# Factors influencing the use of Deep Learning for Medicinal Plants Recognition

# Factors influencing the use of Deep Learning for Medicinal Plants Recognition

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**Abstract.** Medicinal plants are very essential in maintaining the physical and mental health of human beings. For providing better treatment, Identification and classification of medicinal plants is essential. In this research paper, main objective is to create a medicinal plant identification system using Deep Learning concept. This system identifies and classifies the medicinal plant species with high accuracy. In this system, five different Indian medicinal plant species namely Pungai, Jamun (Naval), Jatropha curcas, kuppaimeni and Basil are used for identification and classification. The dataset contains 58,280 images, includes approximately 10,000 images for each species. The leaf texture, shape, color, physiological or morphological as the features set for leaf identification. The CNN architecture is used to train the collected dataset and develop the system with high accuracy. As result of this model, 96.67% success rate in finding the corresponding medicinal plant. This model is advisable to use as early detection tool for finding the medicinal plant because of its best success rate
**Keywords—**Deep Learning, Medicinal Plant Identification, Neural Networks.

## 1. Introduction

A medicinal plant is delineated as a plant that is collectedfromthewildorplantedplantfor itsmedicinal value. Plants have been utilized in curing human diseases for thousands of centuries and are thesource of a significant percentage of medicines. Medicinal plants have a prolonged history of consumption withhundreds of classes. In recent years, some computational approaches have been introduced, particularly in image processing domain, for plant classification. In this regard, Neural Networks represent novel techniques for image processing, with large potentials. The most commonly used Neutral Networks for imageprocessing is Convolutional NeuralNetwork (CNN). Medicinal plant species classification is critical for medicine production and conservation. Local peoples don't have enough knowledge about urban medicinal plants and their usages. Therefore, classifying the medicinal plant image using Convolutional Neural Network by high accuracy image classification model could be useful to identify different types of species.

There are many research have been done to detect medicinal plants using image classification technique. However, there are different proposed techniques to classify objects or flowers, and some of them employed deep learning approaches. In the early stages of plants identification, the authors applied low-level features such as shape, color, and texture of leaves to differentiate among species [1]-[5].

In [3], proposed a tree identification algorithm in following steps: preprocessing, extraction, and finally sorting. Different leaf features, such as morphological features, Fourier descriptions and a new

features are introduced in terms of shape. These features become the input to the artificial neural network (ANN). The model was trained by giving the 817 leaf samples from 14 different fruit trees and reached the 96% of accuracy.
In [4], a deep learning method is developed to learn unique features from leaf images along with a classification for plant species. Authors have implemented and ensured that learned features from a Convolutional Neural Network (CNN) results in better features for leaf images when compared with the hand-crafted features.
In [5] presents a method for identifying plant species based on specialized algorithms using plant-inspired descriptors. A 2-step boundary segment algorithm based on the polygon leaf pattern is implemented to obtain the outline of the leaf. Extracted features are high level geometric descriptors that can be semantically deducted.
In [6], a venation based CNN model is proposed, DLeaf for plant leaves classification. For DLeaf feature extraction and classification, CNN and ANN is applied. The proposed idea achieved accuracy of 94.88%in classification.
In [7], an automatic identification system is proposed for certain leaves of the medicinal plants. The following features selection techniques boundary based features, moment features and color features are applied for finding the different leaves. The proposed classification model achieves 92% efficiency.
In [8], an ANN-based model was introduced to categorize the medicinal plant species using the following features color, texture and shape of leaves. This prototype model includes totally 63 leaves, 36 leaves for training, 7 leaves for validation and 20 leaves for testing. Out of 20 different features of leaves, 8 minimal prominent features were found to classify the leaves. This method achieves an accuracy of 94.4%.
In [9], a computer vision based approach was developed to identify the feature set to categorize the given leaves of the medicinal plant and to extract its medicine related information. To find the classes of leaves, this model applied a Probabilistic Neural Network classifier. The method include four modules: preprocessing, retrieval, feature extraction, classification of medicinal values. The classification includes the feature vector calculation and similarity matching.
In [10], the model was introduced for leaf acquisition and techniques to convert the acquired image to device independent l color space, and used to find VGG-16 accuracy for l-VGG-16 with feature map. The SVM is applied in this feature set and obtained 97.6% accuracy for l-VGG-16 and 98.2% PCA methods.
In [11], a machine learning model was proposed, and computer vision based technique to categorize the leaves of the medicinal plants identified in the Western Ghats.. This model reached accuracy of 96% in feature extraction with expensive computation.
In [12], a model to identify the optimum combination of features needed to categorize the leaves of the medicinal plant which increases the accuracy level in classification. The overall 99% of accuracy is reached with MLP classifier for Geometric-Colour-TextureZernike combination with 38 features.
In [13] proposed a Hessian matrix based leaf vein segmentation. The model includes the pre-processing, Thinning, visual evaluation and Hessian matrix segmentation. Around 54% of the images of leaves achieved a segmentation score of 2, and around 43% of leaves scored 1.
Guillermo et al. [14] deep Convolutional Neural Network model was introduced to categorize the medicinal plants using leaf venation. The vein segmentation used the unconstrained version of Hit or Miss Transform. A central patch of 100x100 pixels retrieved from the segmented vein pattern and retrived the features of interest. This model includes the five layered network which outperformed the six layered network for S1 and S2 with the accuracy of 96.9%.
In [15] developed a model to retrieve the shape features of leaves of the medicinal plants by applying the algorithm called RELIEF feature selection. PCA was applied to refine the features collected. For testing and training, Flavia and RMH dataset were applied. For classification, Multi-Layer Perceptron Neural Network (MLP NN) and k-NN with four neighbors were applied in this model. This MLP NN model achieved the accuracy of 47.08% in classification.

## 2. Collection of Data Set

Numerous medicinal plant species are available. In this system, five different Indian medicinal plant species namely Pungai, Jamun (Naval), Jatropha curcas, kuppaimeni and Basil are used for identification and classification. The dataset contains 58,280 images, includes approximately 10,000 images for each species. The features extracted for identification are leaf texture, shape, color, physiological or morphological. CNN architecture is applied for the dataset to train and develop the system with high accuracy. Basil most popularly known as Tulasi has been used for thousands of years in ayurvedha for its diverse healing properties. The Leaves strengthen the stomach and help in respiratory diseases. It is also used to cure diabetes, stress, and Kidney stones. Traditionally Kuppaimeni is used to get rid of unwanted hair growth, for treating skin problems like pimples, psoriasis to get rid of cough and cold, to treat intestinal worms and also for treating piles. Medicinal values Jatropha provides is to treat skin, cancer, digestive, respiratory and infectious diseases. Highly nutritious jamun , refreshing and succulent fruit flooding the summer markets has innumerable health benefits. It is also called as Java plum or Indian blackberry in English. The berry was strongly recommended by Ayurveda for treating different conditions related to heart, asthma, arthritis, stomach pain, flatulence, bowel spasm and dysentery. Jamun fruit flushes the toxins out of the kidneys with its diuretic effects, while the high fiber content aids in digestion and avoids nausea and vomiting. Pungai leaves used as a digestive and laxative for treating the wounds and inflammation. Leaf juice aids in treatment of Leprosy, gonorrhea, diarrhea, cough and cold. In this study, the follow steps are used for data collection.

i) Articulate the problem; knowing what one wants to predict helps in deciding the data valuable to collect. Data Exploration in the categories of Classification, Clustering, Regression, and Ranking helps with the decision.

ii) Establish Data Collection Mechanism; Process of collecting the Data which can be Automated or Manual based on the requirement.

iii) Format Data; File format of the images stored need to be same for maintaining the consistency.

iv) Reduce Size; Data need to be collected based on the target needs to be achieved which is critical for our Dataset.

v) Complete Data Cleansing; Data with missing, erroneous or fewer representative values is removed to make prediction more accurate.

## 3. Background Study and Methodology

Convolutional Neural Network (CNN): A Convolutional Neural Network is a deep learning architecture. Image classification is one of the problems that a CNN could do and is a trained network that can classify images into one of a thousand pre-determined categories.

One can employ a CNN to do image processing including image detection, segmentation, and classification. The important benefit of CNN when compared to a traditional NN is that it automatically identifies the significant features without any supervision control. A CNN is consists of various layers that transform an input into the output. The complexity of the learned features increases in every hidden layer. For example, detection simple features are learned in the first hidden layer, like edges, and the detection of more complex shapes in the last one. A CNN model is includes two main components: the feature extraction component and the classification component. In order to understand CNN architecture, we introduce several concepts.

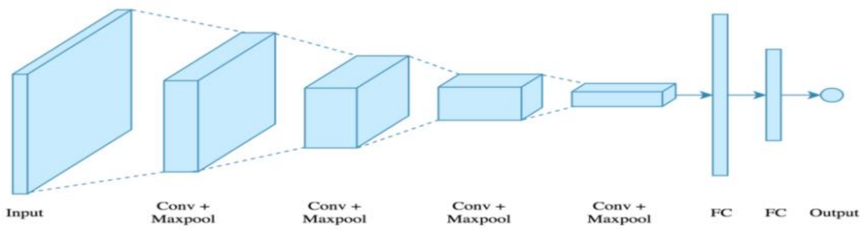


**Figure 1** The Overview of a CNN and its main components

Compared to a typical neural network in which each input layer's neuron is linked to the hidden layer's neurons. In a CNN we have Local Receptive Fields, a small number of input layer's neurons which are connected to the hidden layer's neurons. The local receptive field use convolution to translate an image into a feature map. Convolution can perform the mathematical convolution operation by moving a filter across the image. At every region, an element-wise matrix multiplication and summation of the result are done. A neural network can achieve this using an activation function by transfering the weighted sum of its inputs to the next layer. CNN use the same function and applies the transformation to the output of each neuron by passing the convolution operation's result through an activation function. The figure 2 shows sample data set images and figure 3 shows feature extraction and classification for leaf image input.

| Jatropha | Kuppaimeni | Navel | Pungai | Tulasi |
|---|---|---|---|---|

**Figure 2** Sample Data set Images

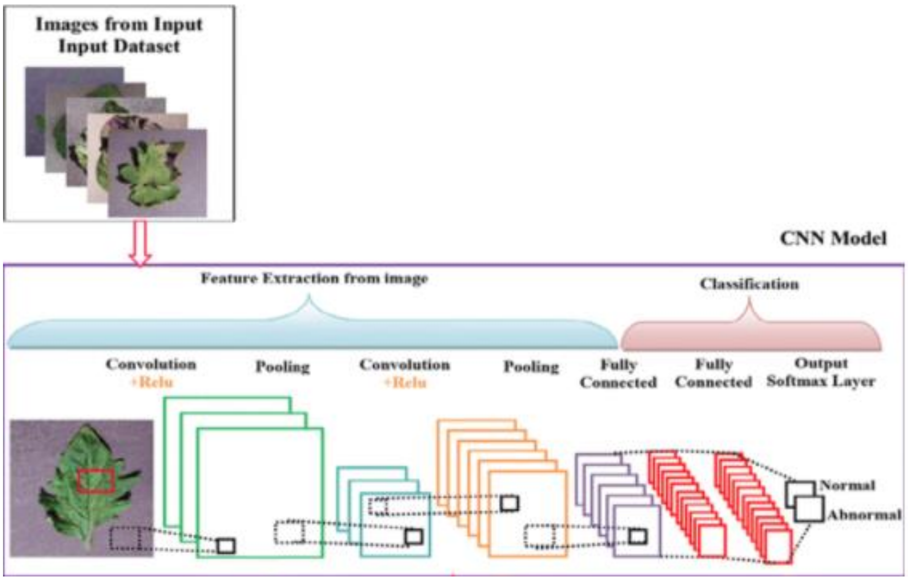


**Figure 3** CNN model for feature extraction and classification

The architectural design consist of five different phases in it. Where each phase is responsible for its own task, starting from the setting up of image directory to the final output of the model.
Flow from directory - This is the first phase of our model. Here the directory of the images resides are selected and introduced into the model for fetching and further proceedings. After they are selected, they are subjected to transformations, scaling.
Model Setup - This is the second phase, here the architecture for our model is 23 being setup. The CNN architecture used here is defined with all the layers and parameters. The building up of the entire architecture is taken up in this phase.
Loss function and Optimizers - In this phase the loss function which is going to be used up in our model is begin setup and also the optimizers are setup. This phase is the most important phase, because based up on the type of loss function and optimizer only the model's efficiency is found.
Callbacks - Callbacks are nothing but defining, "what has to be done if the model is learned a very good accuracy values", and "what has to be done if our model has to improves it learning rate if it has

to gain accuracy". Here depending upon the number of epochs and steps defined inside the epochs. The callback will be executed.
Saving the Model - This is the final phase where our model is given a file name for saving the model. So that during testing saved filed can be used for classification.

## 4. Result and Discussion

Here the model construction, compilation, and validation are discusses. To construct the model, the InceptionV3model is used as a pre-trained model/base model. The model is available in keras application library. The model construction includes the following steps:
1. First, we initialize InceptionV3model as our base model. The parameters trained on ImageNetdataset.
2. Then, we include a Global Average Pooling (GAP) layer to the model to decrease the spatial dimensions of a three dimensional tensors, which eventually leads to minimize overfitting. It reduces h * w * d dimensions to 1*1 * d dimensions by finding the average values of h and w.
3. Then, we add a fully connected layer, FC, of 1024hidden nodes.
4. Finally, the FC layer is connected to our output layer to predict output.

The FC layer mainly takes the output from GAP as input and provides output to our final output layer to predict the best label for each image. We use 'Softmax' as the activation function, because the amount of output classes are more than two. We use 65 layers in the model and make 249 layers non-trainable. Figure 4 shows Reduce of the spatial dimensions of a three dimensional tensors using Global Average Pooling layer (GAP)**Figure 4** Reduce of the spatial dimensions of a three dimensional tensors using Global Average Pooling layer (GAP).
In this section, we explain data distribution, data augmentation, and data rescaling and resizing. First of all we divide dataset into three subsets including train, test, and validation set. The initial dataset

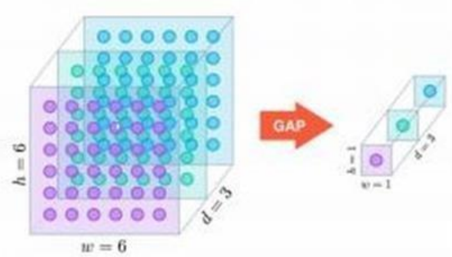

Figure 4. Spatial dimensions of GAP

was included 859 images. The dataset is separated for training, test, and validation set are 80%,10% and 10% respectively. The size of each class is shown in Table 1. As we can see, the proportion of each class is equaling the three subset.

| | Jatropha | Kuppaimeni | Navel | Pungai | Tulasi |
|---|---|---|---|---|---|
| **Train set** | 11323 | 10589 | 14165 | 10624 | 11579 |
| **Test set** | 50 | 50 | 50 | 50 | 50 |
| **Validation set** | 5 | 5 | 5 | 5 | 5 |

**Table 1** The size of the samples in Train, Test and Validation

Data distribution for training and testing set is as shown in figure 5 and 6. The proposition of each observed category of training set are Jatropha 18%, Kuppaimeni 16%, Navel 23%, Pungai 23% and Tulasi 20%. The proposition of each observed category of testing set are Jatropha 20%, Kuppaimeni 20%, Navel 20%, Pungai 20% and Tulasi 20%.

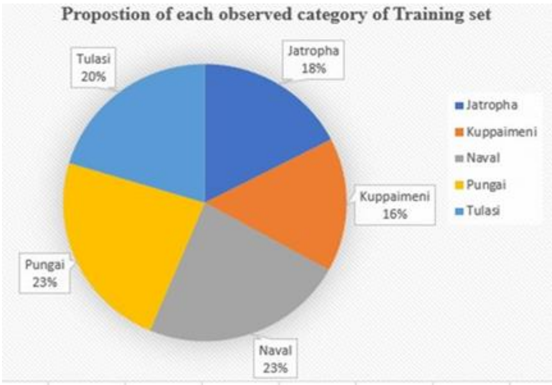


**Figure 5** The proportion of samples in train set

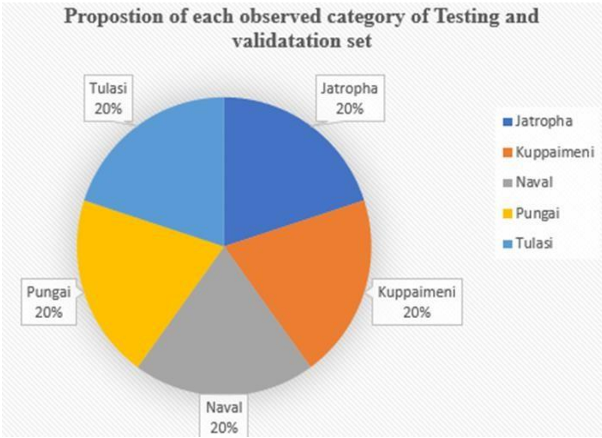


**Figure 6** The proportion of samples in test, and validation set

| **The total number of layers** | **Non trainable layers** | **Trainable layers** |
|---|---|---|
| **314** | 249 | 65 |

**Table 2** The summary of the final constructed model

The result is one of the most important parts of any project. In this project, we achieved 100% test accuracy on the InceptV3 model. It requires 3 epochs to achieve this accuracy.
Table 3 displays the detailed result of all epochs. The first 2 column includes training loss and training accuracy while the rest 2 column includes validation loss and validation accuracy. Finally, 96.67% test accuracy was achieved using the classification model.

| **Epoch** | **Train loss** | **Train accuracy** | **Val loss** | **Val accuracy** |
|---|---|---|---|---|
| **1** | 1.4994 | 0.4218 | 0.4378 | 0.9348 |
| **2** | 0.4605 | 0.8592 | 0.1888 | 0.9459 |
| **3** | 0.2046 | 0.9593 | 0.1158 | 0.9612 |
| **4** | 0.1588 | 0.9812 | 0.0869 | 0.9667 |

**Table 3** Training and Validation result

| *Final loss* | ***0.0102*** |
|---|---|
| Final Accuracy | 0.9667 |

**Table 4:** Testing result

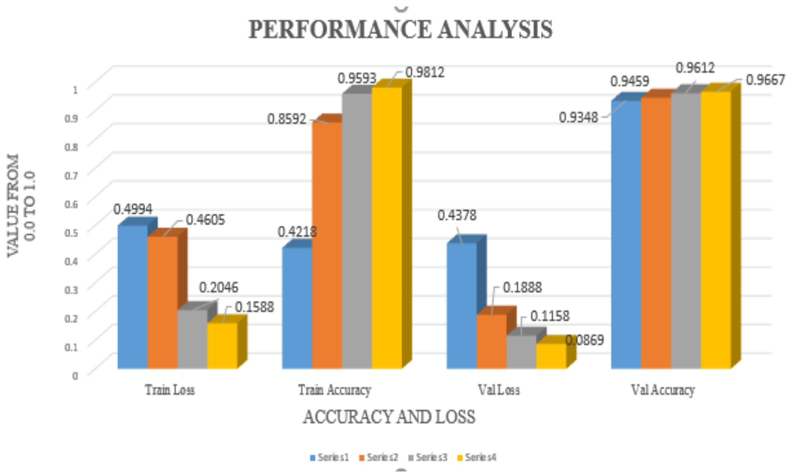


**Figure 7** Series of 1, 2, 3 and 4 are represent the Epoche 1, 2 ,3 and 4 respectively

## 5. Conclusion and Future Work

In this implementation phase and result, we conclude: This CNN model is not generic for all different types of plant species. It is just limited to only four different classes. The developed model is for only of five different plant Species, namely Pungai, Basil, Kuppaimeni, Jamun, Jatropha curcas. Here the index values are arranged in the order of [0, 1, 2, 3, 4] respectively for the above cited classes labels and accuracy of 96.67% is achieved.
The current work is only for 4 different classes, and our future work is to increase the number of classes with also having a good accuracy in different heterogeneous data. This only can be achieved by modifying the architecture to meet the point cited above. The most difficult thing is that we should not increase the depth of our model, at times it could led to over fitting problem, and this is a common problem which arises often in NN. So we have to keep an eye on this while developing a new architecture.

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