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RESEARCH ARTICLE

Deep Learning for the Classification and Recognition of Medicinal Plant Species

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Abstract

Objective: The Indian Forest is the primary source of many medicinal herbs. Medicinal plants have long been the subject of extensive inquiry and contemplation due to their significance in human survival. Botanist professionals must classify and identify these plants, which is a hard and time-consuming process. As a result, a vision-based technique may help scientists and the general public to identify herb plants more quickly and accurately. As a result, this study proposes a vision-based smart strategy for recognizing herb plants that involve developing a deep learning (DL) model. Although there is a range of helpful plants, we limit ourselves to only 15 from the Kaggle database. **Methods:** Despite numerous studies, accurately identifying plant species using automation remains a challenge. In this system, we used 15 distinct Indian plants for experiment purposes. We use a dataset of 82,500 images, with around 5500 images of each species. We use leaf shape, texture, and color as the features, whether physiological or morphological. Four deep learning classifiers named Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs) and Multilayer Perceptrons (MLPs) are deployed on an optimized medicinal plant leaves dataset. **Findings:** The web based system can identify species by simply uploading an existing image. The multi-layer perceptron classifier performs well with an accuracy of 99.01%. Convolutional neural networks have an accuracy of 98.3%. **Novelty:** The novelty of our study lies in the intersection of comparison of advanced deep learning techniques. While earlier research has focused on plant identification issues, our approach contributes to the larger fields of explainable AI, and the construction of reliable models. In real-world applications, the background of leaves may change hence photographs with various backgrounds are employed for instructional purposes. Models trained on various backgrounds and can withstand alterations in the background.

Keywords: Deep learning; Generative Adversarial Networks; Multilayer Perceptrons; Recurrent Neural Networks; Convolutional Neural Network; Machine Vision

1 Introduction

A "deep learning " uses multi-layered artificial neural networks. These sophisticated networks are capable of changing a variety of sectors through their predictive skills. They can independently learn complex relationships and patterns in large datasets, excelling in tasks like the detection of images, classification, and complicated problem-solving[1,2]. Rotations flips, or color modifications are just a few of the transformations that data augmentation algorithms employ to enrich datasets[3].

Rapid and precise identification and classification of medicinal plant species are essential for efficient biodiversity management and study. The focus of deep learning is on teaching multi-layered artificial neural networks to extract data representations on their own[4]. Applications for it include the classification of species of medicinal plants. In the field of machine vision, deep learning techniques have shown impressive results. Applications like image enhancement and detection are widely used in industries, such as but not limited to industry, healthcare, agriculture, education etc.[5,6]. A unique strategy based on deep learning techniques is the best answer for detecting medicinal plants in the Ardabil region. The Transfer Learning approach uses a well-known pre-trained CNN architecture called mobile net v2 and obtained an accuracy of 98%.[7]. The Deep Learning (DL) model consists of a CNN block for feature extraction and a classification block for classifying extracted features. The classifier block consists of four layers: Global Average Pooling (GAP), dropout, dense, and softmax. As a result, the vision-based system achieved more than 99.3% accuracy across all picture definitions[8].

Researchers demonstrated how to identify Ayurvedic botanicals using machine learning as well as deep learning technology. The project intends to improve the precision and effectiveness in recognizing medicinal herbs applied to Ayurvedic medicine by utilizing these cutting-edge technologies, helping to preserve and apply traditional knowledge[9]. Narrowing the study's scope to six frequently utilized medicinal herbs enhances its focus, facilitating a comprehensive evaluation of specific species. Employing MobileNet as the preferred deep learning model is deemed suitable, especially for real-time and mobile applications. To augment the study's comprehensiveness and practicality, discussing potential challenges or constraints in deploying the model across various plants or environmental conditions would be beneficial[10]. The research suggests using a convolutional neural network (CNN) based on the VGG-16 model with deep learning to identify therapeutic plants. The study emphasizes the drawbacks of conventional methods due to the intricate appearance of medicinal plants. A sizable dataset, an astounding 98% detection percentage, and an emphasis on real-world utility for medical professionals are among its strong points[11]. The literature review offers an analysis of earlier studies on the classification of medicinal plant species using deep learning. The application of PRISMA principles and a careful selection procedure improved the study's rigor. One important conclusion is a worldwide data shortage[12]. With a focus on medicinal plants found in the Borneo region, the work addresses the need for efficient plant-type recognition using computer vision and deep learning techniques. The suggested approach consists of a smartphone application for instant detection and feedback, a knowledge library, and a deep learning model. Using a model based on EfficientNet-B1 outperforms the baseline, achieving 87% and 84% Top-1 accuracies on public and private datasets, respectively. Using the smartphone application, real-time testing on samples had a somewhat lower accuracy. The unique combination of geo-mapping and crowdsourcing feedback adds to the study's practical significance. The findings indicate a workable path toward a field-problem-solving real-time plant-type detection system[13]. In light of the difficulties caused by similar-looking plants and their restricted availability, this research investigates the critical role that precise plant identification plays in Ayurvedic treatment. Deep learning techniques are becoming increasingly popular to get more accurate classification because traditional machine learning methods have produced inconsistent results. Using a dataset of thirty species of medicinal plants from Mendeley Data, the study uses hybrid transfer learning methods. Remarkably, the model outperforms other popular transfer learning techniques with a test accuracy of 95.25%. In an attempt to provide more accurate and successful treatment outcomes, the research attempts to close the knowledge gap between machine-driven identification and the experience of Ayurvedic practitioners[14]. In a groundbreaking approach, OTAMNet is developed by incorporating Log-Gabor filters into the DenseNet201 architecture. The model's remarkable accuracy of 98% on the MyDataset[14] underscores its significance and efficacy[15]. Images of medicinal plants are used from the Indian Medicinal Plant Datasets collection on the Kaggle dataset. Without regard to environmental restrictions, the photographs are captured against a variety of backgrounds[16].

A novel plant leaf classification model using optimal feature selection and better segmentation is presented in this study[17]. Its preprocessing steps include RGB to greyscale conversion, median filtering, and histogram equalization. An optimized U-Net model is for leaf segmentation. The Crow-Electric Fish Optimization (C-EFO) algorithm is used to extract and decrease features such as shape, colour, and texture. The Enhanced Recurrent Neural Network (E-RNN) is used for classification, and it produces better results than traditional models like k-NN, VGG16, LSTM, and RNN. The suggested approach is feasible and practical, as demonstrated by the experimental findings on two plant leaf databases. The study offers an analysis of current studies on deep learning-based picture classification. It includes recent developments intended to improve deep learning models' performance in picture categorization tasks. The review also explores the detection of potential issues and difficulties related to deep learning technology[18].

2 Methodology

2.1 Dataset Collection

Medicinal Plants dataset is available for use[16]. Furthermore, we have individually taken and pre-processed pictures of the medicinal leaves to include in the dataset. The mobile camera is used to take pictures of the leaves, and the direction of the leaves in the photos is not restricted. A total of 82500 photos representing 15 different types have been taken, with 5500 images of each type.

2.2 Proposed system 1: Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are incredibly efficient at image classification. Multiple layers in CNN models convert input data into output. Fully Connected, Pooling, and Convolutional layers are the main parts utilized in the processing of RGB images. Convolutional layers use local correlation in pictures to extract low-level characteristics such as corners, edges, and patterns. Feature selection and down sampling from higher-level feature maps are achieved via pooling layers. As a result, overfitting is avoided and network parameters and training time are reduced. Maximum and Average pooling are the two most used varieties of pooling layers. After applying Convolutional and Pooling layers, Fully Connected layers take over. These layers link each neuron to each other using neurons, biases, and weights. As seen in Figure 1, the architecture of the image recognition model consists of five convolutional blocks and a classifier block. In Figure 2, an architecture diagram is displayed. Each of the five convolutional blocks uses the output of the previous block as an input for the subsequent one. Form, colour, and texture attributes are extracted using two convolutional layers with 3x3 kernels and a stride of 1 pixel in each convolutional block. Activation functions like ReLU layers come after every convolutional layer. Batch normalization layers are applied after convolutional layers to enable deeper CNNs and minimize the amount of training iterations needed. Feature maps are made smaller by employing max-pooling layers with a stride of two and a size of 2 by 2. To avoid overfitting, a 0.1 dropout layer is incorporated throughout every block.

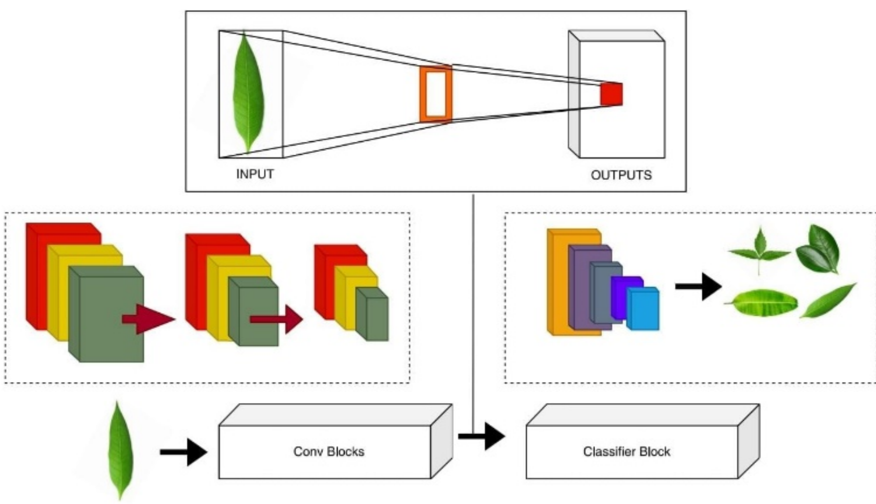

Fig 1. The architecture of the CNN model for image recognition [2]

2.3 Proposed system 2: Recurrent Neural Networks (RNNs)

Recurrent neural networks are potent neural network applications utilized in image processing and speech synthesis applications. The suggested approach presents a method for identifying leaves of plants using edge morphology and Recurrent Neural Networks (RNNs), taking advantage of the distinctive shapes of plant leaves. This method incorporates Edge feature estimates to increase precision and effectiveness. A kind of neural network that operates sequentially is called a recurrent neural

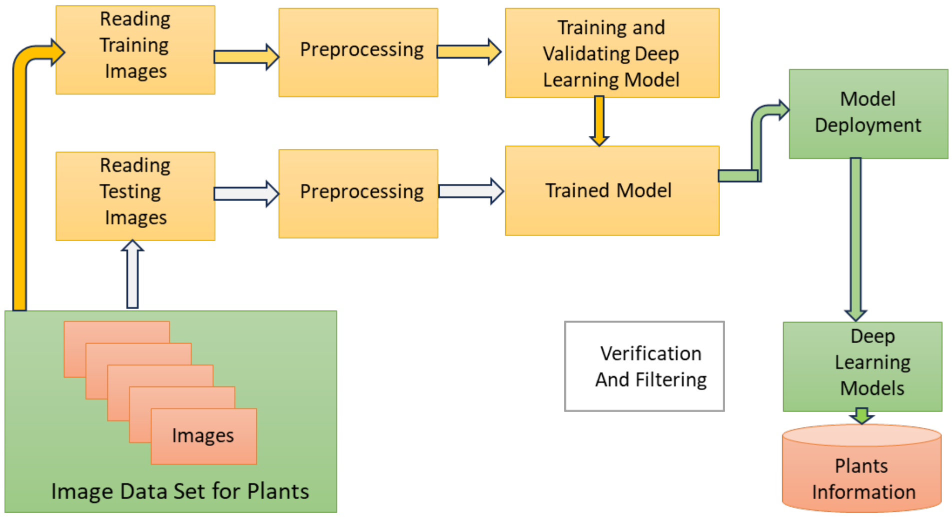

Fig 2. Architecture diagram

network. This would imply that the recurrent neural network can learn the challenges and offer a more thorough comprehension of the issues. The reason for this is that a sequential algorithm needs memory to retain the input that has already been sent to the machine.

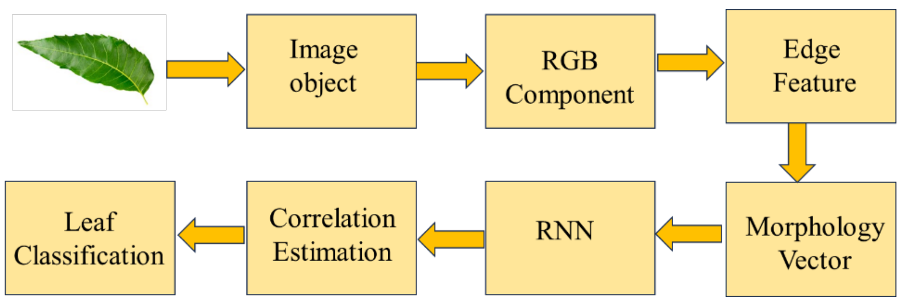

Fig 3. Overview of the Proposed Methodology

2.4 Proposed system 3: Multilayer Perceptrons (MLPs)

Multilayer Perceptrons (MLPs) belong to the family of feedforward neural networks, which are made up of activation function-equipped layers of perceptrons. Fully interconnected input and output layers, sometimes with several hidden layers, are the defining features of MLPs. Their adaptability reaches to software creation for machine translation, picture and speech recognition, and other fields.

In current research, a multiple-layer feed-forward network technique is used to identify medicinal leaves. Form, color, and vein properties are taken into account. The leaf images are preprocessed and segmented, and the features—like area, diameter, length, width, perimeter, eccentricities, solidity, major and minor axis length—are extracted from the segmented leaf image. Furthermore, the mean, variance, skewness, and curves of the RGB spectrum characteristics are calculated. Canny edges detection and Wiener filtering are used at different thresholds to identify vein features such as Vn1, Vn2, Vn3, and Vn4. The identification procedure entails calculating grey-level values from the grey-level histogram. MLP has numerous layers of nodes in a directed graph, with each layer fully connected to the next. Except for the input nodes, each node is classified as a processing element or neuron with a nonlinear activation function. MLPs use backpropagation to train their networks. The perceptron learns by adjusting connection weights depending on output errors vs expected results.

Table 1. P arameters for MLP classifier

Parameter	Value
Input Layers	1
Hidden Layers	28
Neurons	18
Learning Rate	0.7
Momentum	0.5
Validation Threshold	18
Epoch	400

2.5 Proposed system 4: Generative Adversarial Networks (GANs)

The potential of GANs is to address issues associated with tiny datasets. GAN, a generative model, consists of two neural networks—the generator and the discriminator—that are trained simultaneously. The generator creates realistic images, whereas the discriminator distinguishes between synthetic and real images. GANs are used to generate synthetic images that resemble authentic photographs for datasets with limited training size.

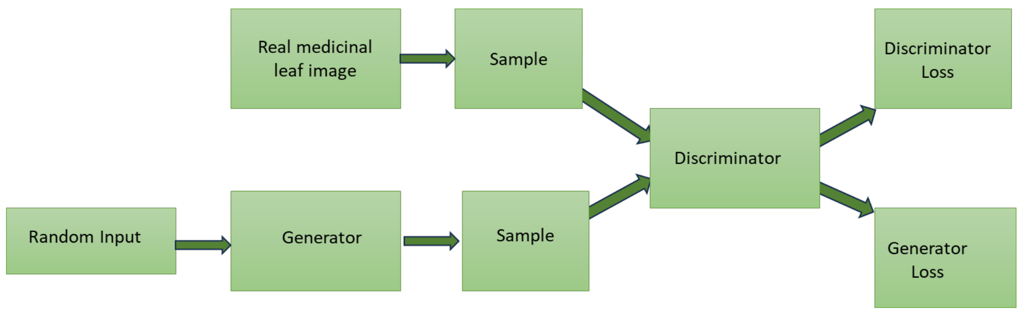

Fig 4. Generative Adversarial Networks

To generate synthetic images, we used WGAN GAN models to train distinct groups with varying amounts of medicinal plant species. We examine classification performance between actual, fake, and mixed images produced by GANs trained on several medicinal plant classes. The Wasserstein GAN (WGAN) stands out as a prominent model for image generation, employing a cost function rooted in the Wasserstein distance between authentic and generated images. This innovative approach addresses challenges such as vanishing gradient and mode collapse, making WGAN a widely acclaimed solution in the field of image generation. WGAN applies discriminator weights within a range defined by hyperparameter c, resulting in a loss function that accurately reflects image quality. If hyperparameter c is not properly set, the model will output low-quality images and fail to converge. We used a model called VGG16 for the extraction of features via transfer learning. Based on the prediction provided by the VGG16 model, we gave the accuracy, recall, precision, and F1-score.

2.6 Evaluation Measurement

A confusion matrix was utilized to demonstrate the relationship between the effectiveness of the algorithm and its true values. A successful recognition system should produce a small number of false positives and negatives. The proposed algorithm's effectiveness was then assessed utilizing the accuracy evaluation, based on the ratio of correctly anticipated observations compared to all observations, as indicated in the equation below.

True Negatives (TN) are cases in which the algorithm accurately predicts the negative class. False Positives (FP) occur when the algorithm predicts a positive class while the true class is negative. False Negatives (FN) occur when the algorithm predicts a negative class while the true class is positive.

$$Accuracy = \frac{TP+TN}{TP+FP+TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = 2\ X\ \frac{Precision\ X\ Recall}{Precision + \ Recall}$$

Cohen's Kappa is a helpful indicator of classification model performance that exceeds what would be predicted by chance.

$$Kappa\ = \frac{P_o - P_e}{1 - P_e}$$

$$P_o = Observed\ agreement = \frac{TP + TN}{TP + FP + FN + TN}$$

P_e denotes the hypothetical probability of random agreement.

$$Expected\ agreement\ = P_e = \frac{(Total\ positive\ predictionns) X\ (Total\ positive\ actual\ instances) + (Total\ negative\ predictionns) X\ (Total\ negative\ actual\ instances)}{(Total\ instances)^2}$$

3 Results and discussion

We made use of 256 × 256-pixel photos. The proposed method 1 develops a convolutional neural network-based categorization method for medicinal plant leaves. Figures 4 and 5 illustrate the outcomes of an end-to-end computer vision system that uses a convolutional neural network (CNN) model to identify different kinds of medicinal plants based on an image. When it comes to handling images and videos, convolutional neural networks (CNNs) perform better than ordinary neural networks. Standard feedforward neural networks are unable to utilize the intrinsic properties of various visual input modalities, which they may be able to exploit.

Typical neural networks do not have an intrinsic understanding of the structure or order of the incoming input. CNNs, on the other hand, take advantage of pictures' inherent spatial coherence. They can significantly reduce the computing complexity needed for image processing because of this crucial feature. CNNs can recognize and depict regional structures and trends. We have proposed a technique that is more effective and efficient than the method that was set out. The model is tested with different image backgrounds and in a variety of environmental settings. Different image backgrounds have an impact on how this system performs.

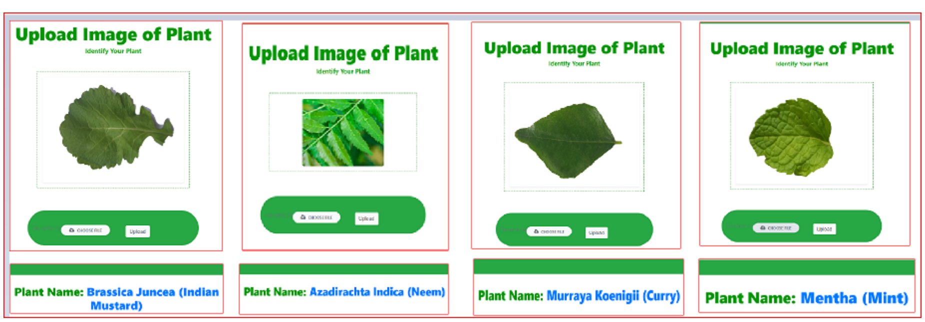

Fig 5. Upload Window with Leaf Image and Plant identification (below)

The proposed method 2, leaf categorization algorithm based on Recurrent Neural Networks (RNNs) analyzed more than 5500 leaf images from 15 species in real-time. After transforming each leaf image into an edge image and creating a morphology vector using these edges it is then saved in a file. All leaf images are painstakingly indexed. The image's shape is concisely represented along a single axis by this morphology array. For the input leaf image, a comparable morphology array is generated during the search process. Next, the degree of correlation between the saved vector with the input leaves vector is measured by calculating their Pearson correlation value. The system compares the input image to the stored image that has the highest correlation value.

Proposed method 3, MLP classifier combined with the K-Means clustering technique demonstrated a method accuracy of 99.01%. Proposed method 4, GANs lack inherent assessment metrics due to their two-network structure (generator and discriminator). GAN models include multiple hyperparameters based on data type and selected features during training, making performance evaluation difficult. Image augmentation with WGAN achieves high accuracy (94% and 96.77%) throughout training.

Table 2. Classification of medicinal plant leaves Recall, ROC, Time, precision and F1 scores, TP, FP and Kappa Statistics

Classifiers	Kappa Statistics	True Positive Rate	False Positive Rate	Recall	F1-Score	Receiver Operating Characteristic	Time (Sec)	Precision
MLP	0.96	0.95	0.009	0.95	0.95	0.99	0.2	0.99
CNN	0.95	0.94	0.011	0.96	0.95	0.98	0.12	0.983
RNN	0.92	0.93	0.02	0.93	0.94	0.97	0.3	0.97
WGANs	0.91	0.92	0.03	0.92	0.92	0.96	0.14	0.96

4 Conclusion

Through the use of custom features, a deep learning-based approach performs better. An improved CNN network with layers for global average pooling, dense learning, dropout learning, and softmax learning for classification has been integrated into a real-time vision-based system. This creative technique lowers the number of parameters while simultaneously increasing accuracy and processing speed. This cutting-edge algorithm can classify medicinal plant photos with different degrees of detail, which will help meet the growing need for medicinal plants in many industries. It might be better with more pictures and layers.

The mean absolute error (MAE) is pre-owned to evaluate the efficacy of the Recurrent Neural Networks-based system. The system's exceptional MAE of 0.08 and accuracy of 98.9 % are demonstrated by the experimental results. The system displays excellent performance in comparison with different leaf classification models. These outcomes highlight the system's effectiveness and precision in categorizing plant leaves according to their morphology.

5 Future scope

Deep learning algorithms improve, and the future vision includes the creation of progressively powerful models capable of accurately distinguishing various species, resulting in advancements in healthcare, preservation of the environment, and pharmacology. Future research can concentrate on expanding the dataset and evaluating the model in more difficult real-world scenarios. This may entail gathering data from various geographic regions, ecosystems, and conditions in the environment to guarantee the model's flexibility in multiple scenarios. Developing models to work in changing and unexpected environments, such as the wild, is important to their effectiveness.

6 Data availability

1. https://www.kaggle.com/datasets/aryashah2k/indian-medicinal-leaves-dataset
2. https://www.kaggle.com/datasets/surajkarki66/medicinal-plant-leaf-images

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