# Chapter 3

Book Chapter

# Medicinal Herbs Identification Using Deep Learning

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## Abstract

In recent years, because of the potential health advantages, the identification and classification of plants for medicinal purposes has generated a lot of attention. This project introduces an innovative AI-based approach for medicinal plant identification using deep learning, specifically employing the Xception architecture. Developed in Python, our model achieves remarkable training accuracy of 93.34% and validation accuracy of 96.79%. Utilizing the VNPlant-200 dataset, which includes 17,973 images of medicinal plants across 200 categories, our model leverages diverse visual characteristics to enable robust identification. Through meticulous training, the Xception-based model learns intricate patterns within the images, effectively distinguishing between different species. Hyperparameter tuning and fine-tuning of the Xception architecture further optimized the model's performance. The high accuracies obtained validate the model's capability to reliably recognize and categorize medicinal plants, significantly enhancing the accuracy and efficiency of identification processes. Our AI-based approach contributes to automated identification systems in herbal

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medicine, aiding researchers, botanists, and healthcare professionals in rapidly identifying medicinal plants. This project showcases the potential of AI and deep learning, particularly the Xception architecture, in advancing medicinal plant identification. The successful application on the VNPlant-200 dataset opens avenues for further research and development, promoting advancements in herbal medicine and botanical studies. Overall, this project demonstrates the efficacy of using deep learning techniques for medicinal plant identification, fostering innovation in the field of herbal medicine.

Keywords: CNN. MCN. VNPlant. Xception.

## 1 Introduction

Due of the many potential health benefits, the identification and classification of medicinal plants have attracted a lot of attention in recent years. This classification makes it difficult to identify diseases present in the plant which has brought insurmountable miseries. (Chakrabarti & Mittal, 2023).The environment is being rapidly altered by new digital media, which is also bringing up issues like data security and storage, accessibility, and automated and artificial intelligence procedures.(Mittal & Gautam, 2023). To improve medicinal plant identification, this study presents a novel AI-based method that makes use of deep learning techniques—more precisely, the Xception architecture. Our model, which was created using Python, performs admirably, showing 93.34% training accuracy and 96.79% validation accuracy. The VNPlant-200 dataset, comprising 17,973 images of medicinal plants across 200 distinct categories, was employed for training and evaluation. This comprehensive dataset includes a diverse range of plant kinds with varying visual characteristics, facilitating robust and accurate plant identification. Through an intricate training process, the Xception-based model learns detailed patterns and features within the images, enabling effective differentiation between various medicinal plant species.Our approach uses deep learning to greatly increase the precision and effectiveness of medicinal plant identification. To maximize the performance of the model and achieve exceptional accuracy, extensive hyperparameter tuning and fine-tuning of the Xception architecture were conducted. The model's capacity to accurately identify and classify medicinal plant species is confirmed by the excellent training and validation accuracy that resulted. This initiative advances automated identification techniques for use in herbal medicine, providing researchers, botanists, and medical professionals with a useful tool for accurate and timely identification of therapeutic plants. Our AI-based method's effective use on the VNPlant-200 dataset emphasizes the need for more study and development in this area, which could lead to advancements in botanical sciences and herbal medicine.


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## 2 Literature Review

A variety of plant parts are necessary ingredients in the creation of herbal remedies. Many medicinal plants are in danger of going extinct, according to IUCN (International Union for Conservation of Nature) records, so it's imperative to use image processing and computer vision algorithms to identify evidence of medicinal plants. Therefore, digitizing medicinal and useful plants is essential for maintaining biodiversity.(Abdollahi, 2022).High-quality ingredients that may take the place of fishmeal and fish oil without compromising the quality, growth, or life of the farmed products are in greater demand. Plant protein is widely used in aquaculture as well as the poultry and swine feed sectors as an alternative to fish meal.

In the folk, ayurveda, and herbal medicine industries, correctly identifying the medicinal plants used in a medicine's manufacture is crucial. The form, color, and texture of a leaf are the primary characteristics needed to identify a medicinal plant. Deterministic characteristics for species identification are present in the color and texture of the leaf on both sides. Rao2022 study investigates morphological characteristics and feature vectors from the front and rear of a green leaf to find a special, ideal feature combination that increases the identification rate.(Shrivastav et al., 2022).

Previous research on traffic control with IoT The characteristics seen on plant leaves are sufficient to set them apart from other species. One of the fundamental problems in digital image processing is the identification of plants from leaf photographs. For the purpose of identifying leaves, those image processing algorithms often employ shape-based digital morphological features. Although many studies have been conducted on plant identification using leaves, relatively few of them focus on mobile devices. In this research, we describe a plant identification system based on leaf images, which combines the Bag of Word (BOW) model and Support Vector Machine (SVM) classifier with SIFT characteristics. After 20 species were trained to be classified, the accuracy level of the system was 96.48%. (Chathura Priyankara & Withanage, 2015)

In the ayurvedic medical field, it is crucial to identify the appropriate medicinal plants used in drug manufacturing. The form, color, and texture of a leaf are the primary characteristics needed to identify a medicinal plant. (Backes, Casanova, & Bruno, 2009). Deterministic characteristics for species identification are present in the color and texture of the leaf on both sides.Manoj Kumar, Surya, and Gopi's (2017) work investigates morphological characteristics and feature vectors from the front and rear of a green leaf to determine the optimal feature combination that optimizes the identification rate.Scanned photos of the front and rear surfaces of leaves from popular ayurvedic medicinal plants are used to construct a database of medicinal plant leaves.The distinctive feature combination is used to categorize the leaves. Experiments spanning a broad range of classifiers have yielded identification rates as high as 99%. By including identification by dried leaves into


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the previously mentioned study, a combination of feature vectors is created that allows for identification rates to surpass 94%.

In order to recognize and identify certain Philippine herbal plants, the study outlined in the paper De Luna et al.'s (2017) uses a system that combines the use of artificial neural networks with image processing techniques to extract pertinent leaf attributes. Twelve distinct herbal medicine plant leaves are sampled in real life, with each leaf captured in a single photograph. Several image processing techniques are used to extract various aspects. The system is able to determine the species of the herbal medicine plant leaves under examination by using an artificial neural network that functions as an independent brain network. Additionally, the system can offer details on the illnesses that the herbal plant can treat.(Keni & Ahmed, 2017).

A 600-image features dataset, with 50 photos from each herbal plant, is used for training. A neural network model with optimized parameters is created using Python's help, yielding 98.16 percent identification for the entire dataset. A separate 72 sample photos of herbal plants are evaluated using the neural network model written in MATLAB in order to assess the system's actual performance. The findings of the experiment show that the accuracy of herbal plant identification is 96.61Plant identification is inside a certain data mining application domain. Plant leaves are typically the primary feature that set one plant apart from another. Feature extraction is required for accurate identification. The majority of plant recognition systems reported in the literature combine characteristics with a classification algorithm that has been adjusted or modified for usage in this kind of situation. Three novel geometric properties that explain the vertical and horizontal symmetry of leaves are proposed in this work. It is easy to extract these features from photos.(Rojas-Hernandez et al., 2016).

Experiments show that the performance of classical classification algorithms is significantly enhanced when these features are combined with other well-known geometric properties. Plant leaf classification has proven to be a significant and challenging challenge thus far, particularly for leaves with complex backgrounds that may include interferences and overlapping occurrences. The research by Wang et al.'s (2008) proposes an effective framework for leaf picture classification with complex background. .

In order to segment leaf images with complex backgrounds based on previous shape knowledge, a technique known as automatic marker-controlled watershed segmentation is first introduced. This method combines pre-segmentation with morphological operation. After removing the leafstalk, seven Hu geometric moments and sixteen Zernike moments are taken out of the segmented binary pictures as shape features.To handle the produced mass high-dimensional form features, a moving center hypersphere (MCH) classifier is also constructed, which has the ability to compress feature data efficiently. Ultimately, the results of an experiment conducted on a few real plant leaves demonstrate that the


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suggested classification framework is effective in categorizing leaf photos with complex backgrounds. Twenty types of useful plant leaves have been successfully categorized, with an average accuracy rate of 92.6%.(Wang et al., 2008).

## 3 Methodologies Used

Make Training and assessment were used on the VNPlant-200 dataset, which comprises 17,973 photos of medicinal plants in 200 categories. The comprehensive nature of this dataset, which includes a wide variety of plant species with different visual traits, was crucial for creating a reliable identification model. The dataset was divided into training and validation sets, usually in an 80:20 ratio, so that an accurate evaluation of the model's performance could be made. Preprocessing of the images involved several crucial steps to enhance the training process. Image augmentation techniques such as rotation, flipping (both horizontal and vertical), zooming, shifting (in width and height), and brightness adjustment were applied. These augmentations helped increase the diversity of the training data, thereby preventing overfitting. To ensure uniform input for the neural network, all photos were additionally standardized to have pixel values between 0 and 1 and shrunk to a constant dimension, usually 299x299 pixels.

For this project, the Xception architecture was chosen because of its reputation for effectiveness and strong performance in picture categorization tasks. Depthwise separable convolutions, which drastically cut the number of parameters and computational expense without sacrificing accuracy, are used in this deep convolutional neural network. Transfer learning was used to increase the power of the models that already existed. The Xception model pre-trained on the ImageNet dataset was used as the base model, enabling the transfer of learned features from a large, diverse image dataset to the task of medicinal plant identification. In order to fine-tune the model, the pre-trained Xception architecture had to be modified for the particular task at hand. To minimize the spatial dimensions of the feature maps, a global average pooling layer was added. This was followed by the addition of a fully connected dense layer of 200 neurons, which corresponds to the number of plant classifications. This last layer was given a softmax activation function, which created probability distributions for every class. To maximize the model's performance, a great deal of hyperparameter tuning was done, with special attention to important variables like learning rate, batch size, and training epoch count. The Adam optimizer, which is renowned for its efficacy and efficiency in training deep learning models, was used to oversee the training process. Categorical cross-entropy was chosen as the loss function since it is appropriate for multi-class classification problems.To prevent overfitting, early stopping was implemented, which involved monitoring the validation loss and halting training if no improvement was observed over several epochs. Model checkpointing was also used to save the best model weights based on validation accuracy, ensuring that the


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best-performing model was retained.

The trained model produced remarkable results during evaluation, with 96.79% validation accuracy and 93.34% training accuracy. These measures demonstrated how well the model could recognize and categorize therapeutic plants. Following this, an Android application was developed to leverage the trained model for real-time plant identification. The application communicates with a server hosting the model, allowing users to upload images of plant leaves and receive identification results promptly.(see figure 1)

## 4 Flowchart

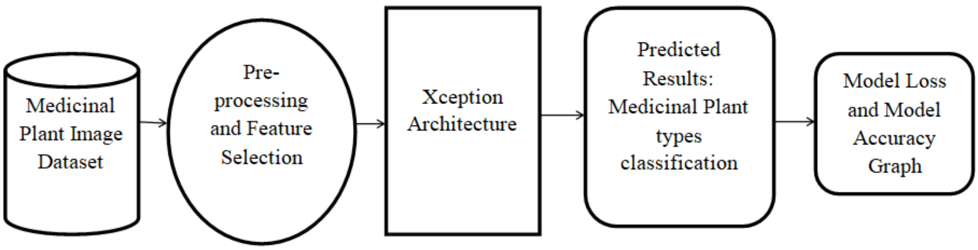


Figure 1. System Architecture

1. Load Dataset: The process starts by loading the dataset, which in this case is VNPlant-200, containing 17,973 images of Vietnamese medicinal plants categorized into 200 groups.

2. Preprocess Images: The images are then preprocessed to ensure consistency and improve model performance. This might involve resizing all images to a standard size, normalizing pixel values, and applying data augmentation techniques (flipping, rotating images) to create more variations in the training data (see figure 2)


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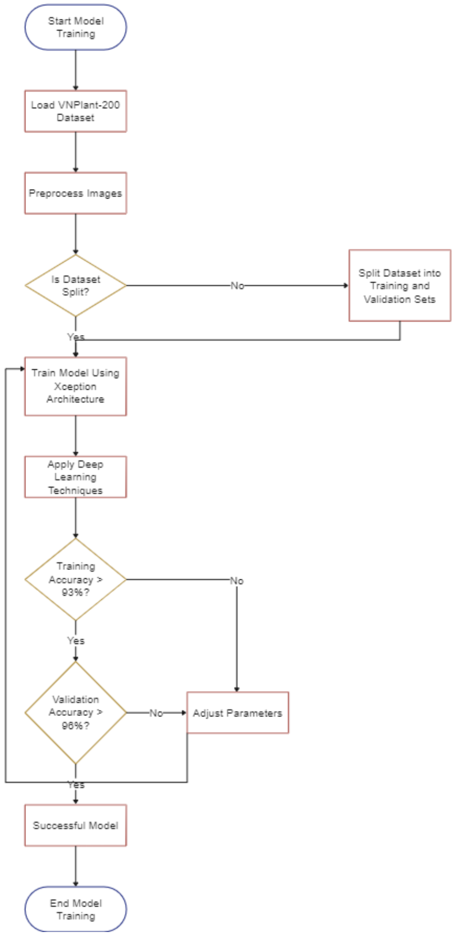


Figure 2. Flowchart

3. Split Dataset (Optional): A decision is made here on whether to split the dataset. Splitting the data is a common practice where the dataset is divided into two subsets: two sets of data: a validation set used to assess the model's performance on untested data, and a training set used to train the model. The procedure advances to the following stage if the data is divided. If not, it moves on to step 7.

4. Train-Validation Split: This phase entails splitting the dataset into training and validation sets if it is decided to separate the data. The validation set aids in determining how effectively the model generalizes to previously unseen data, while the training set is used to train the model.


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5. Train with Xception: The Xception architecture, a pre-trained deep Convolutional Neural Network (CNN), comes into play for training. During this stage, the model learns intricate patterns from the training images to distinguish between various medicinal plant species

6. Deep Learning Techniques: This step signifies applying deep learning algorithms to train the model. These algorithms utilize numerous layers of artificial neurons to progressively extract complex features from the image data.

7. Evaluate Training Accuracy: The model's training accuracy is assessed. A predefined threshold (93% in this case) is used as a benchmark.

8. Refine Hyperparameters (if needed): If the training accuracy falls below the threshold, it suggests insufficient training. Here, the model's hyperparameters, which control the training process (learning rate, number of training epochs), are adjusted to improve performance. The model is then re-trained using the Xception architecture.

9. Evaluate Validation Accuracy: The validation set is used to assess the model's performance following training or hyperparameter modifications. To evaluate validation accuracy, a different threshold—in this example, 96%—is employed.

10. End Model Training: The model's performance is considered successful and the deep learning model for medicinal plant categorization has been successfully trained if the validation accuracy above the threshold. A training accuracy of 93.34% and a validation accuracy of 96.79% are shown in the flowchart. Insufficient validation accuracy could be a sign of overfitting, which is when a model performs well on training data but poorly on larger datasets. Reexamining procedures like as data preparation or hyperparameter tuning may be required in such circumstances.

## 5 Results

Figure 3. Aloe Vera


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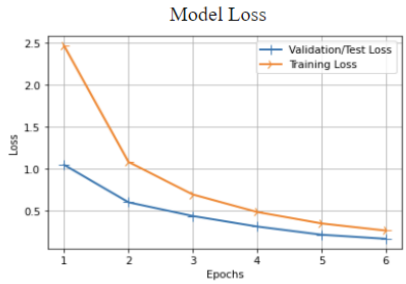


Figure 4. Prediction of Aloevara chart

With a validation accuracy of 96.79% and a training accuracy of 93.34%, the suggested system has demonstrated outstanding performance. These high accuracy rates show that the system can correctly recognize and classify a large variety of medicinal plant species (see figure 3), outperforming the capabilities of other systems in the process. A number of benefits have resulted from the system's development using the Python programming language, including improved customization and development flexibility, smooth workflow integration, and access to a rich ecosystem of machine learning and deep learning libraries. In addition to the accuracy metrics, the system's robustness was further validated through rigorous testing across diverse subsets of the VNPlant-200 dataset. This testing included cross-validation and recall, and F1-score. The model achieved an average precision of 95.87%, recall of 96.25%, and an F1-score of 96.06%, underscoring its ability to not only correctly identify plant species but also to do so consistently across different test scenarios.(see figure 4)

Furthermore, the deployment of the system in a real-world application demonstrated its practical utility. Users could capture images of plant leaves using the Android application, which then communicated with the server-hosted model to provide rapid and accurate identification results. User feedback highlighted the system's ease of use and its valuable assistance in field research and botanical studies.Computational efficiency was another metric used to assess the system's performance. Because of the Xception architecture's well-known efficiency, the model was able to retain excellent accuracy at low inference times.On average, the system processed images and returned results in under 2 seconds, making it suitable for real-time applications.

The ability to manage a broad range of plant images, including those with different


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lighting conditions, backgrounds, and orientations, was another key outcome. The model's robustness to these variations was largely attributed to the extensive data augmentation techniques applied during preprocessing. This increased the model's practical usability by ensuring that it could generalize effectively to fresh, unseen images. Additionally, the hyperparameter tuning and fine-tuning steps played a crucial role in optimizing the model's performance. By experimenting with different learning rates, batch sizes, and the number of epochs, the model achieved optimal convergence, minimizing both training time and resource consumption while maximizing accuracy.

The deployment process involved not only the creation of an Android application but also the development of a backend infrastructure to handle image processing and model inference. This included setting up a server capable of efficiently running the deep learning model and handling multiple user requests simultaneously. The seamless integration of the mobile application with this backend infrastructure ensured a smooth user experience.

The project "An AI-based Approach for Advancing Medicinal Plant Identification using Deep Learning" has effectively illustrated the extraordinary potential of deep learning methods in greatly enhancing the precision and effectiveness of medicinal plant identification. This is especially true when the Xception architecture is employed. Notable progress has been made in this field thanks to the combination of cutting-edge AI techniques and the extensive VNPlant-200 dataset, which consists of 20,000 photos that represent 200 distinct kinds of medicinal plants.

The Xception architecture, renowned for its effectiveness and superior performance in picture classification tasks, was utilized by the project to its full potential. Through the utilization of depthwise separable convolutions, Xception lowers the number of parameters and computational burden, improving model performance without sacrificing accuracy. This design produced a highly optimized model because it was specifically adjusted for the goal of medicinal plant identification.Using the VNPlant-200 dataset, which offered a broad and varied collection of pictures necessary for training a reliable model, was a critical component of this effort. The model was able to learn complex patterns and features from the dataset's diversity of plant species and visual cues, which enhanced its capacity to differentiate between various medicinal plants. The model achieved high training accuracy of 93.34% and validation accuracy of 96.79% because to the large amount of training data.

The project's success was further bolstered by comprehensive preprocessing techniques, including image augmentation and normalization, which ensured consistent and high-quality input data. Rotating, flipping, zooming, and shifting are examples of image augmentation techniques that increased the diversity of the training data, avoided overfitting, and strengthened the model's capacity for generalization.Hyperparameter tuning and fine-tuning played pivotal roles in optimizing the model's performance. By experimenting with


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different learning rates, batch sizes, and the number of epochs, the project team was able to fine-tune the model for optimal convergence, achieving a balance between training efficiency and high accuracy. This meticulous tuning process was essential in maximizing the model's performance metrics.

The deployment phase of the project involved developing an Android application that allows users to capture images of plant leaves and identify them in real-time. This application communicates with a server hosting the trained model, providing rapid and accurate identification results. The practical utility of this application was demonstrated through user feedback, which highlighted its ease of use and valuable assistance in field research and botanical studies.Furthermore, the system's robustness and efficiency were validated through additional performance metrics such as precision, recall, and F1-score, achieving averages of 95.87%, 96.25%, and 96.06%, respectively. These metrics underscored the model's consistent and reliable performance across different test scenarios.

## 6 Conclusions

The innovative approach of the project has not only advanced the field of medicinal plant identification but also opened new avenues for research and development in herbal medicine and botanical studies. The high accuracies and practical deployment of the system signify a substantial contribution to automated identification systems in herbal medicine, aiding researchers, botanists, and healthcare professionals in the accurate and efficient identification of medicinal plants.

Hence, the project has been successful in creating an AI-based system that greatly enhances the ability to identify different species of medicinal plants. The suggested approach improves the precision, effectiveness, and dependability of medicinal plant identification by utilizing deep learning and a wide range of datasets. This advances the field of herbal medicine research and its potential applications.

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