

Identifying Medicinal Plants Leaves using Densenet 121 Techniques

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Abstract: This study presents the recently assembled dataset "MediLeaves," which is a diverse collection of leaf images of ten distinct medicinal plants from various parts of, Bangladesh. The 10 diverse clusters are Azadirachta indica, Centella asiatica, Hibiscus rosa-sinensis, Justicia adhatoda, Kalanchoe pinnata, Mikania micrantha, Ocimum tenuiflorum, Phyllanthus emblica, and Terminalia arjuna, and also Calotropis gigantea. There are 2,029 original leaf photos in the dataset, in addition to 38,606 enhanced photos. Every original picture was diligently taken with the right background and in natural lighting. Experts correctly identified every image, ensuring its seamless incorporation into various machine learning (ML) and deep learning (DL) models. With the help of this extensive dataset, researchers can use a variety of Deep Learning & Machine Learning techniques to significantly advance the pharmaceutical and healthcare industries. It lays the groundwork for important advancements in these fields and is a useful resource for upcoming research. The therapeutic flora is highlighted in this paper, which is crucial for biodiversity conservation and global health enhancement. More precisely, it emphasizes how important it is to classify medicinal plant species accurately in order to preserve and use them appropriately. Plant features are challenging for conventional classification techniques due to their complexity and the dearth of annotated datasets. To solve this issue, the paper proposes a deep learning-based framework for convolutional neural networks (CNNs)-based picture classification of medicinal plants.

Keywords: Deep Learning, Preprocessing, CNN, augmentation, classification, densenet201

1. **Introduction:** As a source of both traditional and modern drugs, medicinal plants are an essential component of healthcare. The WHO estimates that there are between 35,000 and 70,000 plant species. are used medicinally, making up between 14 and 28% of the estimated 250,000 plant species and between 35 and 70% of all plant uses globally. [1,2]. Additionally, about 70% of people worldwide rely on plants to the main reason for their health [3]. Due to their distinct bioactive chemicals that have physiological effects on humans, these plants—whether they are cultivated or wild—have therapeutic utility [4][5]. The majority of locally cultivated medicinal herbs are actually essential to traditional medicine and food preparation, making them socioeconomically significant [6]. Medicinal plants are vital for maintaining their cultural, economic, and livelihood worth for individuals who depend on them in addition to their health advantages. Consequently, to conserve the biodiversity of medicinal plants, international guidelines and initiatives have been developed [7]. The preservation of biodiversity and the upholding of traditional knowledge depend heavily on the accurate identification of medicinal plants. However, because some plant species have similar appearances, manual identification becomes unreliable. The development of automatic classification systems is made possible by advances in computer vision and machine learning. Plant Net and Leaf Snap are the two most broadly used application-based plant identification systems. All of these approaches, meanwhile, still have problems with plant appearance variability, including variations in leaf shape, color, and texture. As a result, deep learning-based systems have been created to increase plant classification accuracy [8–10] as well as texture. In order to improve the accuracy of plant classification, deep learning-based algorithms have been developed [8–10]. Deep learning methods, especially Convolutional Neural Networks, or CNNs, have shown remarkable success in image recognition applications using large datasets and powerful computational models. CNNs automatically build hierarchical representations, which leads to better results for plant species classification than standard machine learning procedures, which rely on manually created features extracted from raw images [11,12].

Since the beginning of time, plants have provided food, clothing, shelter, and medicine to all of humanity. Eighty percent of people in Asia and Africa are thought to rely on herbal medications made from plant extracts, according to WHO figures. Numerous herbal remedies made from the plant's leaf, stem, bark, and root extracts were used to cure a variety of illnesses, including fever, headache, and diarrhea. It is necessary to conserve the medicinal plants and their applications in digital form for upcoming generations. Due to its non-toxicity and lack of adverse effects, herbal medicine derived from plant extracts has been used extensively in ancient India to treat a variety of medical conditions. Nonetheless, a large number of these therapeutic plants can be found in natural forests. Only a specialist can recognize these plants by their characteristics, such as their size, texture, color, and leaf form, and use visual judgment to categorize them as therapeutic plants. Excellent techniques have been developed for the general use case, and efforts are underway to develop Automated Systems [13] for automatic plant species detection without the assistance of experts. Another crucial area in which a progressive study is

conducted is leaf recognition [14] in the detection of plant species. Finding therapeutic plants that are uncommon in untamed forests is the main challenge. Identification of therapeutic plants [15] is a major challenge for scientists studying chemistry, botany, and allied disciplines. It requires a lot of expertise to identify medicinal plants based on the size, shape, color, and texture of their leaves because they are intended to treat a variety of ailments. Accurate and effective leaf image recognition is made possible by computer vision techniques. Applications for plant identification rely on characteristics like bark, leaves, roots, and flowers. There are many different kinds of medicinal plants throughout the world, depending on the soil, water, climate, and native vegetation. As a result, no single system can be used to identify every kind of medicinal plant. One area of study in computer vision is the detection of plant leaves. With the aid of machine learning and technological breakthroughs, the problem of medicinal plant leaf detection may be resolved. We are working on developing a system that can identify whether a leaf image belongs to a medicinal or non-medicinal plant classes. Convolutional neural networks (CNN) [17], artificial neural networks (ANN) [16], and other methods are used in a variety of current medical leaf identification algorithms. There are certain difficult problems with the computer models for leaf recognition that are currently in use. Among these is the precise classification of plant species by the extraction and display of plant characteristics. In order to categorize the species and create algorithms among all the current approaches, experts typically concentrate on leaf structure. The development of deep learning and computer vision frameworks has led to an upsurge in research on plant leaf classification. A subtype of deep neural networks called CNN was created to handle problems pertaining to visual imagery. The main elements of the existing architecture are preprocessing, feature extraction, selection, and classification. The many properties of photos may now be understood thanks to the remarkable success of CNN architectures in recent years.

2. Data Description

The 10 species of medicinal plants that are part of the "MediLeaves" dataset are listed below, along with a brief explanation of their therapeutic advantages:

Phyllanthus emblica: Also referred to as "Amalaki" in India, *Phyllanthus emblica* has been used extensively in Ayurveda for its therapeutic qualities as well as its use as a tonic. It is incredibly nutrient-dense and a good source of vital elements such as minerals, amino acids, and vitamin C [18]. Each part of the plant, especially the fruits that are rich in fatty acids, vitamins, oil, and amino acids, is used for its medicinal properties.

Terminalia arjuna: Known in Bengali as "Arjun," *Terminalia arjuna*. This plant has been traditionally used for many years in the treatment of a wide range of diseases. It is well known for its diverse medicinal properties, including antibacterial, antifungal, antihypertensive, anticoagulant, anti-inflammatory, and cardioprotective effects. [17].

Justicia adhatoda, also called as "Basak" in India, is a common medicinal plant used in Ayurvedic and Unani medicine. It is used as a main component in many allopathic medications to treat respiratory ailments such as asthma, colds, and coughs [19]. Furthermore, a variety of herbal treatments are prepared using its leaves, flowers, and roots.

Kalanchoe pinnata: In Bengali, *kalanchoe pinnata* is commonly referred to as "Patharkuchi." Around the globe, it is also referred to as a "wonder plant." Its pharmacological features, including antioxidant, antibacterial, antidiabetic, antiviral, antitumor, antiallergic, and depressive, are widely established in addition to its strong wound-healing capabilities [20].

Centella asiatica: Known in India as "Thankuni," *Centella asiatica* is a traditional Ayurvedic herb. It is utilized throughout Asia to cure a range of ailments. Its chemical components offer several therapeutic advantages, including antibacterial, anti-inflammatory, anti-cancer, neuroprotective, antioxidant, and wound-healing qualities. [21]. The herb's aerial parts and roots are also used medicinally.

Mikania micrantha: The medicinal plant *Mikania micrantha* is found in Bangladesh and other tropical Asian countries. Due mainly to its invasive, antimicrobial, and therapeutic qualities, this plant has been used as traditional medicine in many parts of the world. According to reports, the aforementioned plant is primarily used to cure a variety of illnesses, including inflammatory problems, skin infections, and respiratory disorders [22]. The botanical specimen

Azadirachta indica, commonly known as "Neem" in South Asian regions, is well-known for its wide range of medicinal properties. It is a key component of traditional medicine because of its remarkable anti-inflammatory, antiviral, antibacterial, and antifungal properties. Neem has been shown to be effective in treating a variety of

illnesses, such as digestive and skin conditions, as well as in combating periodontal pathogens and bacteria that cause tooth plaque and are the cause of dental caries [23].

Hibiscus rosasinensis: The leaves of this plant, known as "Joba" in India, have been employed in traditional medicine due to its potential anti-carcinogenic properties as well as their analgesic, antipyretic, antiasthmatic, and anti-inflammatory properties. Hibiscus rosa-sinensis leaves and flowers have also been shown in numerous studies to possess antibacterial, antifungal, and antioxidant qualities [24].

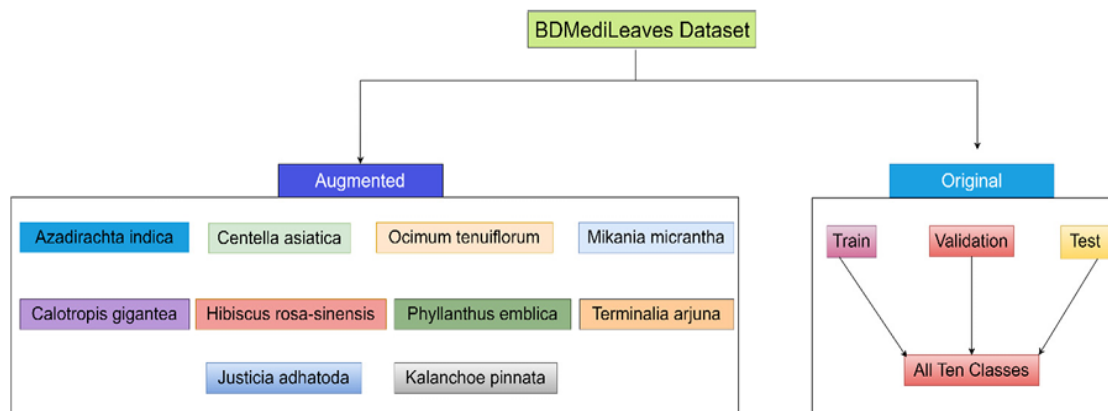


Figure 1 shows the proposed Medi Leaves dataset's directory tree.

Ocimum tenuiflorum: A common medicinal herb in South Asia, *Ocimum tenuiflorum* is also referred to as "tulsi" in India. S. Islam, Md.R. Ahmed, and S. Islam et al. have extensively documented *Ocimum tenuiflorum*'s numerous medicinal qualities, such as antioxidant, antibacterial, antidiabetic, antifungal, hepatoprotective, anti-inflammatory, and antiulcer actions, are attributed to its bioactive components [25].

Calotropis gigantea: familiar as "Akanda" in India, *Calotropis gigantea*, a recurrent herb that has been shown to have significant therapeutic advantages. It has qualities including wound-healing, antibacterial, and antiparasitic actions. *Calotropis gigantea* has a variety of phytochemicals that have been used in many diseases' preventative and control strategies. The plant's medicinal potential and the effects of substances like flavonoids, tannic acid, cardiac glycosides, and terpenoids that are found throughout the leaf are highlighted by the fact that it can be used to cure conditions including leprosy, cancer, ulcers, and elephantiasis. [26].

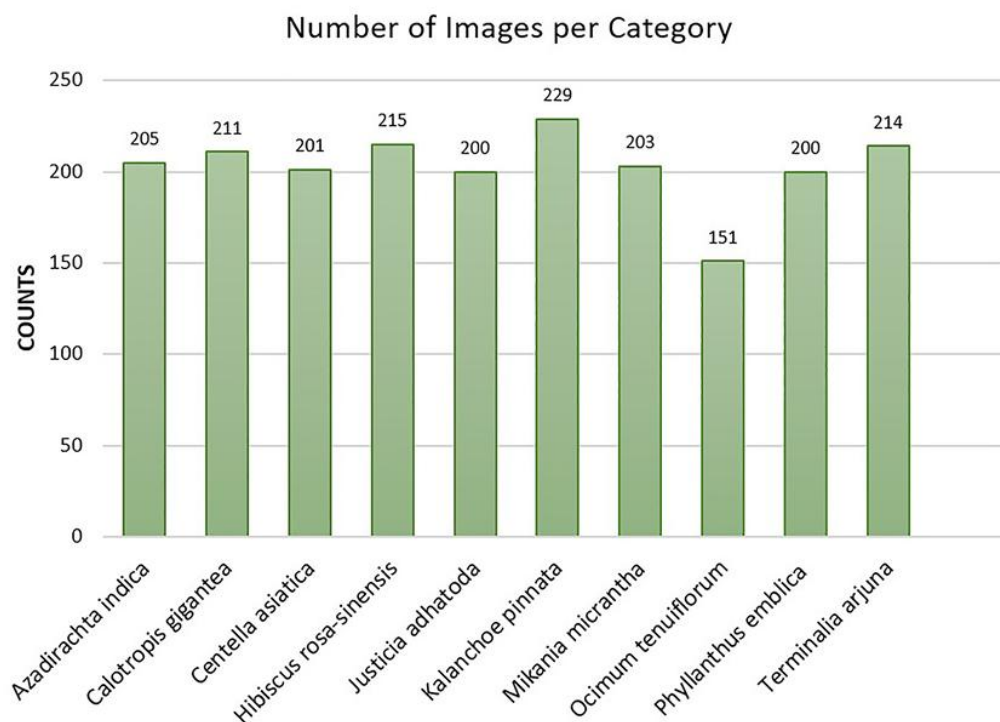


Fig 2: distribution of images by class in the Medi Leaves dataset.

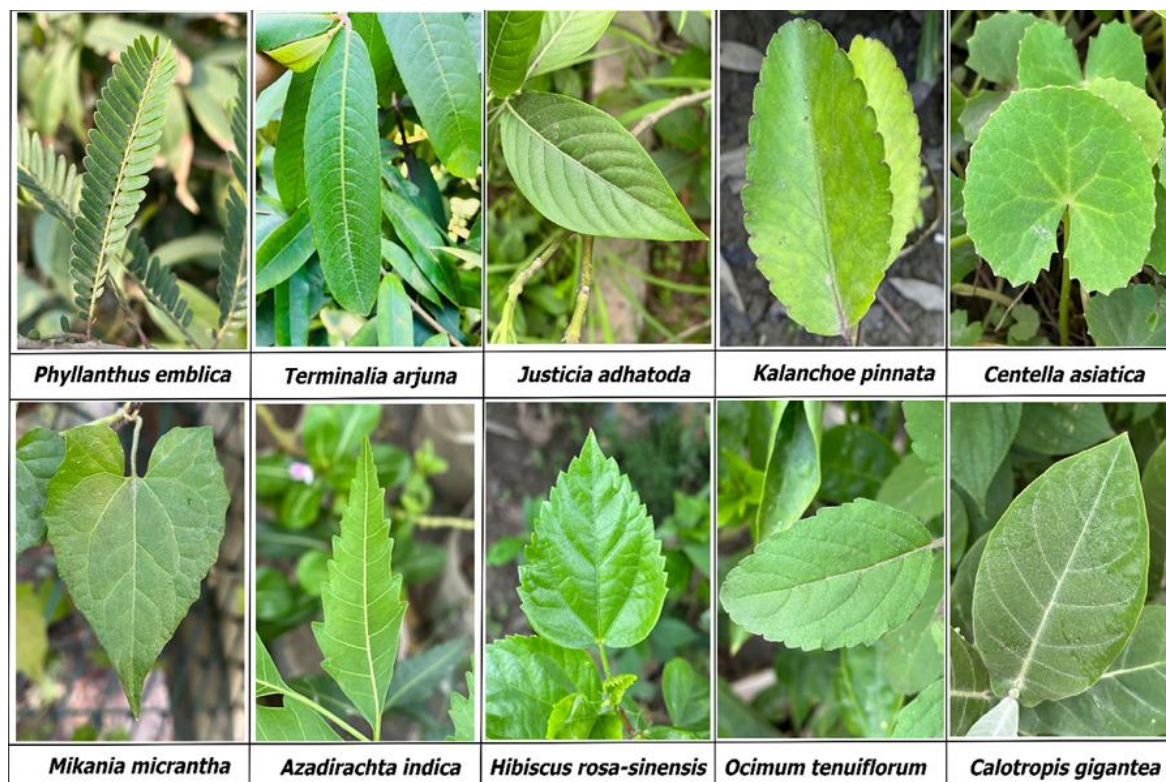


Fig 3: Examples of images from every Medi Leaves dataset class.

Class name	Number of original images				Number of augmented images
	Train	Validation	Test	Total	
<i>Phyllanthus emblica</i>	140	40	20	200	3,863
<i>Terminalia arjuna</i>	150	43	21	214	3,841
<i>Justicia adhatoda</i>	140	40	20	200	3,863
<i>Kalanchoe pinnata</i>	160	46	23	229	3,837
<i>Centella asiatica</i>	141	40	20	201	3,881
<i>Mikania micrantha</i>	142	40	21	203	3,919
<i>Azadirachta indica</i>	144	41	20	205	3,957
<i>Hibiscus rosa-sinensis</i>	151	43	21	215	3,861
<i>Ocimum tenuiflorum</i>	121	30	15	151	3,789
<i>Calotropis gigantea</i>	169	43	21	211	3,795
Total Images				2,029 (original)	38,606 (augmented)

Table 1: The number of images in the suggested Medi Leaves dataset for each class.

3. Literature Review:

Computer vision and machine learning have made significant strides in plant leaf classification and disease detection studies in recent years. Modern deep learning algorithms and conventional image processing are both part of the present research environment, and each adds to the continuous search for increased robustness and accuracy in the task of recognizing plant species and illness detection. An overview of the development of data processing techniques, feature extraction approaches, and classification models developed for plant leaf analysis can be found in the following studies— in other words, the range and versatility of the present methodologies in plant identification.

3.1 Conventional techniques for classifying plant leaves

Features are essential for categorization in the study of plant leaves, where computer vision holds considerable promise for detecting various plants and their diseases. Wu et al. [27] presented a technique that reduced the number of scopes in a probabilistic neural network by applying PCA after extracting twelve morphological characteristics from five fundamental geometrical features. They obtained an average accuracy of 90.3% using their own Flavia dataset. Herdiyeni and Wahyuni [28] achieved a classification accuracy of 74.5% by combining fuzzy local binary pattern, fuzzy color histogram, and a probabilistic neural network (PNN) classifier using a dataset of 2448 pictures (270 x 240 pixels) of medicinal plant leaves from Indonesian forests. Ma et al. [29] reported 90% classification accuracy for leaf pictures from the Image CLEF 2012 dataset using a strategy that combined Top-hat modification, Haar Wavelet Transform, and Pyramid Histograms of Oriented Gradients (PHOG).

The study [30] suggests a technique for the automated, real-time identification of plant species, particularly for Borneo-native medicinal herbs. To address the recognition problem, an enhanced Efficient Net-B1 model was trained and evaluated using both publicly available and privately owned plant species datasets. The suggested approach outperformed the traditional model by more than 10% on test data in both datasets. This study is noteworthy for its innovative use of public feedback and geo-mapping of plants in the Borneo region, both of which were made possible by a smartphone application. Early results from the suggested approach, however, indicated potential as a real-time method for identifying therapeutic plants.

The investigation's goal was to determine whether automated recognition could reliably identify therapeutic plants [31]. This study presents a new database of medicinal plants that includes images of one non-medicinal species and 10 medicinal species. They published a MobileNetV3-based model for the economical, dependable, and efficient classification of medicinal plants. The recommended method improves accuracy on the difficult assignment by utilizing transfer learning. Overall, the results showed that developing a robust and effective classifier for medicinal plants is doable.

A deep CNN framework may be created and its settings modified to increase the gratitude rate in light of the findings [32]. This study emphasizes how important the multi-layer strategy's effects on low-number samples are to getting good results. Furthermore, data augmentation boosts productivity more broadly. Simple changes like resizing, flipping, and rotating can significantly increase accuracy as long as invariance is taken into account and

the model is kept from learning unnecessary information. As a new leaf database containing various medicinal plants from Malaysia was created, the experiment's outcomes improved.

Six different medicinal species are categorized in the study [33] based on a variety of morphological, color, and textural traits. They collected 90 leaf photos of six distinct medicinal plant species on the outskirts of Assam, India. Each attribute was used independently for the categorization task before being combined for increased accuracy. Effective leaf recognition is achieved by using the back propagation neural network (BPNN). Thorough testing on 90 photos of six different kinds of leaves shows that the suggested approach increases accuracy. The results demonstrate that the recommended approach effectively distinguishes between leaves with various color, morphological, and textural traits.

Research [34] in artificial intelligence offers a group learning approach to the DL subject that enables the quick identification of plant classes from leaf pictures. Thirty different types of medicinal plants are included in the collection. A transfer learning method was used to build and pre-train the neural network model. The input picture features were obtained using these models, which were trained using the relevant database and a classifier made up of a SoftMax connected to a Dense Layer. Three and fivefold cross-validation were used to confirm the veracity of the findings. They used a classification technique called Ensemble Deep Learning-Automated Medicinal Leaf Identification (EDL-AMLI), which averaged the results of many models. The EDL-AMLI outperformed the most advanced pre-trained algorithms.

To improve the detection accuracy for herb recognition, the suggested approach [35] draws attention to missing problems in the datasets. The picture segmentation technique is enhanced by the addition of dimension factors to the data sets. Deep knowledge-based identification is the process of verifying a result utilizing an ML classifier and an Exclusive-OR gate operation. The accuracy of recognition needed to identify herbal leaves is increased by the two-stage authentication (TSA) technique. They can develop a robust and effective architecture by fusing machine learning with image segmentation. The accuracy rate is increased when leaves are extracted from photos using the best image segmentation techniques. The results show that the suggested approach outperforms conventional performance indicators like accuracy.

4. Proposed Methodology:

The five processes involved in creating the "MediLeaves" dataset include image capture, preprocessing, partitioning, augmentation, and classification. This section provides a brief explanation of each of these processes.

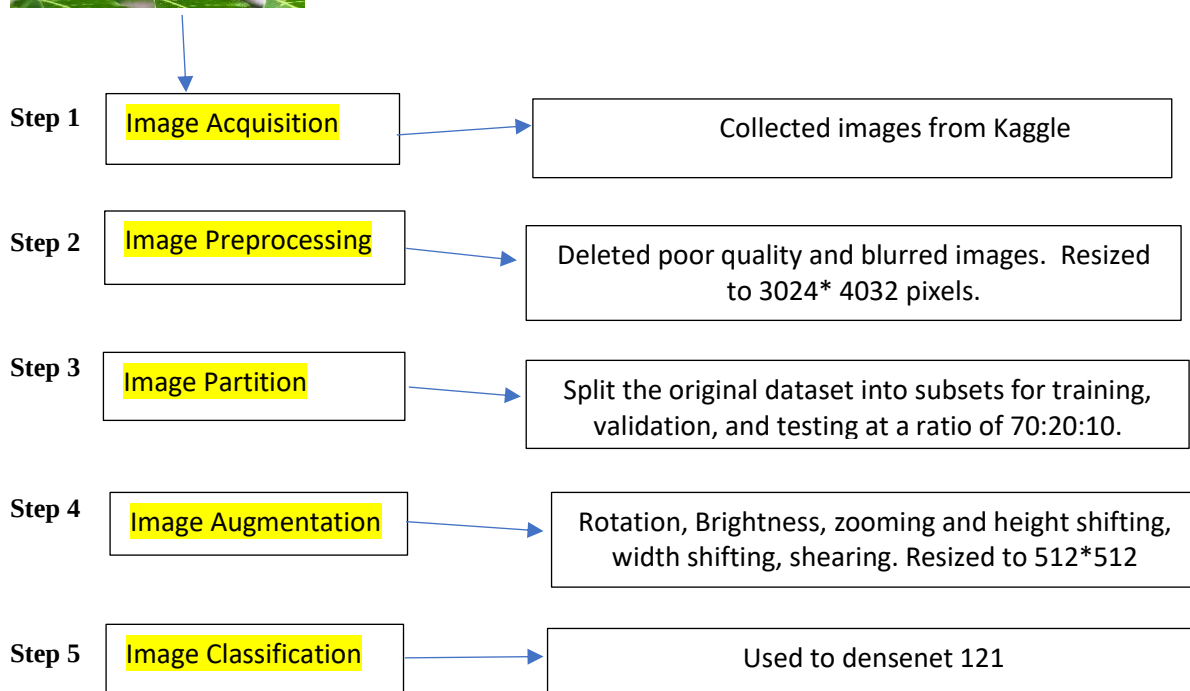


Fig 4: The Medi Leaves dataset's development process.

4.1 Image Acquisition

Ten different classes of medicinal plants make up the dataset. Natural lighting served as the backdrop for all of the photos. We employed diffused lighting to accentuate leaf characteristics and minimize shadows during the image acquisition process. Additionally, we kept the background steady and organic during the photo shoot. We carried out routine inspections throughout the acquisition procedure to guarantee constant image value. This mandatory checking the lighting, focus, and taking pictures from different views to take into consideration changes in the leaves. We performed quality control processes after collecting each photograph. Images with poor clarity, fuzzy areas, low contrast, or excessive brightness were eliminated from the dataset. This particular step was crucial in guaranteeing that only high-quality photos were included for additional analysis. We have maintained the integrity of the dataset and improved the reliability of subsequent analysis by eliminating these poor-quality images. The dataset suggested for this investigation was formed by selecting 2,029 of the 2,310 leaf photos that were originally taken.

4.2 Image Pre-processing

Every original image has dimensions of 3024×4032 pixels, a bit depth of 24, and 96 dots per inch (DPI) for both horizontal and vertical resolution. In reference to the enhanced photos, they were processed using 512×512 pixel resolution. The dimensions of the photos were adjusted using the Image class from the Python Imaging Library, or PIL. In order to represent a picture in the PIL, the picture module offers a class called "Image." Additionally, the module offers several additional features, including the ability to import photos from files and create new images.

4.3 Image Partition

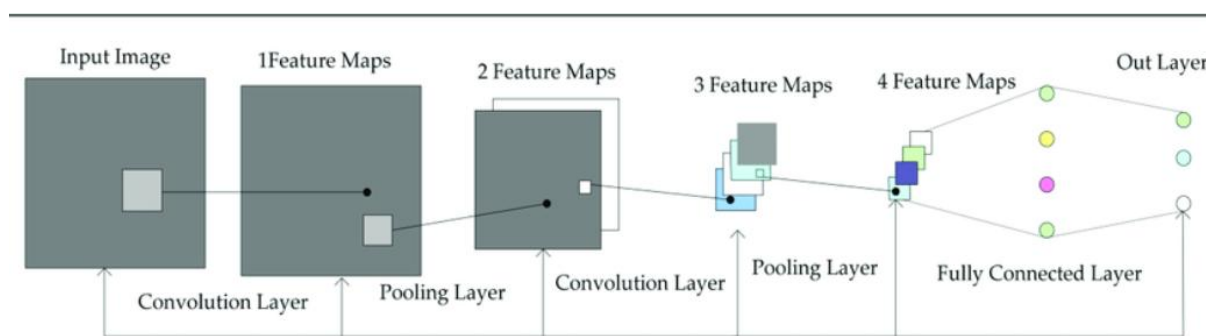
We offer 2,029 original photos of the leaves of ten distinct medicinal plants. The original raw images were randomly split into training, validation, and test subsets at 70:20:10 ratios for each category in order to train and assess the ML and DL-based models.

4.4 Image Augmentation

By adding diversity to images, the augmentation procedure improves the generalizability and effectiveness of ML and DL-based classification models. The Keras Image Data Generator class has been utilized to increase the number of images. The aforementioned class was subjected to a range of image augmentation methods with the fill mode property set to closest, including 60% rotation, 10% magnification, flipping horizontally and vertically, brightness adjustment (between 0.2 and 0.3), 15% shearing, and 10% height and width shifting. Prior to partitioning, all of the gathered photos underwent image enhancement before being arranged into class-specific folders so that researchers could work on them as needed. Every one of the enhanced photos was downsized to 512×512 pixels.

4.5 Image Classification

Except for the first convolutional layer, which receives the input, each convolutional layer in a traditional feed-forward Convolutional Neural Network (CNN) receives the output of the previous convolutional layer and generates an output feature map that is then passed on to the subsequent convolutional layer. Densely Connected Convolutional Network architecture called DenseNet-121 was created to enhance gradient propagation, feature reuse, and information flow in deep CNNs. DenseNet passes along all previous feature maps via concatenation rather than summation, connecting each layer to every other layer within a block, in contrast to standard CNNs where each layer connects only to the next.



With 121 layers, DenseNet-121 is renowned for its well-balanced trade-off between accuracy and computing efficiency. Perfect for jobs that need a reasonable amount of processing power. To train the models, every image was downsized to $224 \times 224 \times 3$. For both designs, all layers—aside from the completely connected layers—were frozen and the pre-trained weights of ImageNet were maintained. After obtaining all of the pre-trained features from both designs, a global average pooling operation and batch normalization were used to generate two fully connected networks (FCNs) with 512 and 256 neurons, respectively.

Experimental Setup:

To address the issue of overfitting in the models, a dropout of 20% nerve cell was inserted between the FCNs and ReLU activation was performed to each of the dense layers. According to the ten-class multiclass classification issue, the number of neurons in the final dense layer was chosen at ten. The softmax activation function was used to implement the last FCN layer.

Layer (type)	Output Shape	Param #
densenet121 (Functional)	(None, 7, 7, 1024)	7,037,504
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1024)	0
batch_normalization_1 (BatchNormalization)	(None, 1024)	4,096
dense_3 (Dense)	(None, 1024)	1,049,600
dropout_2 (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 512)	524,800
dropout_3 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 10)	5,130
Total params: 8,621,130 (32.89 MB)		
Trainable params: 1,581,578 (6.03 MB)		
Non-trainable params: 7,039,552 (26.85 MB)		

Table 2 Pretrained densenet121 architecture summary

- Result analysis:** The last dense layer's neuron count was set at 10 based on the ten-class multiclass classification challenge. The final FCN layer was implemented using the softmax activation function. The Receiver Operating A characteristic curve (ROC) is a visual aid for assessing the effectiveness of binary classification models. At different classification levels, it shows the True Positive Rate (TPR), also known as sensitivity or recall, against the False Positive Rate (FPR). The trade-off between a model's sensitivity and specificity is easy to see using this graph.

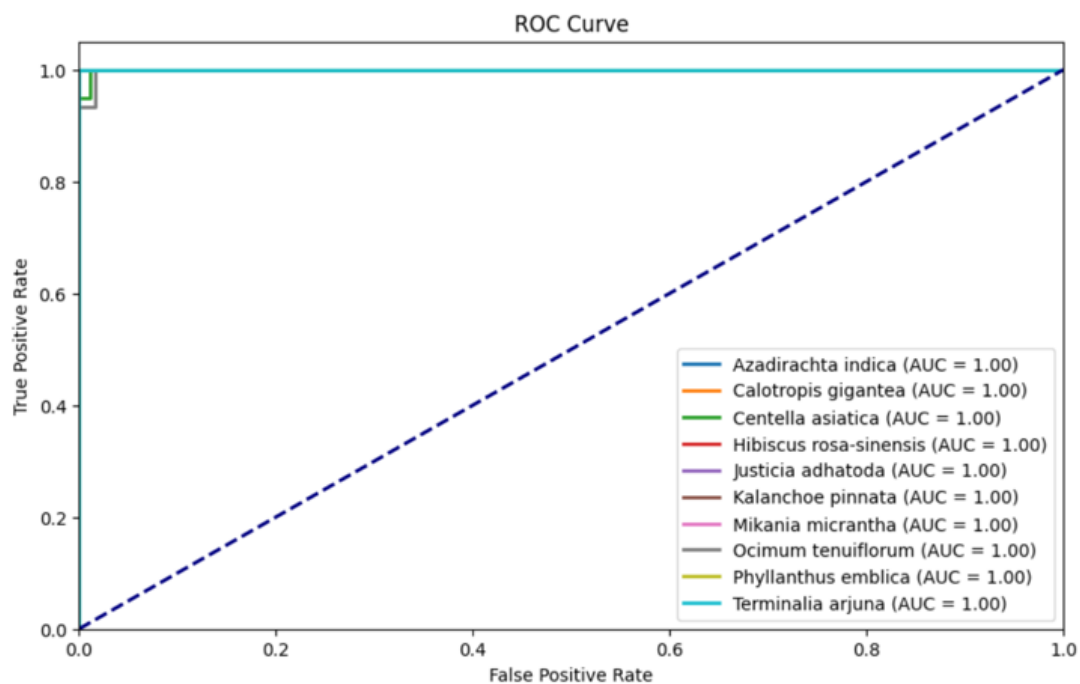


Fig5: ROC Curve

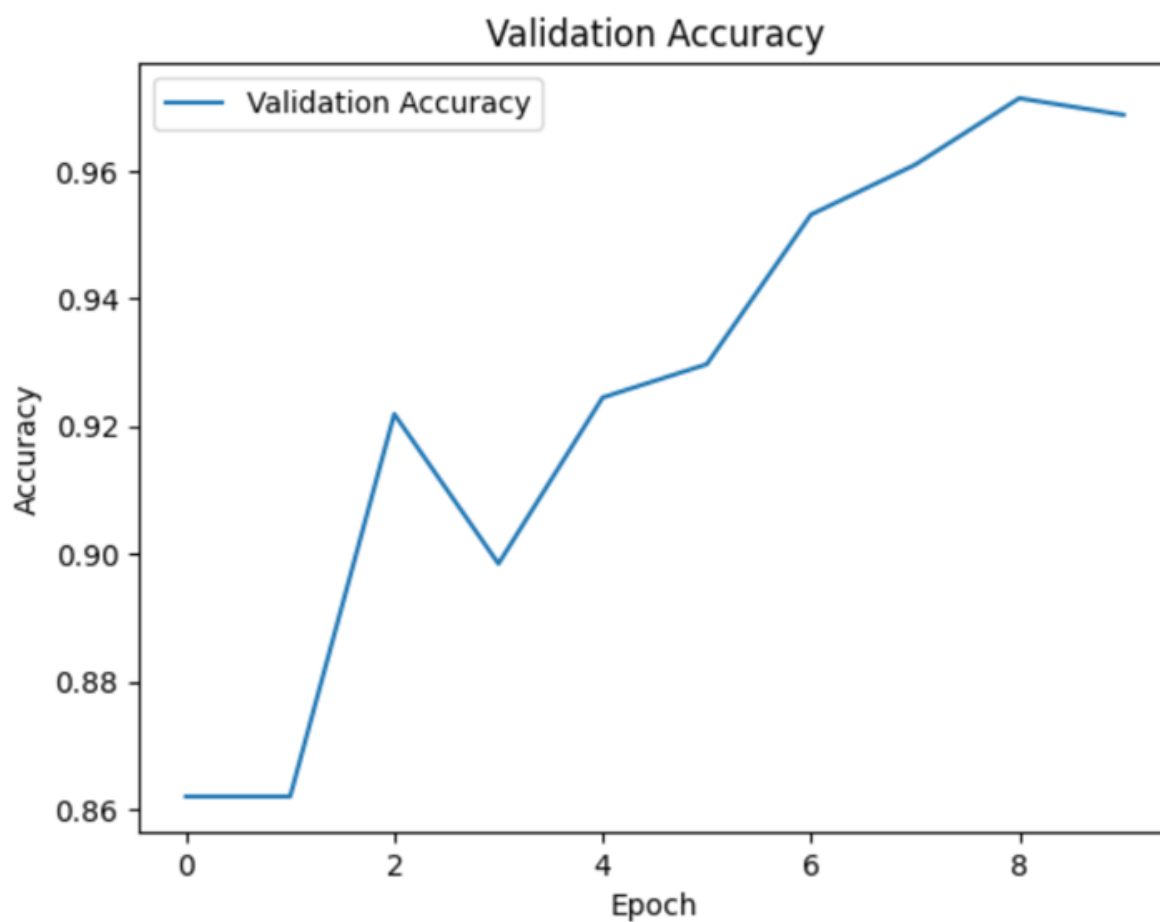


Fig6: Validation accuracy



Fig 7: Validation Loss

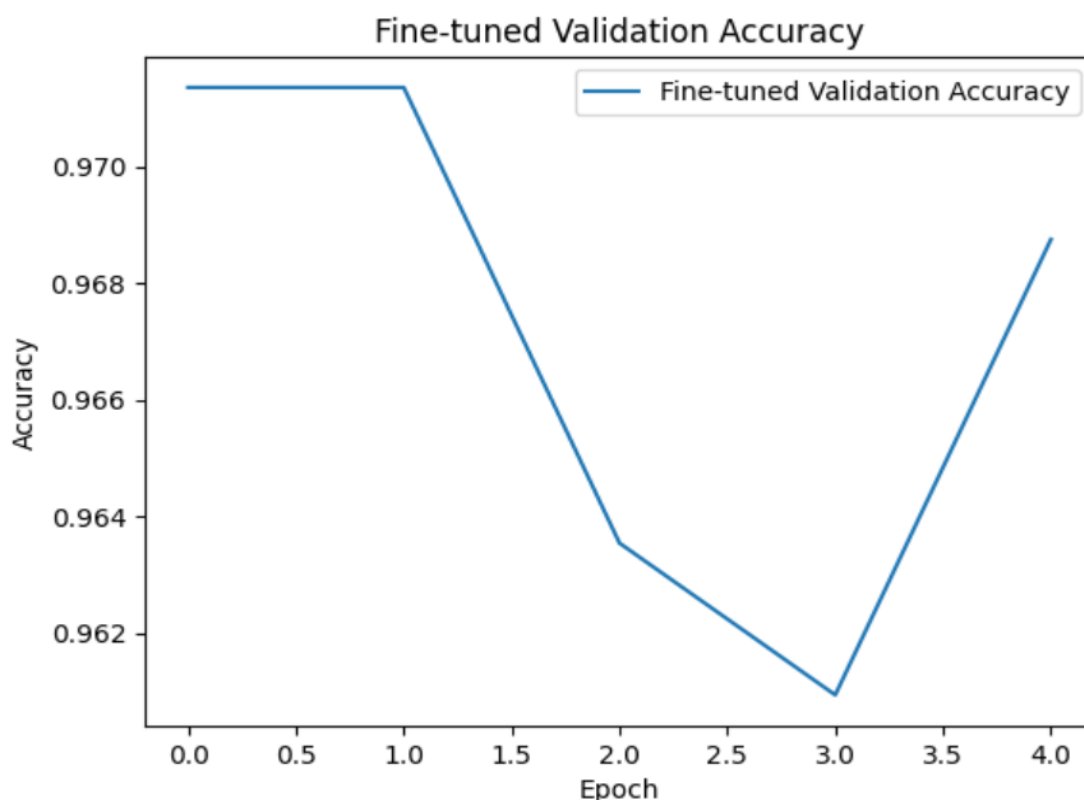


Fig7: Fine-tuned Validation Accuracy

Result:

Model	Train Accuracy %	Validation Accuracy %	Test Accuracy %	Validation Precision %	Validation Recall %	Validation F1-Score
Densenet 121	100.00	97.14	98.51	98.54	98.51	98.51

Conclusion: The experimental findings show that the DenseNet-121 model worked well for the task at hand. High validation accuracy and better outcomes upon fine-tuning demonstrate the model's strong performance. Furthermore, a steady declining trend in the validation loss demonstrated stable learning and little overfitting.

The ROC curve highlights the model's robustness in classification performance and further validates its capacity to differentiate between classes with high reliability. Improved accuracy was a result of fine-tuning the model, highlighting the significance of tailoring pre-trained architectures for particular datasets. Overall, DenseNet-121 appears to be a good and effective model for this issue based on the combination of validation accuracy, validation loss, ROC analysis, and fine-tuned performance.

References:

- [1] M. Dileep, P. Pournami, Ayurleaf: a deep learning approach for classification of medicinal plants, in: TENCON 2019-2019 IEEE Region 10 Conference (TENCON), IEEE, 2019, pp. 321–325.
- [2] S. Das, T.H. Sardar, D. Sahana, An ensemble technique using genetic algorithm and deep learning for the prediction of rice diseases, in: Machine Learning Hybridization and Optimization for Intelligent Applications, CRC Press, 2025, pp. 289–303.
- [3] N. Duong-Trung, L.-D. Quach, M.-H. Nguyen, C.-N. Nguyen, A combination of transfer learning and deep learning for medicinal plant classification, in: Proceedings of the 2019 4th International Conference on Intelligent Information Technology, 2019, pp. 83–90.
- [4] C. Amuthalingeswaran, M. Sivakumar, P. Renuga, S. Alexpandi, J. Elamathi, S.S. Hari, Identification of medicinal plants and their usage by using deep learning, in: 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), IEEE, 2019, pp. 886–890.
- [5] B. Hicham, N. Neşet, B. Khedidja, B.-S. Leila, S. Talia, Abderahmane, The evaluation of hertia cheirifolia L. extract by GC-MS coupled with in silico study as potent inhibitors of human pancreatic lipase, J. Biomol. Struct. Dyn. (2024) 1–12.
- [6] R.U. Rao, M.S. Lahari, K.P. Sri, K.Y. Srujana, D. Yaswanth, Identification of medicinal plants using deep learning, Int. J. Res. Appl. Sci. Eng. Technol. 10 (2022) 306–322.
- [7] J. Abdollahi, Identification of medicinal plants in ardabil using deep learning: identification of medicinal plants using deep learning, in: 2022 27th International Computer Conference, Computer Society of Iran (CSICC), IEEE, 2022, pp. 1–6.
- [8] B. Hicham, A. Djeridane, R. Mahfoudi, Xanthine oxidase inhibitory activity and uric acid dissolution power of some plant extracts: in vitro therapeutical approach for gout treatment, Rev. Bras. Farmacogn. 34 (2024) 1340–1352.
- [9] N.E.H.S.B. Aissa, A. Korichi, A. Lakas, C.A. Kerrache, C.T. Calafate, Assessing robustness to adversarial attacks in attention-based networks: case of eeg-based motor imagery classification, SLAS Technol. (2024) 100142.
- [10] A.K. Mulugeta, D.P. Sharma, A.H. Mesfin, Deep learning for medicinal plant species classification and recognition: a systematic review, Front. Plant Sci. 14 (2024) 1286088.
- [11] M. Deshmukh, Deep learning for the classification and recognition of medicinal plant species, Indian J. Inf. Sci. Technol. 17 (11) (2024) 1070–1077.
- [12] N.E.H.S.B. Aissa, A. Lakas, A. Korichi, C.A. Kerrache, A.N. Belkacem, Robust detection of adversarial attacks for EEG-based motor imagery classification using hierarchical deep learning, in: 15th International Conference on Innovations in Information Technology (IIT), November 2023, IEEE, 2023, pp. 156–161.

- [13] VijayaLakshmi, Balasubramanian, and Vasudev Mohan. "Kernel based PSO and FRVM: An automatic plant leaf type detection using texture, shape, and color features." *Computers and Electronics in Agriculture* 125 (2016): 99-112.
- [14] Su, Jianyu, Meihua Wang, Zhenxin Wu, and Qingliang Chen. "Fast Plant Leaf Recognition Using Improved Multiscale Triangle Representation and KNN for Optimization." *IEEE Access* 8 (2020): 208753-208766.
- [15] Sabarinathan, C., Abhisekh Hota, Ashish Raj, Vivek Kumar Dubey, and V. Ethirajulu. "Medicinal plant leaf recognition and show medicinal uses using convolutional neural network." *Int. J. Glob. Eng* 1, no. 3 (2018): 120-127.
- [16] De Luna, Robert G., Renann G. Baldovino, Ezekiel A. Cotoco, Anton Louise P. De Ocampo, Ira C. Valenzuela, Alvin B. Culaba, and Elmer P. Dadios Gokongwei. "Identification of philippine herbal medicine plant leaf using artificial neural network." In *2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, pp. 1-8. IEEE, 2017.
- [17] Quoc, Trung Nguyen, and Vinh Truong Hoang. "Medicinal Plant identification in the wild by using CNN." In *2020 International Conference on Information and Communication Technology Convergence (ICTC)*, pp. 25-29. IEEE, 2020.
- [18] Sharrab, Y., Al-Fraihat, D., Tarawneh, M., & Sharieh, A. (2023). Medicinal plants recognition using deep learning. In *2023 International Conference on Multimedia Computing, Networking and Applications (MCNA)* (pp. 116-122). IEEE. <https://doi.org/10.1109/MCNA59361.2023.10185880>.
- [19] Medicinals Botany. United States department of agriculture <https://www.fs.usda.gov/wildflowers/ethnobotany/medicinal/index.shtml> (accessed February 22, 2023).
- [20] A.H. Mohammed, Importance of medicinal plants, *Res. Pharmacy Health Sci.* 5 (2) (2019) 124–125.
- [21] Ogidan, O. K., Onile, A. E. (2019), Automatic recognition and classification of medicinal plants: a review, *The Therapeutic Properties of Medicinal Plants*, 271-284.
- [22] Begue, V. Kowlessur, U. Singh, F. Mahomoodally, S. Pudaruth, Automatic recognition of medicinal plants using machine learning techniques, *Int. J. Adv. Comput. Sci. Appl.* 8 (4) (2017) 166–175.
- [23] S.G. Wu, F.S. Bao, E.Y. Xu, Y.X. Wang, Y.F. Chang, Q.L. Xiang, A leaf recognition algorithm for plant classification using a probabilistic neural network, in: *Proceedings of the IEEE International Symposium on Signal Processing and Information Technology*, IEEE, 2007, pp. 11–16.
- [24] Y. Herdiyeni, D.I. Lubis, S. Douady, Leaf shape identification of medicinal leaves using curvilinear shape descriptor, in: *Proceedings of the 7th International Conference of Soft Computing and Pattern Recognition (SoCPaR)*, IEEE, 2015, pp. 218–223.
- [25] A.K. Ansari, Study of plant tulsi and its benefits for human beings, *Int. J. Appl. Res.* 1 (3) (2015) 148–151.
- [26] P.M. Kumar, C.M. Surya, V.P. Gopi, Identification of ayurvedic medicinal plants by image processing of leaf samples, in: *Proceedings of the 3rd International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, IEEE, 2017, pp. 231–238.
- [27] S.G. Wu, F.S. Bao, E.Y. Xu, Y.-X. Wang, Y.-F. Chang, Q.-L. Xiang, A leaf recognition algorithm for plant classification using probabilistic neural network, in: *2007 IEEE International Symposium on Signal Processing and Information Technology*, IEEE, 2007, pp. 11–16.
- [28] Y. Herdiyeni, N.K.S. Wahyuni, Mobile application for Indonesian medicinal plants identification using fuzzy local binary pattern and fuzzy color histogram, in: *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, December 2012, IEEE, 2012, pp. 301–306.
- [29] L.-H. Ma, Z.-Q. Zhao, J. Wang, Apleafis: an Android-based plant leaf identification system, in: *International Conference on Intelligent Computing*, Springer, 2013, pp. 106–111.
- [30] Malik OA, Ismail N, Hussein BR, Yahya U. Automated real time identification of medicinal plants species in natural environment using deep learning models—a case study from Borneo Region. *Plants*. 2022;11(15):1952.
- [31] Valdez DB, Aliac CJG, Feliscuzo LS. Medicinal plant classification using convolutional neural network and transfer learning. In: *2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAET)*. IEEE; 2022. p. 1–6.
- [32] Zin IAMd, Ibrahim Z, Isa D, Aliman S, Sabri N, Mangshor NNA. Herbal plant recognition using deep convolutional neural network. *Bull Electr Eng Inform.* 2020;9(5):2198–205.
- [33] Saikia AP, Hmangaihzuale PVL, Datta S, Gope S, Deb S, Singh KR. Medicinal plant species classification using neural network classifier. In: *2021 6th International Conference on Communication and Electronics Systems (ICCES)*. IEEE; 2021. p. 1805–11.
- [34] Sachar S, Kumar A. Deep ensemble learning for automatic medicinal leaf identification. *Int J Inf Technol.* 2022;14(6):3089–97.