Advanced Medicinal Plant Classification and Bioactivity Identification based on Dense Net Architecture

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***Abstract*—Plant species identification helps a wide range of stakeholders, including forestry services, botanists, taxonomists, physicians and pharmaceutical laboratories, endangered species organizations, the government, and the general public. As a result, there has been a spike in interest in developing automated plant species recognition systems. Using computer vision and deep learning approaches, this work proposes a fully automated system for finding medical plants. As a result, work is being done to classify the correct therapeutic plants based on their images. A training data set contains image data; this work uses the Indian Medicinal Plants, Photochemistry, and Therapeutics (IMPPAT) benchmark dataset. Convolutional Neural Network (CNN) with DenseNet algorithm is a classification system for medicinal plants that explains how they work and what they're efficient. This study also suggests a standard dataset for medicinal plants that can be found in various parts of Manipur, India's northwest coast state. On the IMPPAT dataset, the suggested DenseNet model has a recognition rate of 99.56% and on the Manipuri dataset; it has a recognition rate of 98.51%, suggesting that the DenseNet method is a promising technique for smart forestry.**

Keywords*—*Indian medicinal plants; convolutional neural network; DenseNet; IMPPAT dataset

I. Introduction

In Siddha, Unani, Ayurveda, and homeopathic medicines, there are around 8,000 herbal cures. Herbal plants are used for medical purposes by nearly 75% of the migrant population, according to survey results [1]. Drugs are used to make herbal medicines in both developed and developing countries, and India's economic importance is taken into account. For accurate plant categorization, more taxonomic traits of a plant are collected from the images.

The most prevalent approach for classifying medicinal plants is by manual identification. To begin, people use their eyes, noses, hands, or other human organs to obtain information about the full plant or specific sections (leaf, flower, fruit, or bark) [2, 3]. They will identify therapeutic plant species based on either references or personal experience. However, the practice has shown that such an identification approach is time-consuming, inefficient, and strongly reliant on people's knowledge and subjective experience.

Computer-based automated image identification is now widely employed in practice, thanks to advancements in image processing and pattern recognition technologies. Because plant leaves are simple to gather, recognize, and catch, they are frequently employed as the primary foundation for identifying medicinal plants. To categorize medicinal plants and transmit their distinct medicinal purposes, this study employs a Convolutional Neural Network (CNN) with the DenseNet method.

II. Literature Survey

This section discusses the method of systematic literature review for research published in Automated Medicinal Plant Taxonomy. Researchers have explored a variety of methods to extract traits and automatically identify plant species. Many characteristics, such as color, form, texture aspects, and so on, are combined in most of these approaches [4-6]. To acquire the optimum discriminant characteristics for recognizing unique plant species, the Hybrid Feature Selection (HFS) technique is applied [7,8].To classify the leaves, the system in [9] employs to train the dataset, use decision trees, and variables such as lengths, breadth, aspect ratio, dimension, leaf boundary, and form of property are extracted from the leaves.

They introduced a new approach for categorizing plant leaves in [10, 11], which uses the Maximum Margin Criterion (MMC) to reduce the dimensionality and the Radial Base as new form storage. In [12-14], the researcher combined shape and textural features from leaf images to classify the medical plants. Researchers from India's Western Ghats reported on a computer vision approach for recognizing Ayurveda medicinal plant species in [15, 16]. Using the K-NN classification approach [17], a collection of SURF and HOG features were extracted from leaf pictures for identification.

Researchers [18-20] devised a CNN-based plant identification tool called CNN codes to collect bottleneck features. Finally, SVM was used to train these CNN codes for classification. D-Leaf, fine-tuned Alex Net, and pre-trained Alex Net are three different Convolutional Neural Network (CNN) approaches used to pre-process the leaf images and extract the properties [21, 22]. According to the analysis, identifying several traits such as form, vein, color, and texture would also have a substantial impact on the classifier's accuracy. Higher accuracy may affect the development of medicinal plant use in medicine, as well as the automatic detection identification number, which would have a significant impact on environmental conservation and preservation. Therefore, this work uses Convolutional Neural Network (CNN) with DenseNet algorithm to classify the medicinal plants and convey their respective medicinal uses [23-24].

III. Proposed Methodology

The proposed DenseNet Classifier-based medicinal plant classification system is discussed in this section. The suggested system's block diagram is shown in Fig. 1. For classifying medicinal plants, the suggested system has four stages: image acquisition, image pre-processing, segmentation, and classification.

A. Preprocessing Adaptive Vector Median Filter

This research work used a combination of an Adaptive Vector Median Filter and an average detection filter to reduce high-density impulse noise from feature extraction. A windscreen is used to process a W (5x5) image that has been influenced by noise sources. Using the non-causal region, the non-causal linear forecasting error for the pixel in question will be computed initially. Let Ix be the pixel undergoing operation, y be the related non-causal area, and W (5x5) be the non-causal region. The pixel window of $W_{(5x5)}$ is calculated using equation (1).

$$W_{(5\times5)} = P(a, b), x-2 \leq a \leq x+2, y-2 \leq b \leq y+2 \quad (1)$$

Where $I(a, b)$ = Processing region of inside pixel.

$$I(a, b) = [I(a, b)R, I(a, b)G, I(a, b)B] \quad (2)$$

The R, G, and B channels make up each pixel in a color image. A substantial correlation exists between pixels in the two-dimensional surroundings. The current pixel value is calculated using this method as a weighted linear combination of the adjacent noise clean pixels. As an outcome, the particles' unity may be lost when aggressive input affects an image. The workflow for preprocessing is shown in Fig. 2.

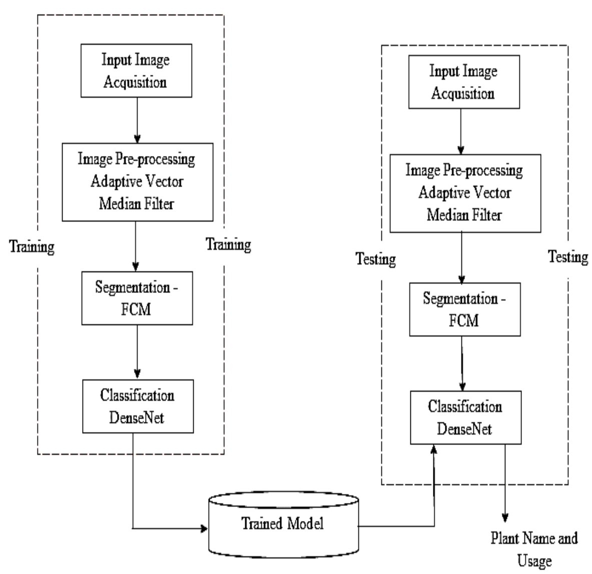


Fig. 1. Block Diagram of Proposed System.

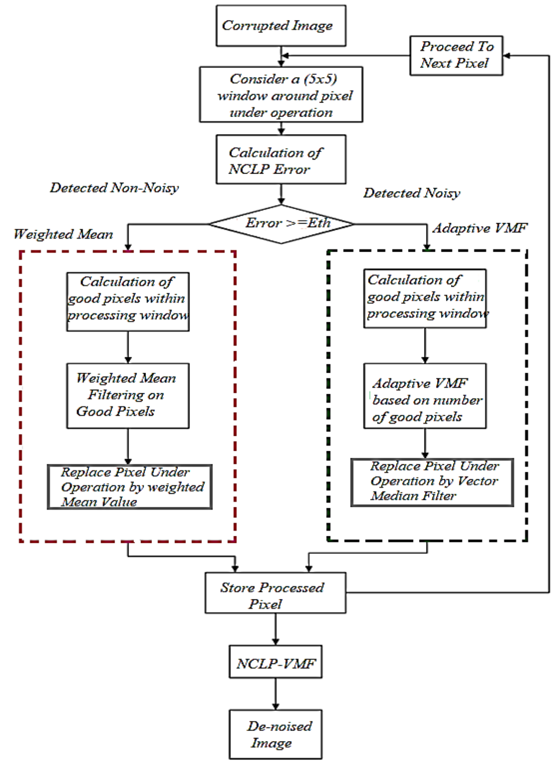


Fig. 2. Flow Chart of Pre-Processing.

B. Segmentation –Fuzzy C Means Clustering

In image processing, fuzzy C – Means clustering has proven to be a very useful strategy for segmenting elements in an image. Unlike other clustering techniques such as k-means segmentation that requires particles to belong to only one classification, FCM permits pixels to belong to several clusters with various class labels. The Fuzzy C - Means (FCM) algorithm is a widely used fuzzy inference approach. It's based on Ruspini's fuzzy partitioning technique; therefore fuzzy c- space for X is discussed below.

For clustering, the Fuzzy C-Means (FCM) algorithm is commonly used. The FCM algorithm's performance is determined by the initial centroids and/or the initial membership value. If a better initial pinpoint the exact that is close to the actual final data point can be found, the FCM algorithm will converge very quickly, reducing processing time significantly. K-means is one of the most basic unsupervised learning algorithms for dealing with the well-known clustering problem. The procedure follows a simple and easy method for classifying a given data set using a fixed number of clusters (assume k clusters). The central concept is to define k centroids, one for each cluster. These centroids should be housed cleverly.

$$M_{fcm} = \{U \in U_{Cn}: u_k \in [0,1]\} \quad (3)$$

$$\sum_{i=1}^{\epsilon} u_{ik} = 1, 0 < \sum_{k-1}^{n} u_{ik} < n\} \quad (4)$$

Where

U_{cn} = real c*n matrices c = integer Value with the range of 2<c<n.

x_k(k=1,........n) = vector in R^p, u_{ik} = membership value for k in cluster i(i = 1, ...,c)

The primary purpose of FCM analysis is to find the best fuzzy c-partition and prototype while keeping the feature subset to a minimum.

$$J_m(U,V;X) = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m \,|X_k - V_i|^2 \tag{5}$$

Where

V = cluster center (v_1, v_2, ...,v_c) $V_i \in R^P$, $||.||$ = Norm of Euclidean

m = Exponent of weighting [1,∞).

The FCM algorithm is a fuzzy constraint minimization technique that uses alternating minimization to minimize the criterion Jm. Choose a value for c, m, and a tiny positive variable; use a clustering U_0 with t=0 as the iteration number in random design. The FCM algorithm is a fuzzy constraint minimization approach that minimizes the criteria J_m using minimization that alternates. Choose a value for c, m, and a tiny positive variable, then construct a clustering U_0 at random using t=0 as the number of iterations. It's a two-step incremental method; approach is illustrated in the diagram below. The $U^{(t)}$ i (i=1, c) method is used to determine the membership values.

$$V_i^{(t)} = \frac{\sum_{k-1}^{n}(u_{ik}^{(t)})^m x_k}{\sum_{k-1}^{n} u_{ik}^{(t)})^m} \tag{6}$$

Given the new cluster centers $V_i^{(t)}$ update membership values$u_{ik}^{(t)}$

$$u_{it}^{(t+1)} = [\sum_{j=1}^{c}(\frac{|x_k - v_i^{(t)}|^2}{|x_k - v_i^{(t)}|^2})^{\frac{1}{m-1}}] \tag{7}$$

The | $U^{(t+1)}$-$U^{(t)}$| is the difference of Gaussians Pyramid. By deleting a low pass filtered copy first, the image's pixel-to-pixel correlation is decreased. The variance and entropy of the difference or error image are low, and the low pass filtered image can be described with a lower sample density. When you cycle the procedure at large enough scales, you have a pyramid data structure. Assume that I represent the original image and J represents the applied low pass filter. The method ends when the specified number of repeats is reached. The term "Laplacian Pyramid" is misleading because each level (i.e., image) is created by smoothing with two Gaussians of different sizes, then deleting and subsampling.

C. Convolutional Neural Network with DenseNet Classifier

Deep Learning (DL) is proposed because approaches can learn substantial characteristics from input images at multiple convolutional levels, which is comparable to how the real brains functions, this is the most prevalent architecture. DL can tackle complex issues successfully and quickly, thanks to its high classification accuracy and low error rate. The composed view of DenseNet architecture is shown in Fig. 3.

The convolutional layer, pooling layer, fully connected layer and activation functions are the essential components in the DL model. In this study, CNN was combined with the DenseNet Classification approach to acknowledge plants. The vanishing gradient problem induced by network depth is likewise addressed by this network. The connection designs of all layers are employed to ensure that the maximum amount of information may travel across levels. Each layer gets input from the layers above it and communicates its feature maps to the layers below it in this configuration. By concatenating the local characteristics at each layer, information is transmitted from one level to the next. This network architecture minimizes the need to remember redundant data, reducing the number of parameters to learn significantly (i.e., parameter efficiency).

DenseNet121 does not suffer from generalizing and performed admirably for categories with a little training data set. In this work, Dense Net was used, and Fig. 4 shows a compressed version of it. DenseNet alternates dense and transition blocks with fully-connected layers and a nonlinear activation classifier. So based on this BN layer, Convolutional Layer (Conv) and leaking rectified linear unit layers are merged with the cascaded format in a dense block such as BN-Conv-LReLU.

The first BN-Conv-LReLU is generating 4r output features using 1x1 kernels, where r is a pre-defined value of 32 in this work. The dense block increases the number of maps by connecting output feature maps to the ability to segment. During the transition, a convolutional unit is used, followed by average max pooling with a pool size of 2x2. The transition construction's goal is to find the best combination of extracted characteristics produced by a large number of convolutional layers while saving time and money. The number of output feature maps in the transition block in this exercise is equal to the number of input nodes.

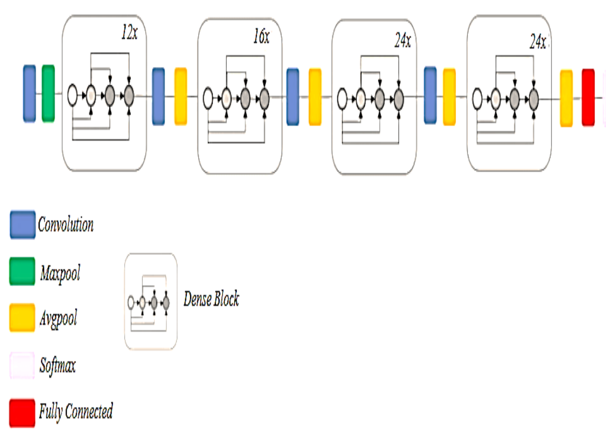
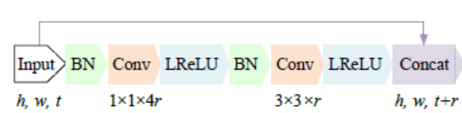
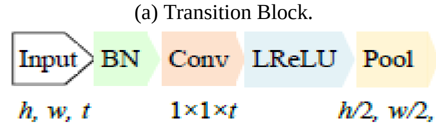


Fig. 3. Composed View of Dense Net Architecture.



(a) Transition Block.



(b) Height, Width, and the Number of the Input Feature Maps, Respectively.

Fig. 4. Details of Dense Block

TABLE I. DENSE NET STRUCTURE AND OUTPUT

Module	Detail	Output
Convolution	1 x 1 x64 conv	128 x128x 64
Max-pooling	2 x2 pool	64 x 64 x 64
Dense block 1	1 x 1 x 128 conv ,3 x 3 x 32 conv	x 2 64 x 64 x 128
Transition block 1	1 x 1 x 128 conv, 2 x 2 pool	32 x 32 x 128
Dense block 2	1 x 1 x 128 conv, 3 x 3 x 32 conv	x 3 32 x 32 x 224
Transition block 2	1 x 1 x 224 conv, 2 x 2 pool	16 x 16 x 224
Dense block 3	1 x 1 x 128 conv,3 x 3 x 32 conv	x 4 16 x 16 x 352
Transition block 3	1 x 1 x 352 conv,2 x 2 pool	8 x 8 x 352
Dense block 4	1 x 1 x 128 conv,3 x 3 x 32 conv	x 2 8 x 8 x 416
Global average pooling		1 x 1 x 416
Full-connection	416 x θfull-connection	θ
Softmax	softmax classifier	θ

Table I shows the DenseNet structure and output, assuming that the input images are 128x128 and the input image size is 128x128, respectively. The algorithm uses the Indian Medicinal Plants, Phytochemistry, and Therapeutics (IMPPAT) benchmark dataset to classify medicinal plants, and it also has a dataset from the Manipuri district.

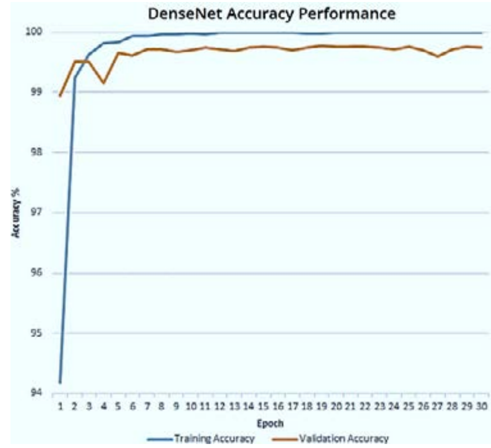
IV. RESULT AND DISCUSSION

The proposed medicinal plant classification system's implementation results and performance analysis are discussed in this section. Table II contains information about the dataset utilized in this study.

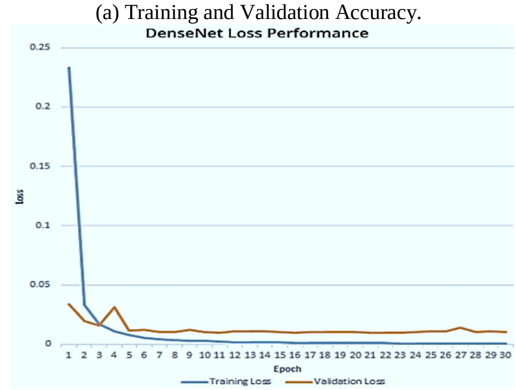
The simulation result of training and validation accuracy and Training and Validation Loss of proposed CNN with DenseNet classifier is shown in Fig. 5 and Fig. 6. By using CNN DenseNet the training and validation accuracy is 99.45% and 99.26% against IMPPAT Dataset. By using CNN DenseNet with IMPPAT dataset the training and validation loss is 0.05MSE and 0.065MSE. By using CNN DenseNet the training and validation accuracy is 99.68% and 99.41% against own dataset. By using CNN DenseNet with its own dataset the training and validation loss is 0.041MSE and 0.052MSE.

TABLE II. DATASET DETAILS

Dataset Name	IMPPAT database	Own database
Number of Images	1742	200
Training Images	1404	160
Testing Image	338	40
Software Used	Python	Python

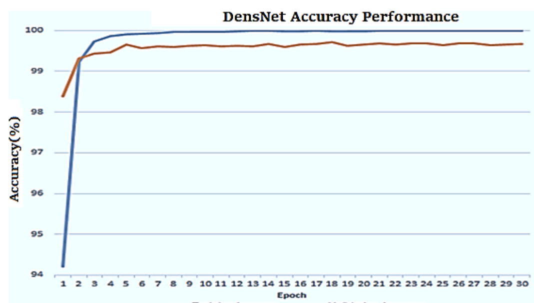


(a) Training and Validation Accuracy.

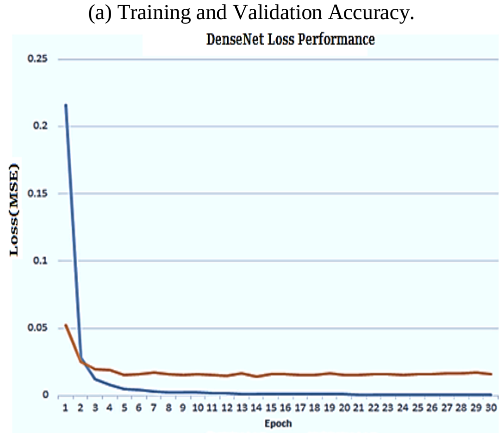


(b) Training and Validation Loss.

Fig. 5. Accuracy and Validation Loss of Impact Dataset.



(a) Training and Validation Accuracy.



(b) Training and Validation Loss.

Fig. 6. Accuracy and Validation Loss of Own Dataset.

A. Performance Analysis

The classifier's performance is assessed by different statistical measurements, such as sensitivity, specificity, accuracy and F1-score. Table III shows the comparing the suggested CNN-DenseNet Classifier-based medical plant classification with existing approaches in terms of total classification ratio analysis. CNN-DenseNet gives good results compared with conventional methods. The sensitivity, specificity, accuracy, and F1-score of CNN-DenseNet against the IMPPAT dataset are 99.25%, 99.56%, 99.78%, and 0.61. The sensitivity, specificity, accuracy, and F1-score of CNN-DenseNet against own dataset is 98.12%, 97.56%, 98.01%, and 1.25.

TABLE III. PERFORMANCE ANALYSIS OF CLASSIFICATION

Methods		**Classification Sensitivity (%)**	**Classification Specificity (%)**	**Classification Accuracy (%)**	**F-Measure (%)**
SVM		89.46	91.23	89.49	15.03
SVM-PCA		90.06	91.56	89.11	12.06
SVM-GA		92.13	93.20	90.27	10.23
AUSP		97.29	97.41	97.73	5.01
CNN-Google Net		98.16	98.08	98.26	2.65
CNN-DenseNet	IMPPAT Dataset	99.25	99.56	99.78	0.61
	Own Dataset	98.12	97.56	98.01	1.25

B. Real Time Experimental Evaluation

This section discusses the working function of real time medical plant recognition using Mat-lab with webcam of proposed CNN-DenseNet Method.

The Real Time Experimental Evaluation of the proposed CNN-DenseNet Method-based medical leaf identification system is shown in Fig. 7. By using the CNN-DenseNet Method, the medical plants are identified and also suggest the bioactivity of that particular plant. In Fig. 7 the identified leaf name is a Gale of Wind and it's widely used to clear jaundice.

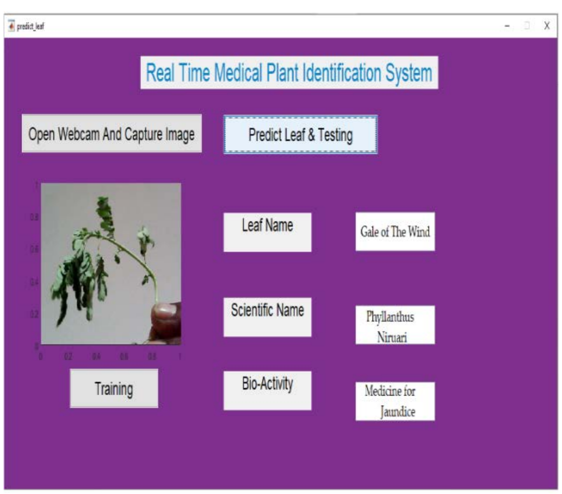


Fig. 7. Real Time Experimental Evaluation.

V. CONCLUSION

A unique deep learning-based technique for automatically identifying and detecting medicinal plants and their applications was examined in this study. The Indian Medicinal Plants, Phytochemistry, and Therapeutics (IMPPAT) benchmark dataset were used in this study and used its dataset, which is common in Manipuri, a state on India's northeastern coast. From gathering the images required for training and validation to data preprocessing and segmentation, and eventually training and perfectly alright the deep CNN-DenseNet, the entire method was covered. The performance of the newly designed model was evaluated through a series of experiments. CNN-DenseNet has 99.25% sensitivity, 99.56% specificity, 99.78% accuracy, and 0.61 percent F1-score against the IMPPAT dataset. CNN-DenseNet's sensitivity, specificity, accuracy and F1-score against the own dataset are 98.12%, 97.56%, 98.01%, and 1.25%, respectively. The challenge of recognizing medicinal plant species was also solved in this study by analyzing leaf photos taken straight from their habitat, regardless of lighting conditions. We intend to build and develop a system that automatically recognizes plant species by analyzing not just leaf photos but also images of other sections of the plant taken directly in their environment, regardless of complicated backdrops or lighting conditions.

VI. FUTURE WORK

A deep learning based detection approach is proposed in future work to recognize and classify the different types of plant actions. Future capturing the abnormal leaf image that contains activation of different leaf and finding specific part of area with more improved efficiency (per-packet classifications) and accuracy of these detections.

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