to India. Our system identifies 98 different classes using a dataset of 15,022 real-world images of weeds, herbs, shrubs, and trees with 92% accuracy and gives the therapeutic uses of each identified plant. This approach will empower people with the knowledge necessary to preserve and enhance traditional medicinal practices, bridging the gap between age-old practice and integrative modern medicine. This system uses Xception as the base model with a custom classification layer which can be modified to ensure scalability, by increasing the dataset to include medicinal plant species found locally and their medicinal benefits. Further development of this system into an application will ensure comprehensiveness of usage and a broader impact on medicinal practices and biodiversity conservation initiatives.

Keywords: Computer Vision, Convolutional Neural Networks, Machine Learning, Medicinal Plants of India.

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1 Introduction

India houses various bio-geographical zones such as the Himalayas, the Western Ghats, the Deccan Plateau, the Indian Desert zone, mangroves, etc., leading to a vibrant and thriving biodiversity [1]. This accounts for 7-8% of the world's diversity. Out of that, 8000 species have been identified as medicinal plants, native to India. Hence our country is counted as one of the eight vavilovian centers of the world for crops.

India has been using traditional medicine as a source of healing and wisdom since the time of the Vedas, the sacred scriptures of our country [1], [2]. Over the years the systematic usage of medicinal plants in medical systems has culminated in being called the AYUSH family of medicine, which stands for Ayurveda, Yoga and Naturopathy, Unani, Siddha, Sowa Rigpa and Homeopathy, and modern medicine. The Indian medicinal plants, evidence-based, are now used worldwide for commercial ayurvedic preparations, they are used for scientific lab study or observational therapeutics and reverse pharmacology [3], manufactured into modern medicines as per the Indian Pharmacopoeia and guidance manuals, and used in home remedies. It has become a well-organized industry; the Ayurvedic sector alone is worth ₹ 0.7 trillion [4]. The Government of India established the Ministry of AYUSH to oversee this aspect of the country; the National Medicinal Plants Board coordinates with matters related to medicinal plants and supports policies and programs for growth, trade, export, conservation, and cultivation. Various institutes and organizations have been started throughout the country, the Indian Council of Agricultural Research has established the Directorate of Medicinal and Aromatic Plants (ICAR-DMAPR) to further delve into the research of medicinal plants [5].

1.1 Motivation

Despite the potential of traditional medicines, the hands-on knowledge of their accurate and efficient usage has diluted over the years as the preference for modern medicine increased, although it did not affect commercial usage of medicinal plants, individual and independent usage decreased.

Although Government initiatives have boosted the medicinal and aromatic plant (MAP)-product industry, the standard operating procedures behind the manufacturing of such products rarely comprise people professionally adept in identifying and dealing with the raw materials involved, which leads to manufacturing units often using incorrect or substituted medicinal plants [6]. Most of these units lack adequate quality control mechanisms to screen these plants. In addition to this, confusion due to variations in local names is also increasing. Some plants arrive in dried form, and this makes the manual identification task much more difficult. Incorrect use of medicinal plants makes Ayurvedic medicine ineffective. It may produce unpredictable side effects too. Besides quality and safety issues [7], the industry in India also faces the challenges of biodiversity conservation, over-exploitation, habitat loss, unscientific harvesting practices, lack of regulation, and biopiracy [8]. Over-harvesting and unsustainable extraction methods augment the depletion of natural plant populations, disrupting ecological balance and hindering natural regeneration. Climate change further compounds these challenges, altering the distribution and growth patterns of medicinal plant species. Preserving India's remarkable biodiversity and endangered medicinal plant species is crucial, as these invaluable resources have been healing sources for centuries.

Post-pandemic, people are slowly going back to their roots. We have started to seek sustainable and self-sufficient pathways to better health, which has led to the positive promotion of integrative medicine, an increase in awareness of the environment, and ways to integrate technology constructively with society.

1.2 Goal of the Paper

Looking at the situation holistically, we have worked on developing a comprehensive integrated system in Kaggle Notebook using medicinal flora solely native to India which identifies medicinal plants and retrieves therapeutic uses of the identified plant. Since present applications are mostly leaf-based, we have focused on training our model with a dataset that includes various parts of the plant.

By leveraging deep learning models, transfer learning, and computer vision, we aim to expand this prototype into a comprehensive end-to-end system accessible on mobile devices, empowering a wide range of users—herb pickers, farmers, botanists, epidemiologists,ethnobotanists, nutritionists and home garden enthusiasts. This system simplifies manual plant identification, ensuring that accurate information about Indian medicinal flora and their therapeutic uses is available at users' fingertips.

2 Literature Survey

Initially, traditional machine learning methods were used for plant identification. The preferred classifiers were Support Vector Machines (SVMs) [9], [10], K-Nearest Neighbor (KNN) [11], and Random Forest (RF) [11]. These applications achieved good performance, although they had a complex process [12], [13]. With the rise of deep learning, studies showed that Convolutional Neural Networks started getting generally used for image identification [14], [15]. Different plant classifications using Neural Networks were made in [19].

For instance, in [16], the PlantCLEF 2015 database has been used which consists of Western European Plant species; their work was carried out using AlexNet and Inception V3 model. Another relevant study, as in [17], utilized the GIST (Global Image Structure Tensor) descriptor along with various machine learning algorithms for plant leaf classification using a modified feature extraction process and scene recognition. The study, as in [18], highlights the significance of accurate medicinal plant identification for preventing adulteration in herbal drugs.

Table 1. Comparative analysis ofa few state-of-the-art approaches for identifying medicinal plant images.

Reference	Year	Dataset used	Technology used	Accuracy
[20]	2019	AyurLeaf Dataset (Leaf samples of 40 medicinal plants)	AlexNet	96.76%
[21]	2020	Custom Dataset (25,083 images of 80 kinds of TCM)	DenseNet201	97.34%
[22]	2022	Mendeley- Medicinal Leaf Dataset (30 classes)	Mask R-CNN	95.7%
[23]	2022	Custom Dataset (45 medicinal plant classes)	Xception	97.65%
[24]	2024	Custom Dataset (2100 images, 6 classes of medicinal herbs)	MobileNet	98.33%

Table 1 provides the details of some of the state-of-the-art approaches for identifying medicinal plant images. Despite these advancements, existing user-end applications developed through these approaches, like Plantix and iNaturalist often lack comprehensive data on native Indian medicinal plants, making it challenging for users to access accurate information. The applications for identification available for public use are more leaf-based and do not always help with medicinal plants. Although it is possible to try training different models separately with different parts of a medicinal plant and then combine the results for prediction, this approach is not feasible, that is, in the long run, it would not be scalable, cost-friendly, or even resource-friendly. The Government sites and publications such as the Botanical Survey of India website, the Biodiversity Portal of India website, The Ayurvedic Pharmacopoeia, The Siddha Pharmacopoeia, One Herb One Standard, Indian Medicinal

Plants, Phytochemistry and Therapeutics 2.0 (IMPPAT 2.0), do provide identification and information of proper usage, but the ease of use is still low.

3 Methodology

3.1 Dataset

Our Indian medicinal plant dataset consists of 98 balanced classes, and 15,022 images in total. Each class label represents the common name of the medicinal plant as shown in Figure 1. Our dataset has been carefully curated through images collected from the internet and self-clicked photos, few of the dataset images have been represented in Figure 2. While collecting images from the internet, we ensured that the pictures were collected from verified sources and government-published medicinal plant databases and, had a non-commercial purpose license or were labeled cc0, which is a Creative Commons Zero license issued by Creative Commons (an International Non-Profit organization for knowledge and culture sharing) as a public dedication tool which enables re-users to use the images with this license with no conditions.

Each class has leaves, flowers, shoots, fruits, seeds, or whole plant images. While developing the dataset, we included plants that have been declared to have medicinal properties as per the Ayurvedic Pharmacopoeia of India and the website of the Ministry of AYUSH. These plants range from grasses, weeds, herbs, shrubs to trees and include plants that have been declared toxic but medicinal. The images we collected were stored in the format of jpg or png.

In our CSV (Comma Separated Value) file, we collected the common names, scientific names, and therapeutic uses of all 98 medicinal plants. The data for the file was collected from government sites and Volume I and II of The Ayurvedic Pharmacopoeia of India.

```
Labels of the training class : ['Adenium', 'Alfaalfa', 'Aloevera', 'Aloevera flower', 'Amar
yllis lily', 'Angeloweed', 'Asoca', 'Avocado', 'Balloon flower-Platycodon', 'Banana', 'Beac
h spider lily', 'Bengal bamboo', 'Betel leaf', 'Bittergourd-Ucche', 'Black pepper', 'Blackb
erry lily', 'Bougainvilliea', 'Brahmi', 'Butterfly Pea-Aparajita', 'Calendula', 'Calla lil
y', 'Camellia sinensis', 'Canna indica', 'Cardomom', 'Castor', 'Chirata', 'Chrysanthemum',
'Cindrella weed', 'Cockleburs', 'Cockscomb', 'Coriander', 'Cosmos', 'Creeping buttercup',
'Crown flower', 'Crown of thorns', 'Curry leaf', 'Cuscuta-swarnalata', 'Dahlia', 'Dandelio
n', 'Dimorphotheca- African daisy', 'Foxglove', 'Frangipani', 'Gaillardia', 'Gazania rigen
s', 'Gladiolus', 'Grass', 'Gulancha', 'Gulmohar-Krishnachura', 'Hibiscus rosa-sinensis', 'H
oary stock', 'Honeyweed', 'Hybrid petunia', 'Indian Gooseberry-Amla', 'Indian bael', 'India
n beech', 'Indian borage', 'Indian pennywort', 'Insulin', 'Jamun', 'Jungle geranium-Ixora',
'Kalanchoe', 'Kanakambar', 'Kash phool-Wild sugarcane', 'Lady tulip', 'Lemon grass', 'Lemon
-Citrus limon', 'Lotus', 'Magnolia champaca', 'Mango', 'Marigold', 'Matricaria chamomile',
'Mint', 'Mogra', 'Morning glory', 'Mustard flower', 'Nasturtium', 'Neem', 'Noni-Indian mulb
erry', 'Oleander', 'Painter_s pallette', 'Palash', 'Pansy-Viola tricolor', 'Papaya', 'Parth
enium hysterophorus weed', 'Peepal', 'Periwinkle', 'Phyllanthus urinaria weed', 'Rain lil
y', 'Red Indian poppy', 'Rose', 'Shami', 'Shiuli', 'Shojne-Moringa', 'Sunflower', 'Sweet wi
liams', 'Tuberose', 'Tulsi', 'Vanda Orchid']
Number of classes in train_df: 98
Number of images in train_df: 10484
Number of images in test_df: 2240
Number of images in val_df: 2298
```

Figure 1. 98 classes of the dataset.

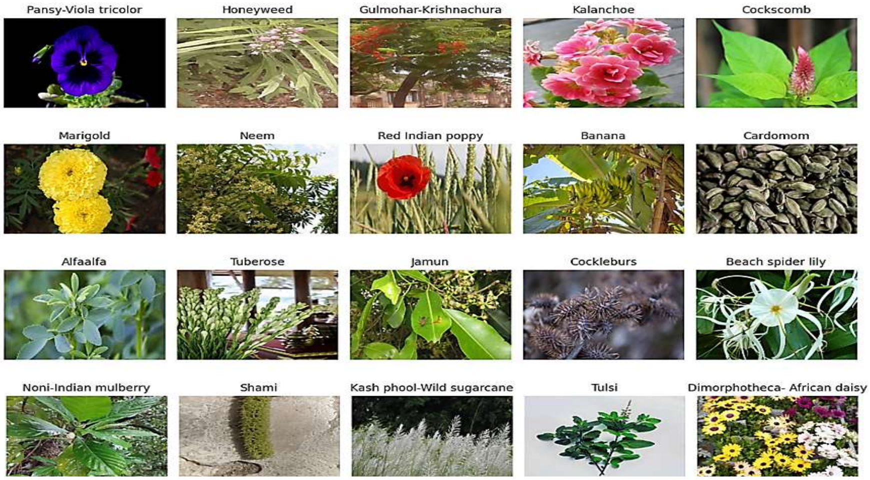

Figure 2. Visualization of our Indian Medicinal Plant dataset.

3.2 Data Preparation, Data Augmentation and Preprocessing

We have used the Kaggle Platform, Keras of TensorFlow, OpenCV, Scikit, and Seaborn libraries to perform the identification of Indian medicinal plants.After our dataset was ready, we uploaded the ZIP archived folder of the dataset and the CSV file into the Kaggle notebook, which offers 214.75 GB of free storage for private datasets, as of July 2024. We used GPU T4 x2 accelerator, a resource of Kaggle that is available for 30 hours and renews per week.

Data Preparation and Augmentation. We preprocessed data by checking for corrupted images, then the dataset was loaded and labeled, and the dataset directory was split into a 70:15:15 ratio. The CSV file was loaded as a separate directory. After splitting, the training, validation, and test directories were converted into DataFrames for easier generation of performance metrics.The dataset was augmented by applying random transformations like rotations, horizontal flips, brightness, shear range, and zoom, and the photos were rescaled to 1/255.This helps the model generalize better and avoid overfitting the specific training data.

3.3 Model Training

Xception Model. We implemented an Xception base model architecture using transfer learning that includes a Global Average Pooling 2D layer, followed by a 20% dropout rate and a dense output layer with softmax activation to classify the images into their respective categories. During the model compilation, we used the Adaptive Moment Estimation (Adam) optimizer and CategoricalCrossentropy loss function. We also used early stopping and learning rate scheduler (minimum learning rate = 0.000001) to regularize the model's performance (see Fig. 3).

Pre-trained Model (Xception architecture). Xception is a convolutional neural network (CNN) architecture pre-trained on the ImageNet dataset for image classification tasks. It extracts features from the input images through convolutional layers and learns patterns useful for image recognition.

Feature Extraction. Xception performs feature extraction through convolutional layers with various filters. These filters learn to detect edges, shapes, and other low-level features in the early layers, progressing to more complex features in higher layers. Xception does not explicitly perform morphological, textural, or color feature extraction but learns these features through its convolutional layers.

Transfer Learning. By leveraging a pre-trained Xception model, the code benefits from the model's learned features for generic image recognition. This reduces training time and improves performance compared to training a model from scratch, especially for smaller datasets.

Hyperparameter Tuning. Hyperparameter tuning experiments are conducted to optimize a model's performance.

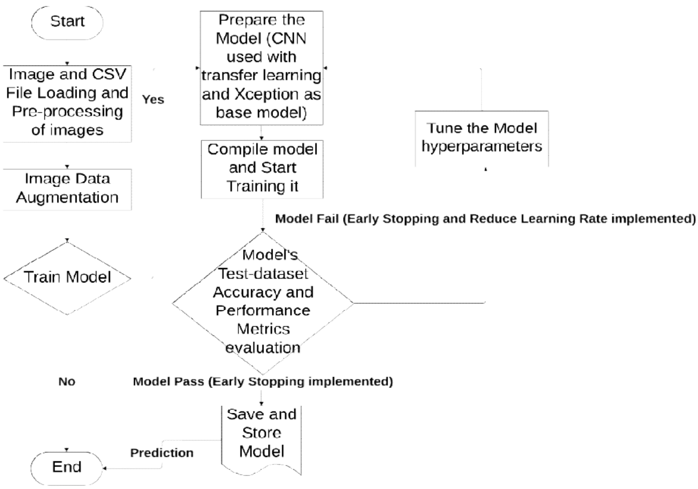

Figure 3. Flowchart of Indian Medicinal Plant identification system.

CategoricalCrossentropy (loss). This loss function is typically used for multi-class classification problems. It measures the difference between each data point's predicted probability distribution and the true target distribution. Displayed equations are centered and set on a separate line.

$$L = -\frac{1}{N}\Sigma_{i=1}^{N} = \Sigma_{j=1}^{C} = y_{ij}\, log(p_{ij}) \tag{1}$$

Where L stands for Loss, N is the number of samples in the batch, i is the index of a particular sample in the batch, j is the index of a specific class in a classification problem, y is the true label indicator, yij represents the true label for ith sample and the jth class. In one-hot encoding, yij is 1 if the ith sample belongs to class j and 0 otherwise, p is the predicted possibility, and pij represents the predicted probability that the ith sample belongs to class j.

4 Results and Discussion

4.1 Model Selection

We used the Xception model as our base model architecture and using transfer learning was an efficient and effective way that allowed us to work on different dataset sizes, that is, transfer learning enables us to fine-tune the custom classification layer as per future requirements. Going through various Kaggle notebooks published by authors in this research area, we started by using 128 dense units and a 50% dropout rate, with a batch size of 32 and a learning rate of 0.000001.

First, we tested our model with 55 classes which mostly had flowering shrubs, we achieved 98% testing accuracy. Then we increased the dataset size to 79 classes by further including herbs and weeds, the testing accuracy was 94%. Then we increased the number of classes to 98, at this point we covered the most common medicinal plants from each family of plants- weeds, grasses, herbs, shrubs, and trees. The dataset portrayed a real-world situation. However, the testing accuracy dropped to 74%. Since the dataset size was satisfactory, to begin with, we then worked on finetuning the hyperparameters of our base model- the batch size, number of dense units, and dropout rate. We tried various other regularization techniques like early stopping, as summarized in Figure 4. We also updated our CSV file with the details of 98 classes. We then achieved 91% testing accuracy after trying Global Average Pooling 2D and a dropout of 20% layers on base model architecture, and on increasing the number of epochs, the testing accuracy improved to 92%. This shows that the model has chances of improvement.

Model	Batch Size	Denseunits	Dropout	Batch Normalization	Regularization	Training Accuracy	Validation Accuracy	Early Stopping	LR/LRS
Xception	32	128	0.5	No	No	70	75	Yes	0.000001
Xception	32	128	0.5	No	No	70	75	Yes	0.00001
Xception	32	128	No	No	No	87	85	Yes	0.0001
Xception	32	256	0.6,0.5	No	No	83	80	Yes	0.0001
Xception	64	256,128	0.5	No	No	98	87	Yes	0.0001-1e-6
Xception	64	128	0.5	No	No	98	90	Yes	0.00005-1e-6
Xception	32	128	0.5	No	No	83	80	3	0.00001-1e-6
Xception	32	256,128	0.3,0.3	Yes	L2	Nan	NaN	3	0.00001-1e-6
Xception	32	256,128	0.3	Yes	No	87	85	3	0.00001-1e-6
Xception	32	256,128	0.3,0.3	Yes	No	98	88	3	0.00001-1e-6

Figure 4. Hyperparameter Tuning details on different trials.

4.2 Performance Metrics

We generated a loss and accuracy graph (see Fig. 5, Fig. 7, Fig. 9), F1 Score (see Fig. 6, Fig. 8),a learning rate scheduler (see Fig. 10), classification report (see Fig. 11), and confusion matrix (see Fig. 12), as a form of performance metrics and visualization of prediction(see Fig. 13) to analyze and understand the behavior and effectiveness of our model. Our prediction included the top three predicted medicinal plants with similarity percentages and retrieval of respective plant details from the CSV file. A few of the prediction results have been displayed in the figures: Figure 14 and Figure 15 show the identification function results and, Figure 16 shows the retrieval function result, in the Kaggle platform.

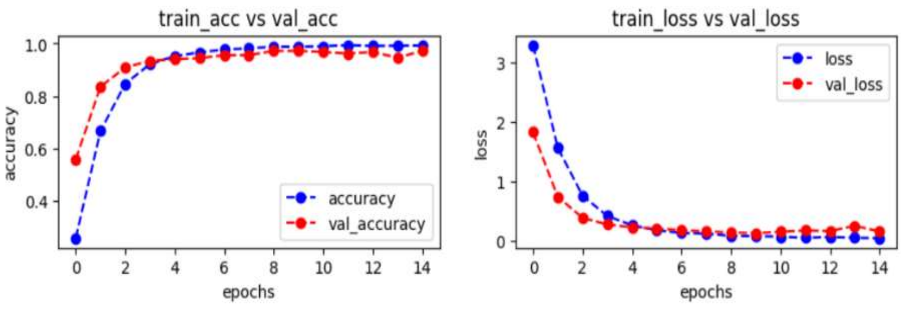

Figure 5. Accuracy and loss graphs of 55 classes having 98% testing accuracy.

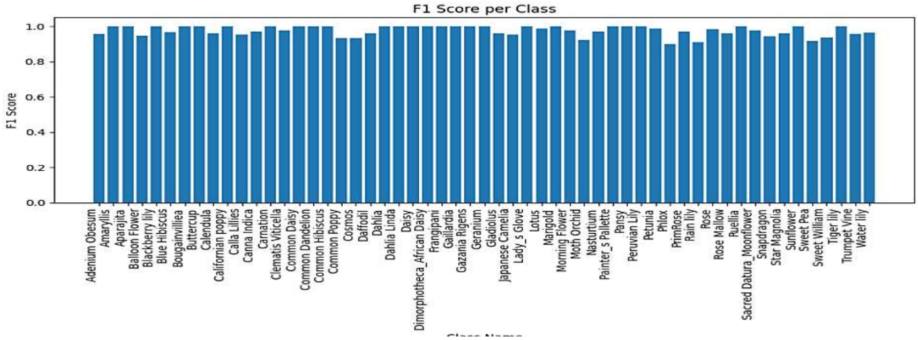

Figure 6. F1 score of 55 classes having 98% testing accuracy.

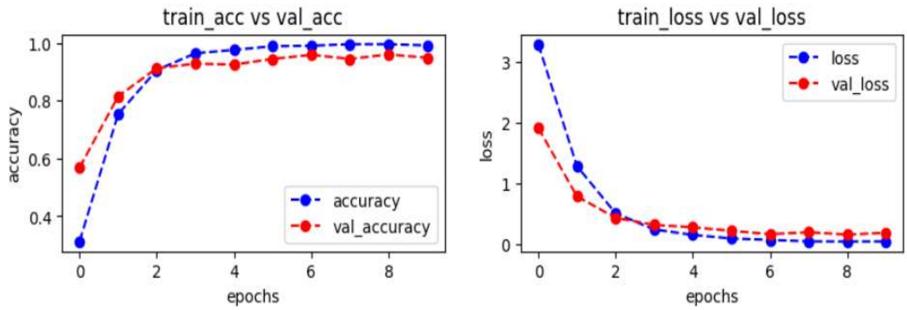

Figure 7. Accuracy and loss graphs of 79 classes having 94% testing accuracy.

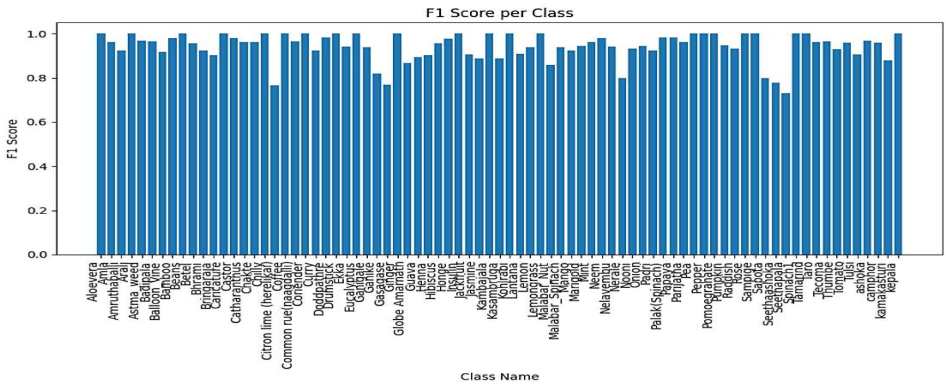

Figure 8. F1 score of 79 classes having 94% testing accuracy.

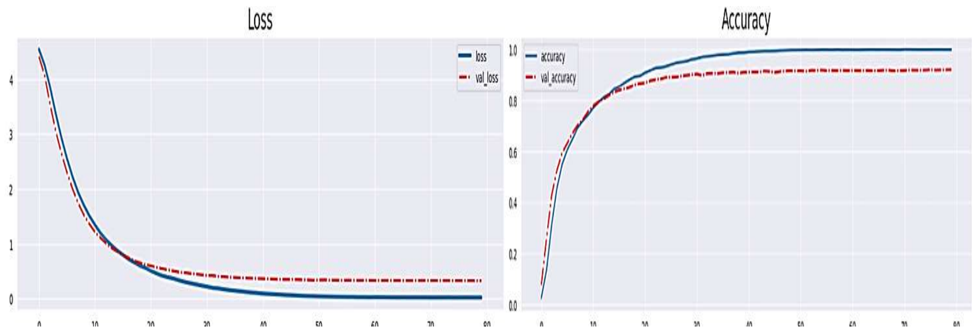

Figure 9. Accuracy and loss graphs of model 98 classes having 92% testing accuracy.

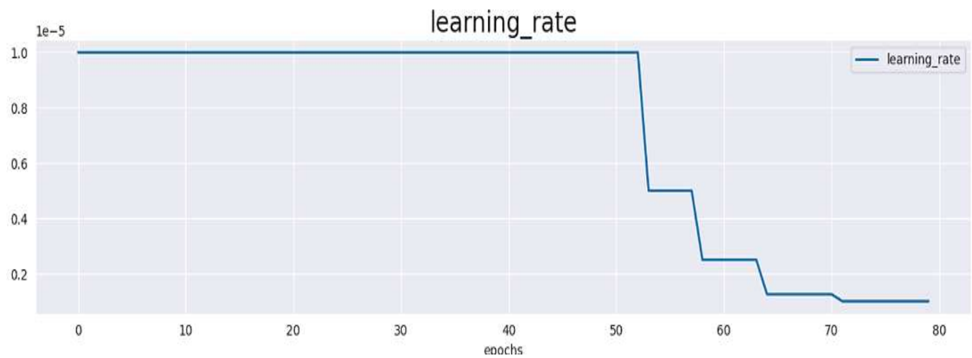

Figure 10. Reduce Learning Rate on Plateau Scheduler.

	precision	recall	f1-score	support
Adenium	0.90	0.83	0.86	23
Alfaalfa	1.00	0.70	0.82	23
Aloevera	0.88	0.88	0.88	25
Aloevera flower	1.00	1.00	1.00	23
Amaryllis lily	1.00	0.96	0.98	23
Angeloweed	0.96	0.92	0.94	25
Asoca	0.95	0.83	0.88	23
Avocado	0.81	0.92	0.86	24
Balloon flower-Platycodon	0.92	1.00	0.96	23
Banana	0.96	0.96	0.96	23
Rose	1.00	1.00	1.00	24
Shami	0.59	0.67	0.63	24
Shiuli	1.00	0.96	0.98	23
Shojne-Moringa	0.87	0.83	0.85	24
Sunflower	1.00	1.00	1.00	23
Sweet wiliams	0.96	0.96	0.96	24
Tuberose	1.00	1.00	1.00	23
Tulsi	0.92	0.96	0.94	23
Vanda Orchid	0.92	1.00	0.96	23
accuracy			0.92	2297
macro avg	0.92	0.92	0.92	2297
weighted avg	0.92	0.92	0.92	2297

Figure 11. A portion of the Classification report of 98 classes-trained model.

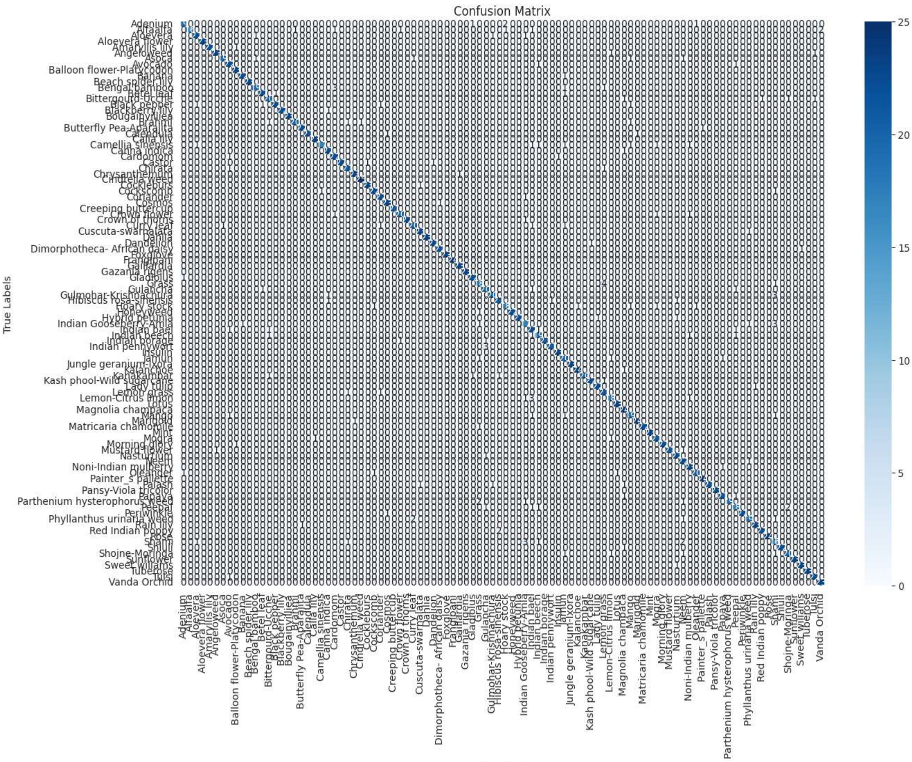

Figure 12. Confusion Matrix of 98 classes.

Figure 13. Visualization of Prediction.

```
Select mode ('medicinal' or 'retrieve' therapeutic details):  medicinal
Enter the image path:  /kaggle/input/test-indmedplants/testing plants/2024-05-14.png
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step
Input image:
```

```
Top 3 similar classes:
    Medicinal Plant Class  Similarity Percentage
59  Jungle geranium-Ixora              99.798858
29              Cockscomb               0.015771
35             Curry leaf               0.012034
Jungle geranium-Ixora (99.80%)
ClassName:  Jungle geranium-Ixora
BotanicalName:  Ixora coccinea
CommonName:  Jungle flame, pendkuli
TherapeuticUses:  It is rich in antioxidants and anti-inflammatory compounds. These properties make
it useful in treating conditions such as arthritis, asthma, eczema, psoriasis, dermatitis, diabete
s, heart disease, cancer, Alzheimer's disease and other chronic illnesses
```

Figure 14. Prediction (Jungle Geranium-Ixora).

```
Select mode ('medicinal' or 'retrieve' therapeutic details):  medicinal
Enter the image path:  /kaggle/input/test-indmedplants/testing plants/2024-05-07.png
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step
Input image:
```

```
Top 3 similar classes:
   Medicinal Plant Class  Similarity Percentage
97          Vanda Orchid              99.851471
85             Periwinkle              0.041231
33          Crown flower              0.018244
Vanda Orchid (99.85%)
ClassName:  Vanda Orchid
BotanicalName:  Vanda coerulea, Vanda ascocenda
CommonName:  Orchid
TherapeuticUses:  The flower's juice is used as eye drops against glaucoma, cataract and blindnes
s. Active ingredients of Vanda coerulea fight against the visible signs of ageing skin, rheumatism,
fever, anti-inflammatory and anti-oxidant.
```

Figure 15. Prediction (Vanda Orchid).

```
Select mode ('medicinal' or 'retrieve' therapeutic details):  retrieve
Enter the plant name (ClassName, BotanicalName, or CommonName):  Brahmi
Input query: Brahmi
Matched rows:
ClassName: Brahmi
BotanicalName: Bacopa monnieri
CommonName: Saraswati
TherapeuticUses: It is used for the treatment of epilepsy, asthma, ulce
rs, and tumors. It is described as a "Medhya Rasayan" drug (as indicate
d by "Ayurveda", the Indian traditional system of medicines, "Medhyaras
ayanas" possess natural therapeutic properties that support memory, re-
establish intellectual deficiencies and enhance mental capacity) which
is utilized to enhance memory. It plays a vital role in Ayurveda for th
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Figure 16. Prediction (Retrieval of Flora details- Brahmi).

5 Conclusion and Future Scope

Our work on Indian medicinal plant identification presented in this paper is a foundational step toward developing a comprehensive end-to-end system so that a broader user base can access it. When combined with detailed and verified therapeutic information, this system aims to empower individuals by promoting self-sufficiency, safe home remedies using traditional medicinal practices, community-led conservation, and citizen science.

To ensure relevance, comprehensiveness, and functionality in a user-friendly application, developing a system that allows for scalability is crucial. Continuous updates to the medicinal plant dataset and CSV file will enhance the identification system's functionality and broaden its user base.

Incorporating Integrative technologies will improve system accuracy, such as using ensemble learning to combine Xception with other deep learning models or employing advanced architectures like Vision Transformers (ViT) alongside Self-Supervised Learning (SSL). Utilizing ViT with SSL will facilitate the continuous expansion of datasets and ensure their diversity, enabling the inclusion of unidentified plants or those with difficult-to-obtain labels.

Furthermore, this application can document and provide information on threatened, endangered, or vulnerable medicinal plant species, such as Vanda coerulea (Orchid species), Aegle marmelos (Indian Bael), Saraca asoca (Ashok Tree), and Bacopa monnieri (Brahmi), thereby supporting and promoting conservation initiatives and habitat restoration projects, contributing to the preservation and responsible use of India's rich medicinal plant heritage.

References

[1] Pulok K. Mukherjee, Atul Wahile, “Integrated approaches towards drug development from Ayurveda and other Indian system of medicines”, Journal of Ethnopharmacology, vol. 103, Issue 1, pp. 25-35, ISSN 0378-8741, 2006.

[2] Adhikari, Partha Pradip, and Satya Bhusan Paul. "HISTORY OF INDIAN TRADITIONAL MEDICINE: A MEDICAL INHERITANCE", Asian Journal of Pharmaceutical and Clinical Research, vol. 11, no. 1, pp. 421 – 426, 2018.

[3] Vaidya AD, Devasagayam TP, “Current status of herbal drugs in India: an overview.”, J Clin Biochem Nutr, vol. 41, pp. 1-11, 2007.

[4] IMARC Group. (2024). India Ayurvedic Products Market: Industry Trends, Share, Size, Growth, Opportunity, and Forecast 2024-2029, (https://www.imarcgroup.com/india-ayurvedic-products-market).

[5] ICAR website, https://dmapr.icar.gov.in/publication/anual_report.html
[6] Md Sanaul Moin, Javed Inam Siddiqui, Mohammed Abdul Rasheed Naikodi, Shayni Khan, Md Aftab Alam and Faiza Khatoon, “Development of Standard Operating Procedures (SOPs) of a Polyherbal Formulation Qurṣ-i Muṣaffī Recommended for the Treatment of Skin Diseases”, vol. 15, issue 1, pp. 74-82 December 28, 2022.
[7] Abinash Choudhury, Preet Amol Singh, Neha Bajwa, Subhransu Dash, Preeti Bisht, “Pharmacovigilance of herbal medicines: Concerns and future prospects”, Journal of Ethnopharmacology, vol. 309, 2023.
[8] Saravanan, Raju & Das, Manish, “Medicinal plants industry in India: Challenges, opportunities and sustainability”, Medicinal Plants - International Journal of Phytomedicines and Related Industries, vol. 16, pp. 1-14, 2024.
[9] J.M. Guerrero, G. Pajares, M. Montalvo, J. Romeo, M. Guijarro, “Support Vector Machines for crop/weeds identification in maize fields”, Expert Systems with Applications, vol. 39, Issue 12, pp. 11149-11155, 2012.
[10] Faisal Ahmed, Hawlader Abdullah Al-Mamun, A.S.M. Hossain Bari, Emam Hossain, Paul Kwan, “Classification of crops and weeds from digital images: A support vector machine approach”, Crop Protection, vol. 40, pp. 98-104, 2012.
[11] Ariyapadath, Sujith, “Plant Leaf Classification and Comparative Analysis of Combined Feature Set Using Machine Learning Techniques”, Traitement du Signal, vol. 38, pp. 1587-1598, 2021.
[12] S Boateng, Ernest Yeboah, Joseph Otoo, and Daniel A. Abaye. "Basic tenets of classification algorithms K-nearest-neighbor, support vector machine, random forest and neural network: A review." Journal of Data Analysis and Information Processing, vol. 8, pp. 341-357, 2020.
[13] Azlah Muhammad Azfar Firdaus, Lee Suan Chua, Fakhrul Razan Rahmad, Farah Izana Abdullah, and Sharifah Rafidah Wan Alwi, "Review on Techniques for Plant Leaf Classification and Recognition", vol. 8, 2019.
[14] Mostafa Mehdipour Ghazi, Berrin Yanikoglu, Erchan Aptoula, “Plant identification using deep neural networks via optimization of transfer learning parameters”, Neurocomputing, vol. 235, pp. 228-235, 2017.
[15] Ali Beikmohammadi, Karim Faez, Ali Motallebi, “SWP-LeafNET: A novel multistage approach for plant leaf identification based on deep CNN, Expert Systems with Applications”, vol. 202, 2022.
[16] Gyires-Tóth, Bálint Pál, et al. "Deep learning for plant classification and content-based image retrieval." Cybern. Inf. Technol 19.1 (2019), pp. 88-100.
[17] Mostajer Kheirkhah, Fateme, and Habibollah Asghari. "Plant leaf classification using GIST texture features." IET Computer Vision 13.4 (2019), pp. 369-375.
[18] Review, Transylvanian & Shaheen, Shabnum & Jaffer, Dr & Ilyas, Sobia & Hanif, Uzma & Khan, Farah & Saddiqe, Zeb & Iftikhar, Tehreema & Sarwar, Samina & Khalid, Sana & Ishtiaq, Saiqa. (2017). Shaheen et al. “Study of Systematic Application of Morpho-Palynological Characterization of Medicinal Plants”.
[19] Lee, C.P.; Lim, K.M.; Song, Y.X.; Alqahtani, A. Plant-CNN-ViT: Plant Classification with Ensemble of Convolutional Neural Networks and Vision Transformer. Plants 2023, 12, 2642.
[20] M R, Dileep & Pournami, P.. (2019). AyurLeaf: A Deep Learning Approach for Classification of Medicinal Plants. 10.1109/TENCON.2019.8929394.
[21] C. Xing, Y. Huo, X. Huang, C. Lu, Y. Liang and A. Wang, "Research on Image Recognition Technology of Traditional Chinese Medicine Based on Deep Transfer Learning," 2020 International Conference on Artificial Intelligence and Electromechanical Automation (AIEA), Tianjin, China, 2020, pp. 140-146, doi: 10.1109/AIEA51086.2020.00037.
[22] Almazaydeh, L.; Alsalameen, R.; Elleithy, K. Herbal leaf recognition using mask-region convolutional neural network (maskR-CNN). J. Theor. Appl. Inf. Technol. 2022,100, 3664–3671.
[23] Bhelkar, Nilesh & Sharma, Avinash. (2022). Identification and classification of medicinal plants using leaf with deep convolutional neural networks. International journal of health sciences. 11596-11605. 10.53730/ijhs.v6nS6.13233.
[24] Kavitha, S., Kumar, T.S., Naresh, E. *et al.* Medicinal Plant Identification in Real-Time Using Deep Learning Model. *SN COMPUT. SCI.* 5, 73 (2024). https://doi.org/10.1007/s42979-023-02398-5.