

Identifying Medicinal Plants Leaves using Resnet 50V2 Techniques

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Abstract: Since ancient times, medicinal plants have been utilized to treat illnesses. Medicinal plants are those that are utilized as raw materials for herbal remedies. According to estimates from the U.S. Forest Service, plants constitute the source of 40% of pharmaceutical medications in the Western world. According to the current pharmacopeia, seven thousand medicinal chemicals are obtained from plants. Modern science and traditional empirical knowledge are combined in herbal medicine. A medicinal plant is thought to be a valuable resource for preventing a number of illnesses. Different plant components are used to extract the vital medicinal component. People in developing nations use therapeutic plants instead of pharmaceuticals. The world is home to many different kinds of plants. Among them are herbs, which come in a variety of forms, hues, and leaf types. These herb species are hard for the average person to identify. Over 5000 plants are used for therapeutic purposes worldwide. India has 8000 medicinal plants that have been shown to provide therapeutic benefits. Because manually classifying the correct species necessitates extensive domain expertise, automatic arrangement of these plant species is crucial. Classifying medicinal plant classes from pictures is a difficult but fascinating task for academics, and machine learning techniques are widely applied in this regard. The effectiveness of Artificial Neural Network classifiers is contingent upon the caliber of the image collection.

Keyword: Image Acquisition, Pre-processing, CNN, augmentation, resnet 50v2

1. Introduction

In India, Ayurveda has been used as a therapeutic alternative for more than 3000 years. Ayurvedic remedies are becoming more popular due to the low cost of minimal adverse effects. 60–80% of people on the planet utilize medicinal herbs to treat a variety of illnesses, however it can be quite challenging for unsuspecting consumers to recognize these plants. Since the beginning of time, plants have provided food, clothing, shelter, and medicine to all of humanity. According to WHO figures, 80% of people in Asia and Africa are thought to rely on herbal remedies made from plant extracts. 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. The therapeutic plants and their applications must be digitally preserved 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. Without the assistance of specialists, attempts are being made to create automated systems for the recognition of plant species, and excellent techniques have been applied to the broad use case. Another crucial area where a progressive learning is conducted is leaf recognition in plant species recognition. Finding therapeutic plants that are uncommon in untamed forests is the main challenge. Identification of therapeutic plants is a major challenge for scientists studying chemistry, botany, and allied disciplines. Because medicinal plants are meant to heal a wide range of illnesses, it takes a great deal of skill to recognize them based on the size, shape, color, and texture of their leaves. Computer vision algorithms enable accurate and efficient leaf picture recognition. Plant traits such as bark, flowers, roots, and leaves are used in applications for plant identification. Depending on the soil, water, climate, and local vegetation, a wide variety of medicinal plants can be found all over the world. Therefore, it is impossible to identify every type of medicinal plant using a single system. One area of study in computer vision is the detection of plant leaves. The issue of identifying medicinal plant leaves may be overcome with the help of machine learning and technological advancements. The goal is to create a system that can determine whether a picture of a leaf belongs to a species of medicinal or non-medicinal plant. As a source of both traditional and modern drugs, medicinal plants are an integral aspect of healthcare. The WHO estimates that between 35,000 and 70,000 plant species are used medicinally, accounting for 35–70% of all plant uses worldwide and 14–28% of the estimated 250,000 plant species.

Moreover, almost 70% of the global population uses plants as their main source of medical care. Because of their unique bioactive compounds that influence human physiological systems, many plants—whether grown or wild—have medicinal promise. Most locally grown medicinal herbs are socioeconomically relevant because they are truly necessary for traditional medicine and food preparation [6]. Medicinal plants are vital for maintaining their cultural, economic, and livelihood worth to those who depend on them, in addition to their health advantages. This has led to the development of international guidelines and policies for the preservation of the biodiversity of medicinal plants.

Accurately identifying medicinal plants is crucial for maintaining traditional knowledge and protecting biodiversity. However, manual identification becomes unreliable due to the identical appearance of several plant

species. Advances in computer vision and machine learning enable the creation of automatic classification systems. The two most popular application-based plant identification systems are PlantNet and LeafSnap. However, plant appearance variability—such as differences in leaf shape, color, and texture—remains a challenge for all of these methods. In order to improve plant classification accuracy, deep learning-based techniques have been developed.

Deep learning techniques, especially Convolutional Neural Networks, or CNNs, have demonstrated great performance in image recognition tasks by using large datasets and powerful computational models. CNNs automatically construct hierarchical representations from unprocessed pictures, which improves plant species classification compared to traditional machine learning techniques that use manually created features.

Recent developments are moving toward hybrid models, which combine several deep learning architectures. Hybrid transfer learning models have shown particular success in the classification of medicinal plants. In order to show the efficacy of hybrid transfer learning, Ghosh et al. integrated principle component analysis (PCA) with convolutional neural networks (CNN). This method outperformed the existing plant classification techniques with a test accuracy of 95.25%. Hybrid models can solve two major problems with plant image datasets: high dimensionality and the substantial computation required to train deep networks from start. Hybrid models may improve classification accuracy and efficiency by incorporating PCA for dimension reduction and using transfer learning from an already-trained CNN. This makes the method relevant to the categorization of medicinal plants in real-world settings since it significantly lowers computational costs while maintaining excellent classification accuracy. There is still a significant research gap in the creation of robust automated systems for medicinal plant identification. While CNNs have been used in a number of studies for image-based classifications, little research has been done integrating multiple deep learning representations, such as hybrid models that merge residual blocks, inverted feature fusion and leftover blocks. Many times, the present classification methods make the assumption that there is a lot of processing capacity and labelled data, which isn't always available. There aren't many studies that discuss how these models can be used practically to help practitioners and local communities.

2. Literature Review:

Our current investigation has a strong foundation thanks to earlier studies in the field of medicinal plant classification. Among the notable contributions is the work of Quoc & Hoang, who conducted extensive research on Vietnam Medicinal Plants. They employed the Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) techniques on a dataset of 20,000 images of herbal plants. The study thoroughly examined two resolution versions with varying accuracy rates: 256×256 and 512×512 . Specifically, in the 256×256 version, the SURF technique obtained 21% accuracy whereas the SIFT approach achieved 28%. In the higher-resolution 512×512 version, the SURF approach's accuracy rose to 34.7%, and the method achieved the SIFT 37.4%.

Liantoni classified herbal leaves using the K-Nearest Neighbor and Naive Bayes methods. Their dataset had 120 images, 96 of which were used for training and 24 for testing. The study showed that the Naive 2 Bayes strategy was superior, with an accuracy rate of 75% compared to 70.83% for the K-Nearest Neighbor technique. Over the course of 100 epochs, both strategies were thoroughly tested.

Naeem et al. contributed to the field by focusing on the classification of leaves from medicinal plants. They divided the 6000 leaf images in their collection into six groups, each containing 1000 images. The study employed a variety of classification techniques, such as Random Forest (RF), Bagging (B), Logit-Boost (LB), Multi-Layer Perceptron (MLP), and Simple Logistic (SL). With two different image sizes— 220×220 and 280×280 —accuracy ratings ranged from 92.56% to 99.01%. It's interesting to note that the Multi-Layer Perceptron method outperformed the others, proving its effectiveness in categorizing medicinal plant leaves.

A model was developed that, for the VNPlant-200 dataset, provides an average accuracy of about 97%. The model's precision and recall were improved by combining common information. Consequently, false positive rates are decreased and identification reliability is increased. Similarly, using a dataset of 64 classes of medicinal plants, a study compares convolutional neural networks with pretrained models VGG-16 and VGG-19 for leaf recognition. CNN's accuracy rate was 95.79%.

In order to detect medicinal plants in Indonesia, the authors created a computer-aided approach that uses probabilistic neural networks. This system uses a basic PNN. technique to increase the accuracy of plant identification using the PDR classifier combination. The technique identified the therapeutic plants based on three characteristics: morphology, shape, and texture. Thirty species of Indonesian medicinal plants were identified using this approach. As a result, the dataset only includes Indonesian medicinal herbs.

An refinement of this study, called "MediLeaf," is an Android application for smartphones that can recognize the medicinal plants in any given leaf image. This system uses a probabilistic neural network to identify the image after extracting leaf textures using a local binary pattern. When these two approaches were combined, the accuracy of recognizing Indonesia's 30 species of medicinal plants was 56.33%.

For the documentation of herbal plants in the Philippines, the authors have developed a specially designed Artificial Neural Network (ANN). With 50 photos per plant, their image processing methods were able to extract the leaf features of the herbal plant, and an ANN was trained using a feature dataset of 600 photos. The image collection size is constrained because this study only includes 12 plants.

In order to identify the leaves of medicinal plants, the scientists have investigated the use of multiple feature sets. Shape, color, texture, vein, and other characteristics of leaves make up the feature set for training in conventional plant identification. Although they might not be identical, the leaf occasionally looks exactly like the image from the training phase. Therefore, calculating the system's accuracy is crucial. Accuracy is a very important consideration when it comes to the identification of medicinal plants. Generally speaking, the pictures are grouped according to shapes such as oval, rectangular, oblong, etc. Nevertheless, this shape trait has not been characterized in any of the research. The approach uses the Abridged Image Database and the Shape Descriptor Procedure for Medicinal Plant Identification (SDAMPI), which classifies the leaf's form. Additionally, it is challenging to detect the shape of the leaf description, which is pixel information. Thus, for its line and form description, the SDAMPI algorithm preserves the leaf shapes in Freeman chain code representation. It provides simplicity and convenience of use for storing shape information. The classifier uses the five structures—vein, shape, base, apices, and margin—as input. To create a description of a plant species, these characteristics are taken from the gathered leaf photos and combined with the descriptors kept in the database. The matching explanation is displayed if a match is discovered in the database; if not, a new record is created in the descriptor database. For accuracy and computational simplicity, chain codes are compared to the current pixel representation.

3. Data Description:

The "BDMedi Leaves" dataset is made up of images from several Indian nurseries and botanical gardens. The 2,029 images in the collection are organized as shown in Fig. 1. It depicts the suggested dataset's directory hierarchy. The main directory, called "BDMedi Leaves," contains two subdirectories: one for raw leaf photos that were first gathered and another for photographs that have experienced a variety of image enhancement methods. With a proportionate distribution of 70%, 20%, and 10% of the photos, respectively, the original directory is divided into three subdirectories: Train, Validation, and Test. Each of the three subdirectories has all ten types of photos. We offer class-wise enhanced photographs in the augmented directory for researchers to utilize based on their requirements. There are 38,606 augmented images in all, each measuring 512 by 512 pixels.

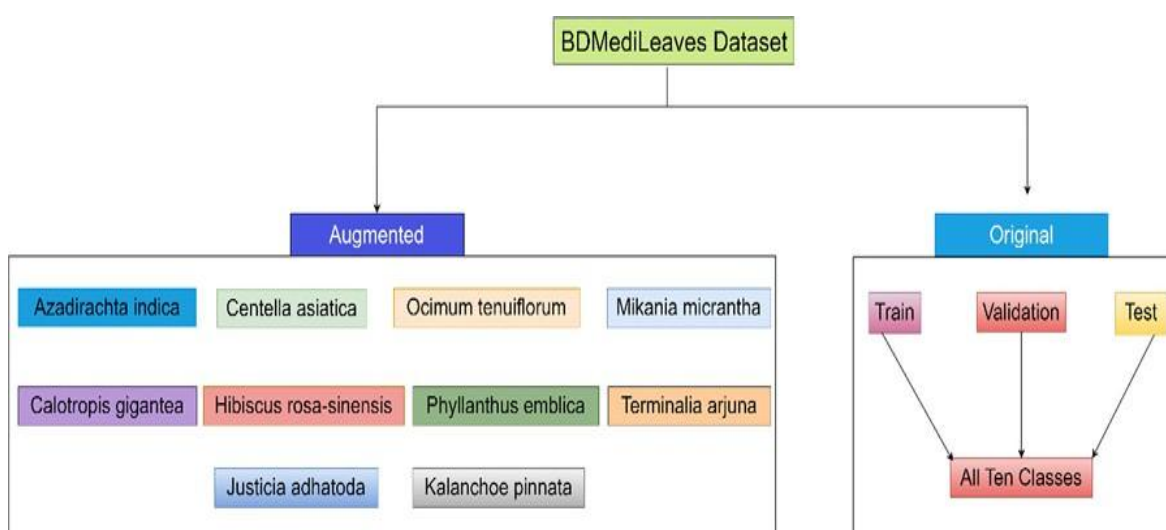


Fig 1 Directory tree of the proposed Medi Leaves dataset.

4. Proposed Methodology:

In this paper the proposed model consists of five phases:

4.1 Image Acquisition, 4.2 Image pre-processing, 4.3 Image Partition, 4.4 Image Augmentation, 4.5 Image Classification. Fig. 2 below illustrates the specific steps.

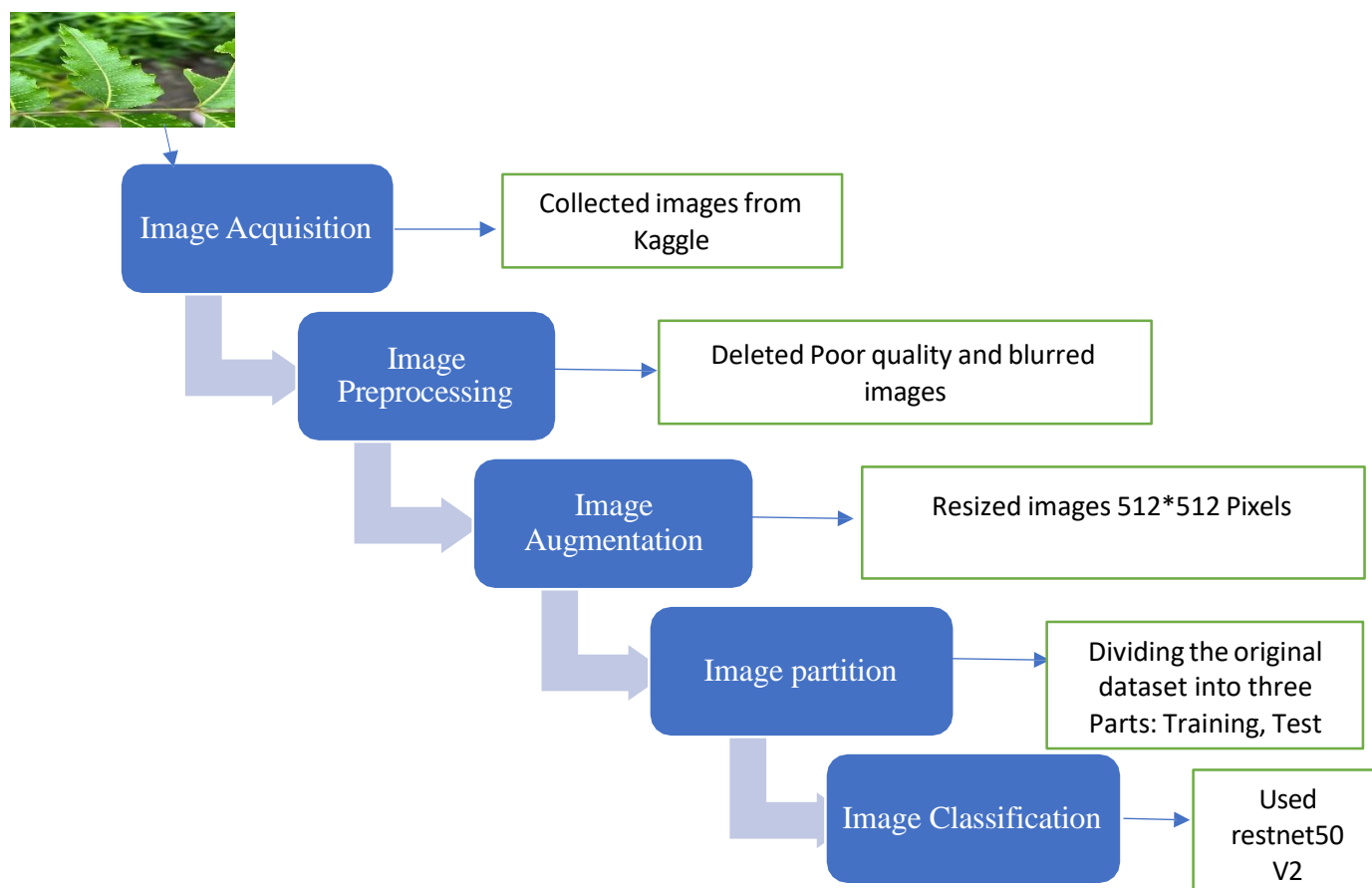


Fig 2 Architecture of Proposed Model

4.1 Image Acquisition: Ten different classes of medicinal plants make up the dataset. *Azadirachta indica*, *Hibiscus rosa-sinensis*, *Terminalia arjuna*, *Kalanchoe pin-nata*, *Centella asiatica*, *Justicia adhatoda*, *Mikania micrantha*, *Hibiscus emblica*, *Hibiscus gigantea*, and *Ocimum tenuiflorum* are the ten different categories. A overall of 2,029 original leaf photos.

4.2 Image Preprocessing: All of the original photos have dimensions of 3024 x 4032 pixels, a bit depth of 24, and 96 dots per inch (DPI) in two the horizontal and vertical indication. In reference to the augmented images, they were processed using 512 × 512-pixel resolution. The dimensions of the photographs were resized using the Python Imaging Library's (PIL) Image class.

4.3 Image Augmentation:

By adding variation to images, image augmentation improves the generalizability and effectiveness of ML and DL-based classifying models. We have used the Keras Image Data Generator class to increase the quantity of images.

4.4 Image Partition: In Image Partition Image Ten different medicinal plants are featured in our 2,029 unique leaf photographs. The original raw pictures were separated into training, validation, and test subcategories at random ratios of 70:20:10 for each group in order to train and assess the ML and DL-based models. A overall of 2,029 original leaf photos. and 3826 augmented images are included in the collection.

4.5 Image Classification:

Convolutional Neural Networks (CNN)-based DL models have been used to assess the performance of the suggested "Medical Leaves" dataset. The improved ResNet50 architecture, known as ResNet50V2, was first presented in the publication "Identity Mappings in Deep Residual Networks." By enhancing the residual learning mechanism, it expands upon the original ResNet framework and enables more effective training of extremely deep neural networks. Image classification and transfer learning challenges are two common uses for this architecture. A variation of the Residual Network (ResNet) architecture, ResNet50V2 uses residual learning to make training extremely deep networks easier. To train the models, every image was downsized to $224 \times 224 \times 3$. For resnet50 v2 architectures, all layers—aside from the completely linked layers—were frozen, and the pre-trained weights of ImageNet were maintained. After obtaining every pre-trained feature from both designs, a global.

$$Y=F(x,W_i)+x$$

- The residual block's input is X.
- The residual block's output is Y.
- The residual mapping that the stacked layers need to learn is represented by $F(x,W_i)$.
- $+x$ is the identity shortcut connection that appends the initial input x to the residual layers' output.
- The weights of the block's convolutions are denoted by W_i .

5. Experimental Setup:

The implementation of batch normalization and average pooling was followed by fully connected networks (FCNs) of 256 and 512 neurons, separately. To address the issue of overfitting in the models, a dropout of 20% neurons was inserted between the FCNs and ReLU activation was performed to each of the dense layers.

Layer (type)	Output Outline	No. of parameters
input_1 (Input Layer)	[(None, 224, 224, 3)]	0
Resnet 50_v2 (Functional)	(None, 10, 10, 2048)	26192906
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 1024)	2098176
dropout_1 (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 512)	524800
dropout_2 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 10)	5130

Table 1 Pretrained resnet50 v2 architecture summary

5. Result Analysis:

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. Figure 3 represents a graphical tool for assessing the effectiveness of binary classification models is the Receiver Operating Characteristic (ROC) curve. At different categorization thresholds, it shows the True Positive Rate (TPR), often mentioned to as sensitivity or recall, against the False Positive Rate (FPR). This curve makes the trade-off between a model's sensitivity and specificity easier to see.

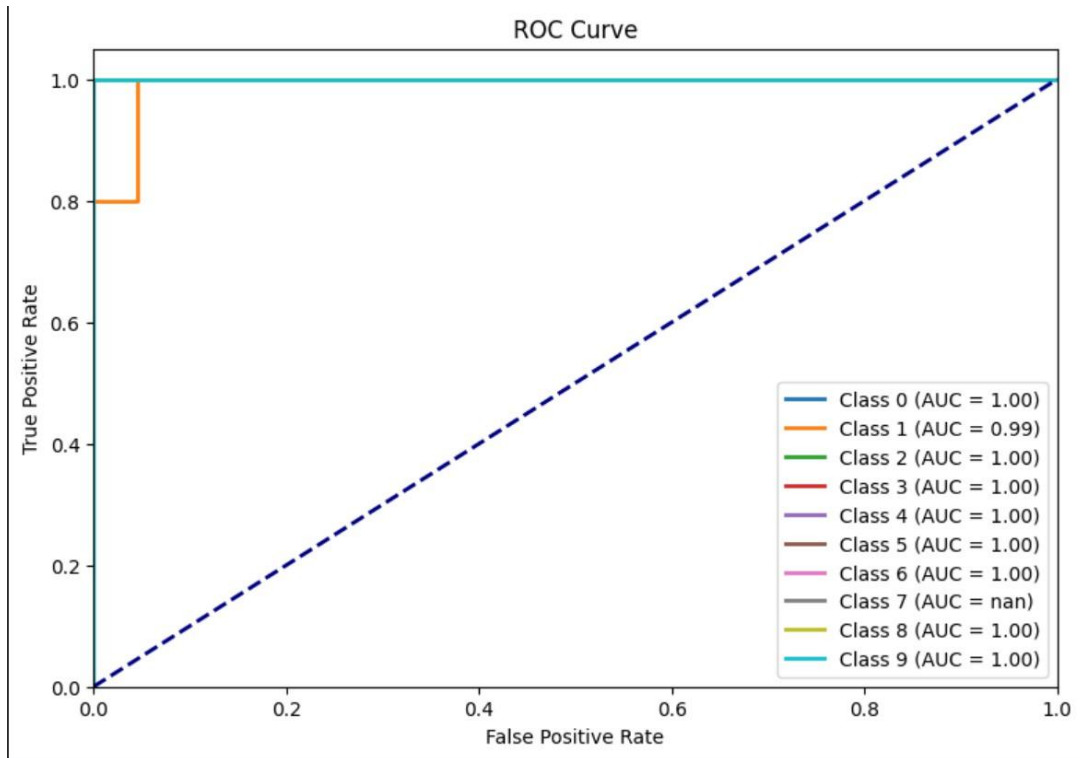


Figure 3: ROC Curve

Figure 4 Shows the accuracy of Resnet50 v2 Rather than highlighting the accuracy of the machine learning model, this validation set is typically utilized to enhance model performance in a different way.

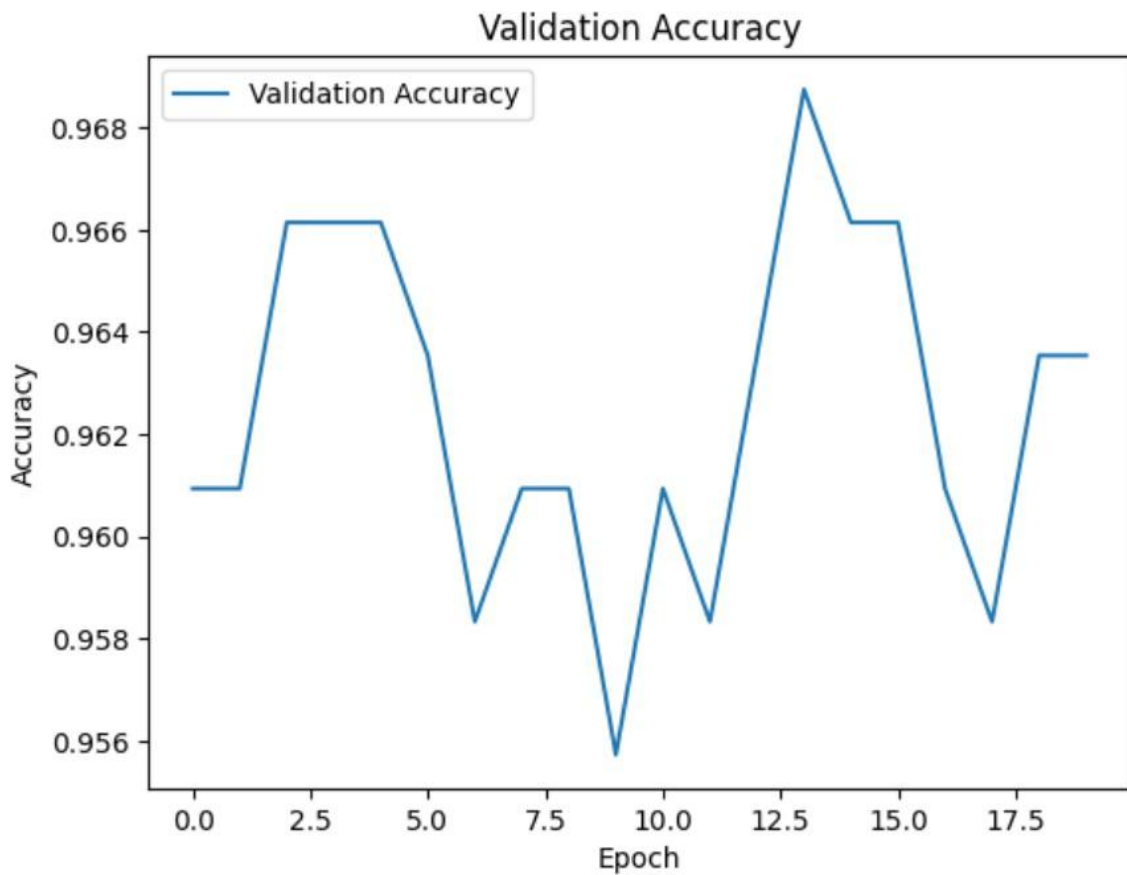


Figure 4: Validation Accuracy

Conclusion:

This paper reviews the research on the use of Convolutional Neural Networks (DCNN) for the identification and classification of medicinal plant leaves. In order to give the comparative study of DCNN architectures, this paper identified the closely connected research articles. The examination of medicinal plant datasets, their size, image pre-processing methods, image augmentation and resnet 50v2 architectures, RoC curves, and validation accuracy performance metrics used to identify and categorize medicinal plant leaves are the main topics of this survey.

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