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Identification of medicinal plant using hybrid transfer learning technique

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ABSTRACT

Ayurveda is one of the oldest holistic treatment systems in the world. Finding an accurate and correct plant is the key to the working of Ayurvedic treatment. Identification of medicinal plants is a tedious job due to the look-alike feature and availability issue of medicinal plants with other plants. This paper emphases on the ideal identification and classification of plants of medicinal use using deep learning approaches. Previously researchers have used traditional machine learning techniques to identify medicinal plants, which lead to mixed results. Such results are good but not enough as the identification of medicinal plants may lead to a worsening situation for patients. This research is conducted to get results closer to an ayurvedic expert. The dataset used for this research has been taken from Mendeley Data. The dataset comprises 30 different species of medicinal plants. Hybrid transfer learning has been applied to this dataset. The model has generated a test accuracy of 95.25% which is better than the other popular transfer learning techniques.

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1. INTRODUCTION

Around 3,000 years ago Ayurveda was founded in the Indian sub-continent with a vision of treating patients with natural resources to minimize the side effects of treatment. In addition to being a source of food, plants are also a major source of medicine. Our daily nutrition is provided by plants and their related products. Plant-based measures are commonly used to meet the healthcare needs of the world's population. Plant species can only be distinguished and recognized by humans with a good understanding of them. The pharmaceutical industry benefits from this, as well as the ecosystem. As a result, sustainable development can also increase agricultural productivity.

Medicinal plants are having an important role in the functioning of ayurvedic treatment. Medicinal plant acts as a fundamental resource for this practice of Ayurveda. An ayurveda expert is capable of distinguishing between a medicinal plant and non-medicinal plant. Such experts are difficult to find and there is a shortage of ayurvedic experts in the world. The conversion of rural land for commercial purposes makes the task more difficult even for an expert. This commercial development has led to shortage of medical plants all over the world and threatens the survival of these useful medicinal plants. To protect medicinal plants, it's necessary to have a thorough understanding of their availability and dispersion across India, as well as how they are commercial developed for improving their survival and availability. This threatening situation is the core reason for development of a computer-based identification and classification system of medicinal use plants. Such a system has been discussed in this research article.

Automated identification and classification of medicinal use plants is possible with help of computer vision methods. LeafSnap [1] and Pl@ntNet [2] are the best examples of app-based plant identification and classification system for identifying medicinal use plants. The deep-learning and deep neural method has proven to be successful among them. For plant classification, most researchers use plant leaves as they possess the variation and unique features. Apart from leaves flowers and bark can also be used for this purpose. A number of datasets have been released, including the Swedish leaves dataset [3] which is having 75 leaves for each species, the Flavia dataset [4] which contains 1,907 leaves images of 32 different families of plants, and many more. For most of the datasets the leaves are scanned on plain background so that highly detailed features should be extracted using hand-crafted algorithms. In addition, a plant image should also be obtained for complex backgrounds which contains many other leaves, flowers, or trees. With speeded up robust features (SURF) and scale-invariant feature transform (SIFT) descriptors, we obtain poor identification results using the VNPlant-200 dataset [5].

There has been a lot of research and attempts were made direction during the past two decades. Approximately one-third of the population of developed countries and around 80% population of developing countries uses products containing medicinal qualities to remain fit and healthy. It has been estimated that there are 11,146 known herbs, of which around 500 are used by Indians in their everyday lives. Medical plants contains many components such as leaf, seed, flower, bark and root that can be used for detection of various plant diseases.

Methods of computer vision assist people in recognizing plants accurately and efficiently. In order to get the information about a plant from queried images, we just need a smartphone. In order to identify plants, many plant elements are used which include the plant's leaves, plants roots, plants flowers, and tree bark. Using a new approach known as gradient local binary patterns, Le-Viet and Hoang [6] identified plants from their bark. Ershad [7] improved the recognition of bark texture by using ternary patterns and multilayer networks. Zhang *et al*. [8] have provided a novel approach for tree classification which uses singular value decomposition (SVD) in conjunction with the sparse representation (SR) method. The dependability of identification based on a single part such as a flower or leaf is not high. An identification method combining flowers and leaves was introduced by Zhang *et al*. [9]. To determine the distinctive features of the multiple flower and leaf organs, the researchers used modified local discriminant canonical correlation analysis (MLDCCA), which lead to in a very high precision of 92.73%. Identifying plants is possible by studying the leaves of trees. Local features were extracted by using global image descriptor (GIST) texture features by Kheirkhah and Asghari [10]. A principal component analysis will be then used to determine their main characteristics. A k-nearest neighbour (KNN), support vector machine (SVM), and PatternNet network are used as classification algorithms. GIST in combination with principle component analysis (PCA) generates a better result on the Flavia data set with 98.7%. A similar study by Bertrand *et al*. [11], used the textural characteristics of bark of a tree and its bark color to analyze the linguistic information in the bark.

Most of the related tasks in machine learning and computer vision have benefited from deep learning methods based on convolution neural networks (CNNs) in given years [12]. The performance of these deep learning methods provides a more accurate and precise output real scenario than the conventional methods. Lee *et al*. [13] employed deep learning techniques by combining CNN architecture using conv-max pool-conv average pool-fully connected (FC) architecture with a deconvolutional network (DN) architecture. As opposed to traditional approaches, CNNs are not used to extract manual user-crafted features. Using deep convolutional neural networks, Geetharamani and Arun [14] successfully identified leaf plant diseases. Lee *et al*. [15] has implemented a CNN on the basis of leaf images of 44 species and proposed a CNN architecture to classify plant leaves. Identification of grass species in region of Australia by Olsen *et al*. [16] was conducted. Inception-v3 and ResNet-50 frameworks were implemented on the dataset of weeds, an artificial intelligence (AI) agent with a camera has captured images of grass in Australia. Based on the BJFU100 dataset, Xiao *et al*. [17] studied how deep CNN worked in identifying real-world species of plants. Beijing Forestry University campus cameras were used to capture all images in this database.

A number of initiatives have been taken in this direction over the past two decades [18]. In developed countries, 30% of the population uses medicinal based products directly or indirectly in the hope of better human health, while 80% in developing countries do the same. Inflammation, diabetes, heart disease, colds, diabetes, and heart disease are some of the conditions that herbs are helpful for treating [19]. A study found that 11,146 known herbs are used in India in their routine lives, of which around 500 are most commonly used. There are different parts of a medicinal plant for diagnosing different diseases, such as leaves, seeds, flowers, bark, and roots. Current advancement in the field of science has now made it possible for computer vision has provided assistance to farmers and other agriculture-based communities. Computer vision researchers use different plant parts for identifying plants, such as flowers and leaves. Identification is often based on leaf characteristics. There are many algorithms that can be used to extract leaf features, including GIST, relative subimage coefficient (RSC) [20], inner distance shape context (IDSC) [21], curvelet transform (CT) [22], leaf skeleton (LS) [23], fuzzy inference neural network [24], [25], and more are utilized for extraction of leaf features [26]. CNN models can perform better if extracted features are provided to them as it requires less computational power [27]–[30] with less number of features [31]–[33].

These studies have led to a few questions: i) which is the best feature extraction method to extract features from plant leaves with minimum loss? and ii) how to quantify the number of features required for better plant classification with the help of plant leaves?

In this article a novel method is devised to collect and analyze the shape of the plant leaf. Then a novel approach is used to find the local and global features of medicinal utility plants using deep CNN for plant identification. In the current scenario the transfer learning technique, visual geometry group (VGG16) is the best artificial feed forward neural network for plant classification. Hence, it is used for transfer learning. Before the classification process the image has been converted to gray scale for less computational consumption. PCA is being used for reducing the number of features.

The CNN model has had tremendous success in recent years, and it has been a crucial component for understanding the various features of images. In order to enhance the accuracy rate of medicinal plant datasets, we use CNN models, such as Resnet50 and DenseNet. This article has been arranged in the following sections: section 2 will discuss the related methodology used and section 3 will discuss the result analysis part. Finally, section 4 will end with a conclusion.

2. METHOD

2.1. Proposed method

For accurate identification of medicinal use plant leaves for identification and classi-fication, PCA is used to calculate a feature map which is then minimized using VGG16 for fast processing. A multi-layer learning technique, deep learning is used to represent the abstraction of multi-level data. A CNN model is capable of detecting new features without any prior knowledge based on underlying representations of input data or previous datasets. We are able to compare the deep features for each leaf sample with the precomput-ed leaf dataset. It is necessary to preprocess the input layer as VGG is having a fixed size input parameter list. Using the proposed new technique to capture leaf samples efficiently and clearly, the images of leaves are clicked in a background having not noise in preprocessing shown in Figure 1. A fully connected convolutional layer is then applied to extract the feature maps for identification and classification purpose, after converting the image to lαβ color space.

Figure 1. Image captured using mobile phone consists of noise

2.1.1. Image acquisition

The author has collected the data of 30 different species. The following factors were systematically varied for each observation of a single leaf: illumination, perspective, and the background. The Figure 2 shows an example of all the images collected during one observation. The top side and back side of each leaf were captured in-situ and non-destructively, as leaf structure and texture are usually substantially different from these perspectives.

2.1.2. Leaf image pre-processing

In order to apply the three preprocessing strategies, multiple duplicate images were generated in order to accommodate non-pre-processed, cropped, and segmented images. Images that were not pre-processed were not altered. A bounding box enclosing each leaf was used to perform the crop. The author has also developed a semi-automated segmentation technique using the GrabCut method to maximize segmentation efficiency. With GrabCut, iterated graph cuts are applied to interactive image segmentation which is accurate and time-effective [26]. Rectangles are used to denote potential foregrounds, whereas corner pixels are used to seed the background.

2.1.3. Feature extraction

Plant leaf image is transformed into numerical features in feature extraction in order to be processed while retaining their original information. As a result, it generates better results than simply applying machine learning to raw data. The feature extraction process can be performed manually or automatically. It is necessary to identify and describe the features that are relevant to a problem and to implement the process of extracting them manually. Features are extracted automatically from signals and images with the help of specialized algorithms or deep networks without any human interaction [27].

Leaf images were examined for the following characteristics for identification: leaf area, leaf roundness, leaf rectangleness, edges, texture, color, and elongation. These char-acteristics are now described in more depth. To calibrate the leaf area in the image, a one-rupee coin was used as a reference object. From a fixed distance (10 cm) from the camera, images of the coin and leaf were captured. Using this information, we were then able to determine the number of pixels in the coin region, which led us to calculate the area of the leaf given by (1):

$$LA = PA.NP \tag{1}$$

where LA=leaf area, PA=pixel area, NP=number of leaf pixels.

Pixel count in the leaf region can also be used to calculate Area. Leaf roundness is calculated by (2):

$$R = 4 * A/n * L * I \tag{2}$$

where, A=area, L=length.

Calculating the leaf length is as simple as finding the Euclidean distance between the end pixel coordinates along the midrib as given by (3):

$$d(p, p) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \tag{3}$$

where:
- p,q=two points in Euclidean n-space.
- qi, pi=Euclidean vectors, starting from the origin of the space (initial point).
- n=n-space.

In the case of roundness, we calculate the length, and in the case of rectangularity, we calculate the width between the vertical end points. The pixel count in the leaf region is used to determine roundness and rectangularity and calculated by (4):

$$R = A/L * B \tag{4}$$

where, A=area, L=length, B=breadth.

By using another image as a reference, the edge and texture information can be extracted. This includes either a completely white picture or a completely black picture. As the reference image, we used a completely black image. Using a color joint photographic expert group (JPEG) image, three planes have been extracted from the leaf image – red(R), green(G), and blue(B). We calculated redness, blueness, and greenness numbers for the leaf portion, similar to the calculation of edges and textures. As a reference, we used a black image. An image's aspect ratio can be determined by its elongation factor. An image's aspect ratio can be determined by the value of the elongation factor given by (5):

$$E = W/L \tag{5}$$

where, E=Elongation, w=Width, L=length.

2.1.4. Dimensional reduction and classification

It is common for datasets to be characterized by many input features, which complicates the predictive modelling task. Due to the difficulty of visualizing or predicting datasets with a large number of features, dimensionality reduction techniques must be applied to such datasets. In this article initially the dimensional reduction has been done with help of PCA. To refine the data more CNN has been used for further dimensional reduction and classifiers have been used for classification purposes. Medicinal plants can be classified using CNN models, advanced computer vision solutions, and transfer learning methods.

2.2. Convolutional neural network

Different plant species are distinguished using our Convolutional neural network (CNN) architecture based on leaf shape information. We use a 256×256-pixel input leaf. A grayscale channel is used to feed CNN. CNN consists of 3 main layers namely the convolutional layer which performs dot products of matrices, the pooling layer for replacement of output, and the fully-connected layer which maps the input with output. We get our final class score by combining all these layers, which allows us to distinguish between different leaf types. Convolutional and maximum pooling layers are used to extract features. Following each convolutional layer is a batch normalization layer. All layers except the final layer are activated by the rectified linear unit (ReLU) [28]. The leaf's shape is determined by the combination of learned features. Using this shape, the leaf's classification is determined.

The CNN output is the result of passing multiple inputs. Weights and images are the inputs. We get softmax as a result. By passing the leaf input image to the CNN, multiple input windows are generated. The output is then sent to the convolution layer. First convolution layer consists of input, convolution and output. There is one channel in the input. Two filters are used in the convolution. The layer uses the ReLU as the activation function. It outputs two tensors. Two tensors from the previous layer of convolution are passed as inputs to the second layer of convolution. There are three filters in this layer. 3 tensors are produced as outputs from this layer. A pooling layer receives three tensors that were previously used as input to a convolution layer. It contains one filter. The output is three tensors. The input picture is reduced in height and width by using a layer of pooling. Convolution layers and pooling layers are combined in the fully connected layer. A set of 3 tensors is passed as input to this layer from the previous convolution layer. A total of 4 neurons are generated. It passes input from 4 neurons of the previous layer to the softmax layer. There, the softmax value is calculated. Weights and input neurons are used for the calculation. Softmax returns the strongest value.

2.3. PCA-VGG16 hybrid deep learning architecture for medicinal plant classification

2.3.1. Principal component analysis

Principal component analysis (PCA) is a dimensionality reduction algorithm which is used to reduce the number of features from any image data to train a model. The working of PCA is heavily dependent upon the number of principal components (PCs) constructed from many features. Ideally, the first PC (PC1) explains as many variations in your features as possible. As far as possible, PC2 explains the majority of the variation in the leftover variation. Most of the variation in total features can be explained by PC1 and PC2. Rather than combining the existing properties, the algorithm constructs a new set of properties. In mathematical terms, PCA consists of a shift from the original set of features to a new set of features made up of principal components. As these new features have only algebraic meanings to us, they have no real meaning to us, so do not think that by combining linearly features, you will find new features that you didn't imagine existed [29]. The algorithm of PCA is given below:

Let there be an image database consisting of M images each of N pixels (for an image size of 60×60, N consists of 3,600 pixels). This database is represented by V=NXM matrix: Let ith row of this matrix V be represented by a vector Vi = X1, X2, X3…. XN.

- Step 1: Calculate the mean of Vi as (6):

$$\mu_i = \frac{1}{M}\sum_{j-1}^{M} V_{ij} \tag{6}$$

- Step 2: Evaluate the NXM matrix ϕ as follows (7):

$$\phi_{ij} = V_{ij} - \mu_i \tag{7}$$

- Step 3: Compute its covariance matrix (8):

$$C = \phi * \phi^T \tag{8}$$

- Step 4: Compute eigenvalues of C: λ1 > λ 2, >, ..., > λM.
- Step 5: Compute the eigenvectors of C: u1, u2, ... ,uM.
- Step 6: Arrange the eigenvectors in descending order and select "k" eigenvalues from it.

In medicinal leaf plant classification, each training image (t) is transformed into its eigenface components by using the operation as given (9):

$$W_k = U_k^T(t - \mu) \tag{9}$$

thus, the complexity of database with M images is reduced to k images, where k<M.

PCA builds principal component spaces by looking for properties that show the most variation between classes. As a result of the PCA algorithm, an eigenvector and an eigenvalue pair are generated, which corresponds to the eigenvector and its specific eigenvalue. Figure 3 shows the basic architecture of PCA for medicinal plant classification.

Information gain is calculated by comparing the entropy of the database before and after transformation as given in (10):

$$Entropy = -(p(0) * \log(p(0)) + (p(1) * \log(p(1)) \quad (10)$$

where p(0)=class 1 and p(1)=class 2.

Figure 2. Pre-processed strategy

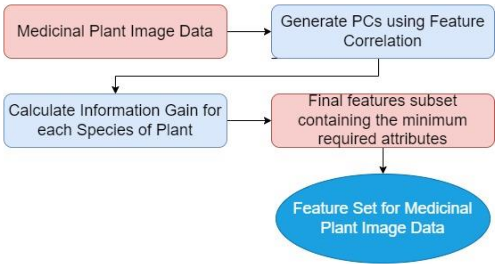

Figure 3. PCA Architecture for medicinal plant classification

2.3.2. PCA-VGG16 hybrid deep learning architecture

VGG 16 is a pretrained classification approach for medicinal plant image classification. VGG16 has a unique feature in that they used a 3×3 filter with a stride 1 and used the same padding and maxpool layers of a 2×2 filter of stride 2. Through the entire architecture, it follows the same arrangement of convolution and max pool layers. Finally, there is a fully connected layer (FC) followed by a softmax. VGG16 has 16 layers with weights, hence the 16th in the name. It consists of 138 million (approx.) parameters and is quite a large network. The composition of PCA with VGG16 provides a better result than the previous applied models. Medicinal plant image data contains a lot of dimensions which makes the classification process slow and inefficient. Here PCA is embedded in the beginning to reduce the dimensions of the image file. Ultimately VGG16 can now perform better runs to get better accuracy, hence making the classification process smooth. Figure 4 shows the architecture of PCA-VGG16 hybrid transfer learning model. The Hybrid PCA-VGG16 architectural plot is given in the Figure 5.

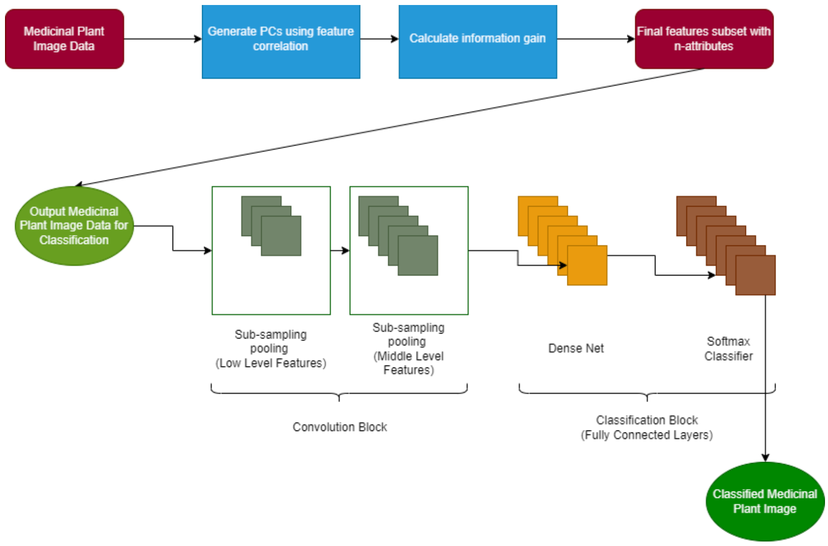

Figure 4. Hybrid PCA-VGG16 architecture for medicinal image classification

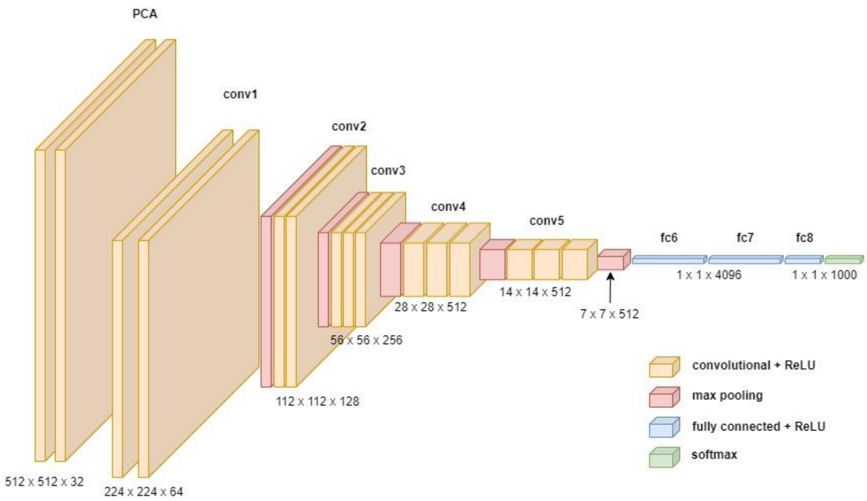

Figure 5. Hybrid PCA-VGG16 architecture plot for medicinal image classification

3. RESULT AND DISCUSSION

3.1. Dataset

Dataset used for this research has been taken from Mendeley data and it is updated on 22-Oct-2020. The dataset comprises 30 different species of medicinal plant found in the Indian sub-continent region. Thirty species of medicinal herbs are included in the dataset, including Santalum album (sandalwood), Muntingia calabura (jamaican cherry), Plectranthus amboinicus/Coleus amboinicus (Indian mint, Mexican mint), Brassica juncea (Oriental mustard), and several others. Fourteen species are represented by 1,500 images in the dataset. These images range from 60 to 100 in quality. Folders are organized according to the scientific or botanical names of the species [30]. Sample medicinal plant images from Mendeley dataset is illustrated in Figure 6. This study utilizes a mobile camera (Model: Samsung S9+) as well as a printer (Model: Canon Inkjet Printer In this dataset, the leaf images are rotated and tilted to maximize the benefit of deep learning and machine learning.

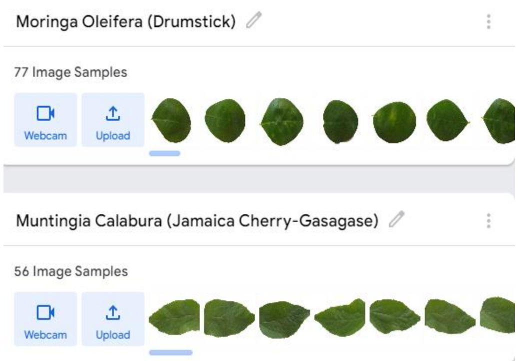

Figure 6. Sample images from Mendeley dataset

3.2. Training and evaluation

The above model has been using hybrid transfer learning model with PCA as feature extraction method and VGG16 as pre-trained model to classify the medicinal plant using leaf identification. The model was run with 10, 25 and 50 epochs and the results are given in the below Table 1. The training and testing of data have been done using python on anaconda notebooks. The epochs chosen were 10, 25 and 50, whereas the learning rate was 0.001 for all the given epochs. Batch size taken was 32.

For each epoch the confusion matrix was also calculated and is given below in figures. Figure 7 shows the confusion matrix for model with 50 epochs for 10 image classes. For each epoch we have also calculated accuracy and loss value, which is given in the below figures. The training and testing accuracy with 10 epochs is given in Figure 8 and loss value variation is also shown in Figure 8. Test accuracy with 10 epochs is around

94%. Initially the loss was high but as the training continued the loss came as low as 8%. The training and testing accuracy with 25 epochs is given in Figure 9 and loss value variation is also shown in Figure 9. Test accuracy with 25 epochs is around 94%. Initially the loss was high but as the training continued the loss came as low as 7%. The training and testing accuracy with 50 epochs is given in Figure 10 and loss value variation is also shown in Figure 10. Test accuracy with 50 epochs is around 95%. Initially the loss was high but as the training continued the loss came as low as 5%.

Table 1. Accuracy result of hybrid transfer learning model for medicinal plant classification

No of Epochs	Batch size	Learning rate	Training accuracy	Test accuracy	Loss function value
10 Epochs	32	0.001	95.62%	94.28%	8.23%
25 Epochs	32	0.001	97.50%	94.98%	7.35%
50 Epochs	32	0.001	98.22%	95.25%	5.22%

	Alpinia	Amaran..	Artoca..	Basella	Barasi..	Carissa	Citrus..	Ficus..	Ficus..	Hibiscus
Alpinia	24	1	0	0	0	0	0	0	0	0
Amaran..	0	21	0	0	0	1	0	0	0	0
Artoca..	0	0	18	0	0	1	0	0	0	0
Basella	0	0	0	19	0	0	0	1	0	0
Barasi..	0	0	0	0	19	0	1	0	0	0
Carissa	0	1	0	0	0	21	0	0	0	0
Citrus..	0	0	0	1	0	0	19	0	0	0
Ficus..	0	0	0	1	0	0	0	21	0	0
Ficus..	0	0	0	0	0	1	0	0	17	0
Hibiscus	0	0	0	0	1	0	0	0	0	20
Total for Class	24	23	18	21	20	24	20	22	17	20

Figure 7. Confusion matrix for 50 epochs

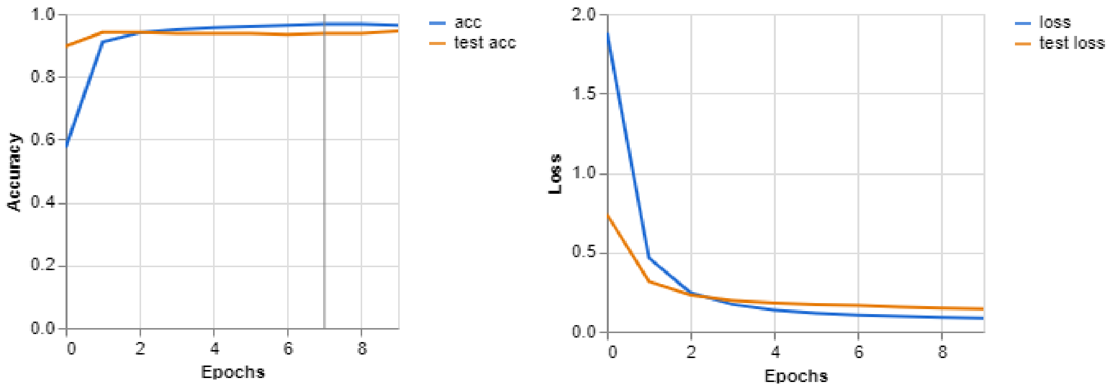

Figure 8. Accuracy chart and loss chart for 10 epochs

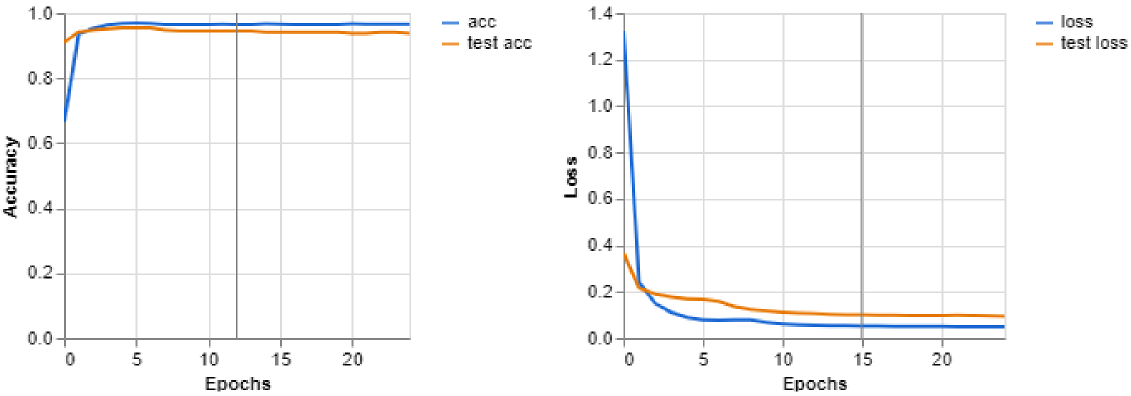

Figure 9. Accuracy chart and loss chart for 25 epochs

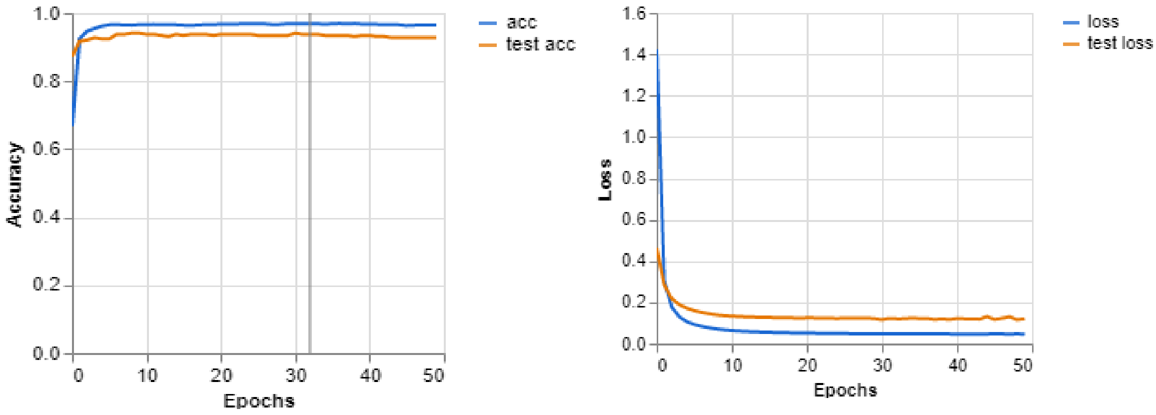

Figure 10. Accuracy chart and loss chart for 50 epochs

3.3. Comparison

The above model has been using hybrid transfer learning model with PCA as feature extraction method and VGG16 as pre-trained model to classify the medicinal plant using leaf identification. The model was run with 10, 25 and 50 epochs and the results are given in the Tables 1 and 2. Table 3 provides the comparison of results on different parameters for state-of-the-art transfer learning model on medicinal plant dataset.

Table 2. Comparison of result on different parameters for medicinal plant classification

No of epochs	Batch size	Accuracy	Precision	Recall	F1 score
10 Epochs	32	94.28%	0.9423	0.9528	0.9471
25 Epochs	32	94.98%	0.9425	0.9526	0.9477
50 Epochs	32	95.25%	0.9526	0.9523	0.9475

Table 3. Model comparison with other state-of-the-art transferring learning models

Models	Accuracy	Trainable parameters	Precision	Recall	F1 score
VGG16	76.00%	24,588	0.7621	0.7625	0.7698
Inception V3	82.50%	512,010	0.8225	0.8262	0.8245
MobileNet V2	87.92%	15,372	0.8747	0.8745	0.8725
ResNet 50	88.00%	70,458	0.8788	0.8787	0.8764
DenseNet 121	88.00%	7,222,755	0.8888	0.8878	0.8875
Xception	88.26%	75,252,722	0.8845	0.8245	0.8278
PCA Based VGG16	95.25%	286,348	0.9526	0.9523	0.9475

4. CONCLUSION

The aim of this research is to propose a PCA based hybrid transfer learning model for the purpose of classifying medicinal plants with help of medicinal plant leaf identification. VGG16, Resnet50, InceptionV3, Xception, DenseNet121, and MobileNetV2 are the experimental models for comparison purposes. Using a 200-neuron fully connected layer, the pre-trained model on the ImageNet dataset is applied with the same weights. The learning rate was 0.001 with a batch size of 32 with 10, 25, and 50 epochs. We require at least 50 epochs to achieve a satisfying result. Increasing epochs may result in better accuracy. The accuracy of our hybrid model was around 95% which is far better than the models used for comparison. From the above discussion we can conclude that PCA based hybrid models can perform better than other pre-trained models. A deep learning-based approach uses hand-crafted features to significantly outperform the traditional method. Adding more images and layers could enhance performance even though we are satisfied with the current performance of the system. Though this system suffers from computational issues it required a high memory consumption for its working and could not be suitable for embedded systems.

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