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A Review of AI Based Classification of Medicinal Plant using VGG 19 Technique

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Abstract

Identification of the correct medicinal plants that goes in to the preparation of a medicine is very important in ayurvedic, folk and herbal medicinal industry. Botanists invest a lot of time in identifying plant species by direct observation. Recognition of medicinal plants among various plant species is very difficult for ordinary people. So, in order to overcome these difficulties, we are developing an AI based Automatic Classification system for classifying medicinal plants among the several plants. This is mostly useful for the society to identify the ayurvedic leaves, which can be used in traditional medicine. By using this system, normal people can easily recognize these medicinal plants. This study outlines a technique for classifying different medicinal plant species using color images of some medicinal plant species. With the aid of the pre-trained classifier VGG-19, the task is carried out utilizing transfer learning to increase accuracy. Image pre-processing, image augmentation, feature extraction, and recognition are the four main classification steps that are carried out as part of the overall model evaluation. By using pre-defined hidden layers like convolutional layers, max pooling layers, and fully connected layers, the VGG-19 classifier is able to understand the features of leaves. After that, the soft-max layer is used to create a feature representation for all plant classes. In order to help estimate the correct class of an unidentified medicinal plant, the model gathers information about various medicinal plants, which contains around nineteen different classes. This system will classify the medicinal plant species with high accuracy. Identification and classification of medicinal plants are essential for better treatment.

Keywords: Medicinal plant Identification, Image Pre-processing, Image Augmentation, VGG19, Confusion Matrix

1. Introduction

The world bears thousands of plant species, many of which have medicinal values, others are close to extinction and still others that are harmful to man. To use and protect plant species, it is crucial to study and classify medicinal plants correctly. Any plant that has compounds that can be utilized therapeutically or that serve as building blocks for the production of effective pharmaceuticals is considered to be a medicinal plant. In other terms, medicinal plants are described as those that have healing qualities or have positive pharmacological effects on people. The evolution of human culture has depended greatly on the use of medicinal herbs. Medicinal plants have historically been a major source of medicine for almost all cultures and civilizations. Many of the current medicines are made frommedicinal plants, which are regarded as rich sources of traditional remedies. In the world, there are several species of therapeutic plants. Studying every medicinal plant species is a laborious and time-consuming procedure for botanists. Because of this, a system for classifying medicinal plant species is necessary for the sustainability of biodiversity and can also be useful to an individual for other purposes. It is challenging to categorize medicinal plants because it primarily involves looking at morphological qualities (such as general characteristics, root, stem, leaf structure, and fruit). Many clues to identifying plant species can be found in plant leaves. Also, compared to other features, a leaf has a much longer lifespan (like fruit and flowers). As a result, a large number of models for identifying medicinal plant species employ libraries of leaf images. The outcomes of many recently proposed research initiatives on medicinal plant species identification have been encouraging, although more accurate models are still required. Earlier classification models for leaf prediction were mostly implemented using the CNN architecture, which required that each CNN layer be created from scratch. Yet, they are lacking in precision. As a result, a strategy that addresses every flaw in newly released research must be suggested.

2. Literature Overview:

Chemical drugs frequently have straightforward, inorganic constituents, in contrast to the complex, organic nature of the human body. Chemical medications are therefore seen to be inappropriate for human ingestion. However, some Chemical medications must be taken continuously by patients with some disorders because they are truly symptomatic (temporary)[1]. The colour, size, texture, and form of leaves may be determined from picture images[2] using a variety of techniques, such as neural networks[3, 4], [5].

Previous research has used Artificial Neural Networks (ANN)[6–7], Gray Level Cooccurrence Matrix and K-Nearest Neighbor Algorithms[8–9], Local Binary Patterns[9–10], and Support Vector Machines[10] to identify herbal medicinal plants based on photographs of their leaves.

3. Methodologies and Approaches:

In our research, we used the effective pretrained classifier VGG19 based on CNN architecture to identify different medicinal plant species using photos of their leaves. Four processes make up the suggested model. They are Image Pre-processing, Augmentation, feature extraction, and model evaluation. The block diagram of the System is displayed in Figure 1.

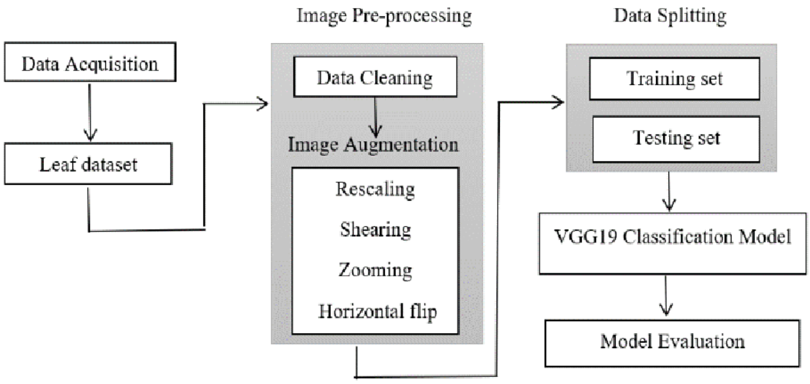

Figure 1: Block Structure of Medicinal Plant Identification System

3.1 Dataset:

In this study, the Segmented Medicinal leaf images dataset was used to train the VGG-19 model. This dataset contains 30 medicinal plant classes with a total of about 1835 images. Photos from this dataset are used to train, evaluate, and test the suggested model.

3.2 Pre-processing of the Image:

Image pre-processing is used to improve the image data before it is fed into the model. Preprocessing operations include rotation, resizing, normalization, rescaling (grey scaling), and shearing. Pre-processing typically takes place in two circumstances:

1.Cleaning data and Augmentation.

3.2.1 Cleaning the data:

Data cleaning is the removal of abnormalities from data using a variety of transformations in order to increase a model's capacity for learning.

Data cleaning, which is a step in the data preparation process, enables accurate, that produces accurate visualizations and models.

3.2.2 Augmentation of the data:

By using a variety of processing techniques, including rotation, scaling, shearing, flipping, and zooming, picture augmentation produces fake training images.

The suggested system performed data cleaning and augmentation, transforming the current samples, and producing more training images.

3.3 VGG19:

The visual geometry group (VGG) model, of which the VGG19 is a part, has 19 layers in total (Fully Connected=3, Convolution=16). They include different variations of VGG, such as VGG11 and VGG16.

The VGG-19 model gets more simple and useful. In order to decrease the volume size, the handler in VGG-19 used max pooling layers. Two FC layer was utilized. Figure2 shows how the resized pictures served as the input for the VGG model.

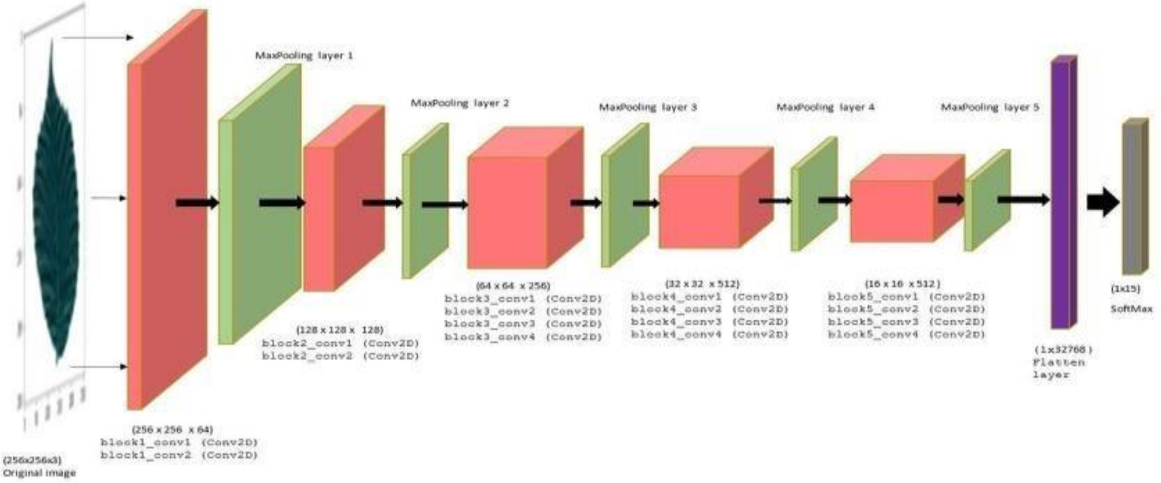

Figure 2: Classification process of a leaf with architecture of VGG19 model.

Convolution, reLU, pooling, and fully linked layers are the four layers used by CNN to extract information from an image. The convolution layer performs a convolution procedure using several feature filters. Each image pixel needs to be multiplied by the matching feature pixel before the layer is applied, after which the feature filter needs to be aligned in the image. Then the sum is calculated by dividing the total number of pixels in the feature by the sum of the values after the values have been added. The centre of the filtered image displays the final observed value. The convolutional result is created by applying this method to each feature filter. As shown in Figure 3, a ReLU, a distinct kind of rectified linear activation function, delivers the input straightaway if it is positive and 0 otherwise.

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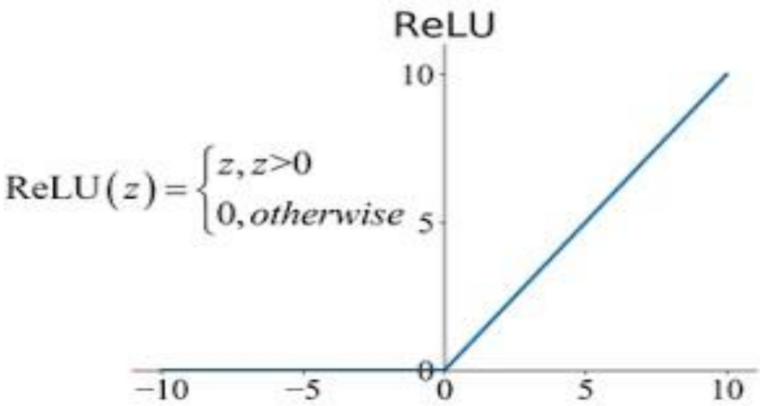

Figure

3: ReLU Activation Function

The pooled feature map is passed to the fully connected or dense layer after being flattened by the flattening layer, which does the actual classification and anticipates the final output using the softmax activation function. A vector of K real values is converted into a probability distribution with K potential outcomes using the Softmax function.

$$\text{softmax}(z_j) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \text{ for } j = 1,\ldots,K$$

4. Challenges and gaps:

Data Scarcity:

- Limited datasets of labelled medicinal plants can hinder the training process of the VGG19 model. Many species may not have sufficient images for robust classification.

Image Quality and Variability:

- Variations in lighting, background, and image resolution can affect classification accuracy. Differences in plant morphology due to environmental factors also pose challenges.

Overfitting:

- With limited data, deep learning models like VGG19 can overfit, memorizing training data rather than generalizing to new examples**.**

5.Future Research Directions:

Data Augmentation:

- Implementing advanced data augmentation techniques to increase the diversity of training datasets could improve model robustness and reduce overfitting.

Transfer Learning:

- Exploring transfer learning from models pre-trained on larger datasets could enhance performance and reduce the need for extensive labeled data.

Hybrid Models:

- Combining VGG19 with other machine learning algorithms or deep learning architectures (e.g., attention mechanisms) may improve classification accuracy and feature extraction.

6.Conclusion:

In this part, experimental findings for the suggested technique have been presented. The number of accurate and wrong predictions a classifier generates is displayed in a table called a confusion matrix. Figure 4 shows the prediction of leaf. In this prediction, a leaf of lemon was taken and predicted whether it is a medicinal leaf or not.

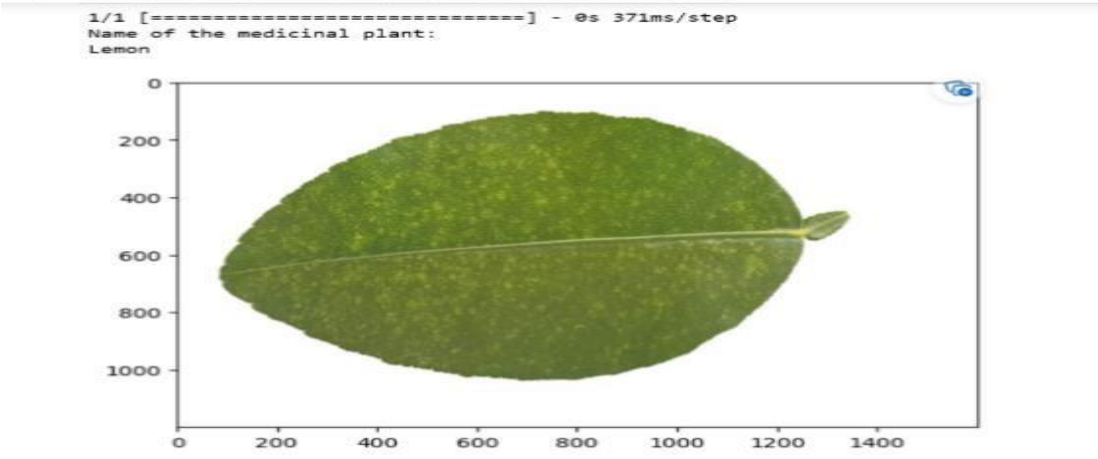

Figure 4: Prediction of an leaf

Figures 5 and 6 show the accuracy and loss for every training and validation period.

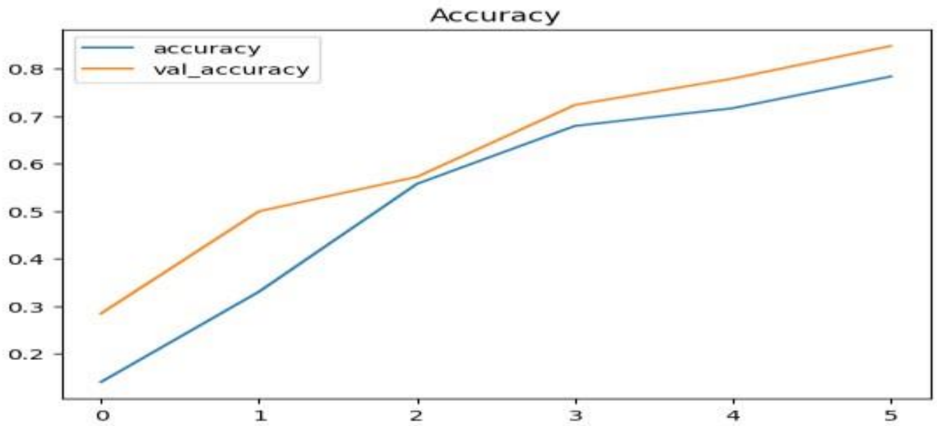

Figure 5: Training & Testing Accuracy

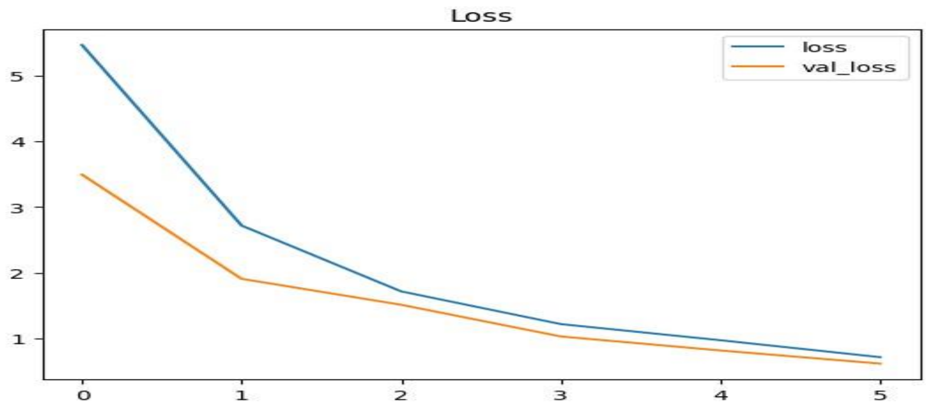

Figure 6: Training & Testing Loss

This paper proposes and applies a transfer learning-based approach for classifying medicinal plant species on a dataset of Segmented medicinal leaves. The pre-trained classifier VGG19 was used to categorise leaf pictures. The job at hand consists of 65 photographs from each of 30 categories of medicinal plant species, totalling 1835 leaves. Two thrid of the images are utilised for training, and the remaining for validation.Also, we deduced that, when compared to cutting-edge models, the suggested approach has the highest accuracy, recall, and precision values. It's important to have a backup plan in case your backup plan isn't working.The main advantages of our approach are its simplicity and high performance, which makes it perfect for large-scale applications of plant species recognition.

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