PLANT RECOGNITION USING DEEP LEARNING

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***Abstract*—A crucial area of study in earth's ecology is the dentification of plants, which helps to preserve the atmosphere. Several of these plants have important therapeutic qualities. These days, identifying a plant solely based on its physical characteristics is difficult. An academic database of works published between 2015 and 2020 is offered by this paper. In the field of image recognition, it has been noted that the latest generation of convolutional neural networks (CNNs) has demonstrated impressive performance. This paper discusses various leaf recognition techniques and the ideas behind deep learning [8] Growing our knowledge and comprehension of the plants that are all around us is essential for sustainable agriculture, economic growth, and medical applications. In computer vision, the identification of plant images has emerged as an interdisciplinary area of interest. Convolutional neural networks (CNN) approach is considered to learn feature representation of 185 classes of leaves taken from Vietnamese herbs dataset in natural environment in Vietnam, [11] under the benign conditions of rapid advancements in computer vision and deep learning algorithms. A five-stage, 50-layer deep residual learning framework is designed for the large-scale classification of plants in their natural habitat.**

***Index Terms*—Recognition, Plants, Fully Connected Neurons, Convolutional Neural Network, Deep Learning, Image Processing.**

I. INTRODUCTION

As primary producers and major contributors to the planet's biodiversity, plants are essential to the survival of life on Earth. Accurate plant species identification and classification is essential for ecological research, agriculture, biodiversity conservation, and even health care. [4] Conventional plant identification techniques mainly rely on human observation, botanical knowledge, and occasionally laborious procedures that could be mistake-prone. However, recent developments in the artificial intelligence sub-field of deep learning have completely transformed the field of plant recognition, providing exciting new possibilities for the automated and effective identification of plant species. Convolutional neural networks (CNNs), in particular, are deep learning models that have demonstrated impressive potential in image recognition tasks. [4] [5]These models are ideal for the complex visual nature of plants because they can automatically learn intricate features and patterns from raw data. These networks, which make use of sizable data-sets of plant photos, are able to identify distinctive traits like leaf forms, textures, flowers, and other differentiating elements, which allows for precise species classification.

This scientific investigation explores the application of deep learning to plant recognition, going over the approaches, difficulties, and developments in the field. It focuses on transfer learning, data augmentation methods, deep learning model development and optimization, and computer vision and botanical science integration. It also looks into the effects of using these models in practical applications like smart agriculture systems, smartphone apps, and ecological surveys. [5]

II. MOTIVATION

To detect and categorize plants, [6] deep learning techniques can be used for a number of convincing reasons. Numerous disciplines, such as agriculture, environmental science, conservation, and others, are represented by these motives. Here are a few of the main explanations: Plant identification can help with the conservation of endangered species and habitats. Conservationists might take targeted protective measures for rare or vulnerable plant species by using deep learning to identify and monitor them in their natural settings. Agriculture and crop management: Tasks like disease diagnosis, pest control, and yield prediction can benefit from deep learning-based plant recognition in agriculture. These technologies may be used by farmers to enhance crop management and raise overall yield. Detection of Invasive Species: Invasive plant species can damage native flora and wildlife and disturb ecosystems. Deep learning can help with invasive plant identification and management, enabling more successful control and eradication operations. Herbal and Medicinal Plants: Traditional medicine and pharmaceutical research may both benefit from identifying and classifying herbal and Medicinal Plants. The identification of these important plant species may be automated with the use of deep learning. Botanical Research: Deep learning methods that speed up the process of classifying and identifying plants can be useful to botanists and scholars. This can make it easier to analyze how plants have evolved, spread, and adapted to various habitats. Education and citizen science: Deep learning-based plant recognition can be a useful instructional tool. It can help identify plants and involve students and lay people in science.

According to [9] A major challenge is identifying plants, particularly for biologists, chemists, and environmentalists. Plant recognition may be done manually by professionals, but it is a laborious and inefficient operation. The automation of plant recognition is a crucial step for industries that operate with plants. In this study, a method for identifying plants using photographs of their leaves is presented. To identify different plant species, k-Nearest Neighbor, Support Vector Machines, Naive Bayes, and Random Forest classification methods are combined with shape and color information collected from leaf photos. 32 different types of leaves and 1897 leaf photos were used to evaluate the proposed methodology. [10]

A. *Methodology and Analysis*

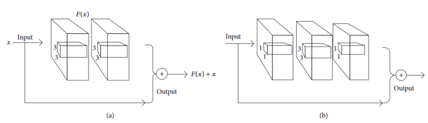

Fig. 1. (a) A basic building block. (b) A "bottleneck" building block of deep residual networks.. [10]

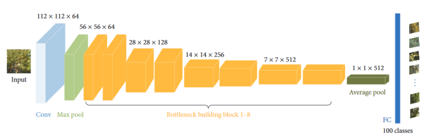

Fig. 2. : Architecture of 26-layer ResNet model for plant identification. [10]

III. Deep Learning in plant Recognition

Historically, research on artificial neural networks is where the idea of deep learning first emerged. (Hence, the term "new-generation neural networks" may occasionally be mentioned.) Often referred to as deep neural networks (DNNs), feed-forward neural networks or multi-layered PLPs are excellent illustrations of models with a deep architecture. One well-known technique for figuring out these networks' parameters is back-propagation (BP), which gained popularity in the 1980s. [7] Unfortunately, for learning networks with more than a few hidden layers, BP alone did not function well in practice at that time. The primary cause of learning difficulties in deep networks is the ubiquitous existence of local optima and other optimization problems in the non-convex objective function. BP typically begins at a few random initial points and is based on local gradient information. When using the batch-mode or even stochastic gradient descent BP algorithm, it frequently becomes stuck in subpar local optima. The severity sharply escalates as the depth of

The networks get bigger. While there had been ongoing work on neural networks with limited scale and impact, this challenge has led most machine learning and signal processing research away from neural networks and toward shallow models with convex loss functions (e.g., SVMs, CRFs, and MaxEnt models), for which the global optimum can be efficiently obtained at the cost of reduced modeling power. [7]

The standard image classification method, which uses a fully convolutional neural network as a classifier and a Deep Neural Network (DNN) as a deep feature extractor, makes it simple to automate the identification of different plant species. Deep neural network-learned image representations outperform manually created features by a significant margin. Moreover, because DNNs automatically learn discriminative features for each task, they are data-driven and require no effort or expertise for feature selection. Furthermore, the automatically learned features are multi-levelly hierarchically represented. Such deep feature sets it apart from more conventional methods.more conventional methods. Since there are currently a lot of DNN architectures in use, a variety of transformer-based and convolutional neural network architectures are tested to see how well they can classify various feature extractor architectures.

IV. Data Collection and Prepossessing

V. Convolutions Neural Networks (CNNs)

It has been shown by authors that convolutional neural networks (CNNs) can produce learned features for leaf images that are superior to hand-crafted features. the identification and querying of plant information using CNN. For their images of medicinal plants, the writers used CNN. The soft-max loss was utilized to optimize the recognition network for the task; subsequently, a triplet loss was added to the recognition network to fine-tune it for the retrieval problem by searching for the most similar images of medicinal plants. Motivated by the latest developments in deep learning for computer vision, I've come to the realization that deep learning techniques could offer strong image representation for medicinal plants.In this paper, I suggest combining various classification techniques with the Convolutional Neural Network (CNN) for medical plant image features.

Dataset	Num. of Taxa	Total Num. of Images	Organ	Life Form
Swedish leaf	15	1125	leaf	tree
Flavia	32	1907	leaf	tree
Leafsnap	185	30,866	leaf	tree
ICL	220	17,032	leaf	tree, herb
Oxford Flower 17	17	1360	flower	herb
Oxford Flower102	102	8189	flower	herb
Jena Flower 30	30	1479	flower	herb
German flowering plants	101	50,500	flower, leaf	herb
PlantCLEF2015/2016	1000	113,205	leaf, flower, fruit, stem	tree, herb, fern
GRASP-125	**125**	**16,367**	**leaf, flower, fruit, stem**	**tree, herb, fern**

Fig. 3. . Summary of the most popular image datasets for plant recognition []

VI. Real-World Applications

A. *Herbal Plants Recognition*

We employ the method suggested in [11] to extract visual features from photos of herb plants and use them as inputs for classifiers to predict the herb classes. This approach is inspired by deep convolutional feature representation in [11]. This method, which is shown in Fig.4. below, involves taking the fully connected layers out of the original VGG16 model

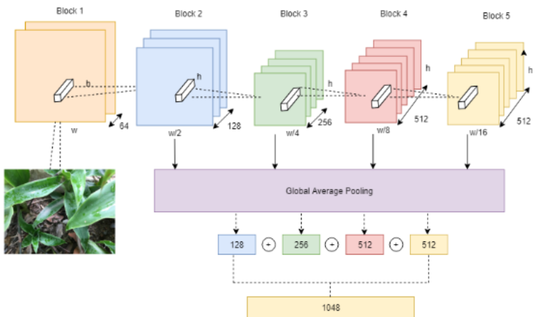

Fig. 4. . Deep convolution features are extracted with a modified VGG16 network proposed in. The fully connected layers are removed, and the global average pooling operation is applied to each block inside the convolutional layers. [11]

and applying the global average pooling operation to every block inside the convolutional layers.

Blocks 2 through 5 are concatenated into a single, 1408-dimensional vector to create the final feature vector, which is then fed into the classification stage. In order to take advantage of the appearance characteristics of herb plants and prevent time-consuming and overfitting of the model, we utilize the entire plant image in this work rather than cropping into numerous sub-regions as done in previous works [11].

B. Classification Methods

1) Random forests: One of the most popular ensemble techniques for both classification and regression problems is the random forests method. The building blocks of a random forests classifier are several trees, each of which is developed using a random tree (such as a decision tree) until it reaches a leaf node, which is regarded as the target class. After averaging all of the posterior probabilities, the final prediction of the input images is determined by taking the argmax. Furthermore, by generating random feature subsets, constructing smaller trees from these subsets, and handling missing feature values, random forest prevents overfitting.

2) Support Vector Machine (SVM): SVM is used to classify the herb classes of an input sample. Given a training set of labeled examples [11] $\{(x_i, y_i), i = 1, \ldots, k\}$ where $x \in R^n$ and $y_i \in \{1, -1\}$,

SVM classifies a new test sample x based on the following functions:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i \gamma_i K(x_i, x) + b\right)$$

where $K \cdots$ is a kernel function, b is a hyperplane threshold parameter, and ai are the Lagrange multipliers of a dual optimization problem that characterizes the separating hyperplane. Support vectors are the training sample of xi with $(ai \leq 0)$, and SVM produces a hyperplane that maximizes the distance between the hyperplanes. [11]

3) Logistic regression: One of the most popular probabilistic classifiers is logistic regression whose probabilistic definition is presented as:

$$P(Y = y \mid X = x) = \frac{1}{1 + \exp(y(\theta, x))},$$

Accoring to [11]where x is a CNN feature vector of a herb image that was extracted in the previous step, and y is the class label vector. We applied the one-versus-all method to the multiple classification. The parameters are estimated and optimized using the following equation, which makes use of gradient descent and maximum likelihood estimation:

$$\begin{aligned}
\theta_{MLE} &= \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{n} \log \frac{1}{1 + \exp(y^{(i)}(\theta, x^{(i)}))} \\
&= \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{n} -\log(1 + \exp(y^{(i)}(\theta, x^{(i)}))) \\
&= \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{n} \log(1 + \exp(y^{(i)}(\theta, x^{(i)})))
\end{aligned}$$

The equation is solved to find a vector f minimizing the above objective expression by using the method of gradient descent with the parameters j inf , each of which is updated in consecutive steps until it becomes smaller than a threshold . is the learning rate of the parameters as the gradient descent iteration increase. [11]

$$\theta_i \leftarrow \theta_j - \alpha \frac{\delta \sum_{i=1}^{n} \log(1 + \exp(y^{(i)}(\theta, x^{(i)})))}{\delta \theta_j}$$

4) Extreme gradient boosting: XGBoost, or extreme gradient boosting, is a popular and very successful machine learning technique [11]. [11] proposed the XGBoost algorithm, which is an end-to-end tree-based boosting system that is scalable. Given a training set,

$$D = (x_i, y_i), \ldots, (x_i, y_i), \tag{1}$$

where $x_i \in R^m$ is used for i^{th}features and $y_i \in L == 0, \ldots, 10$ indicates the class label of the herb plant, and represents the feature. XGBoost predicts the target label using the following formula by utilizing a tree-based ensemble model with K additive functions [11]

5) Adaboost: Adaboost is a supervised algorithm based on boosting strategy which learns a strong classifier H(xi) by combining an ensemble of weak classifiers h(xi) . The likelihood of a feature being chosen is based on the weights of the training samples, which are updated each iteration. A training sample has a lower chance of being used in the following round if it is correctly classified. The weights of the weakly classified samples are increased, and the strongly classifier sample weights are decreased.

6) K-nearest neighbors: According to [11], Non-parametric in nature of the K-nearest neighbor classifier has found widespread application in pattern recognition and classification

Input: Given $(x_1, y_1), \ldots, (x_m, y_m)$
$x_i \in X, y_i \in \{-1, 1\}$
Initialize weight weak classifier
$h_t : X \rightarrow \{-1, 1\}$ with minimum error
w.r.t distribution D_t ; $D_1(i) = 1/m$
Output:
The strong classifier $H(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x))$
for t = 1,..., T
1. Choose $\alpha_t \in R$,
2. Update
$D_{t+1}(i) = \frac{D_t(i)exp(-\alpha_t y_i h_t(x_i))}{Z_t}$
where Z_t is a normalization factor chosen so that D_{t+1} is a distribution

Fig. 5. Adaboost algorithm [11]

Input: D is the set of feature vectors of training images, z is a feature vector of the test image, L is the set of class labels used to assign a label to z.
Output: $c_z \in L$, the class label of z
for each $y \in D$ **do**
Compute $d(z, y)$, distance of z and y;
end
Select $N \subseteq D$, the set of k closest training feature vectors from z;

$$c_z = \underset{v \in L}{\operatorname{argmax}} \sum_{y \in N} I(v = class(c_y));$$

where $I(.)$ is an indicator function that returns the value 1 if its argument is true and 0 otherwise.

Fig. 6. K-nearest classifier [11]

tasks, including applications related to natural and medical image analysis as shown in figure 6.

VII. Result Of Application

Among the many applications, medicinal plant classification is the identification of the appropriate species of medicinal plants for the associated disease. Plant identification by hand takes a lot of time and requires professional assistance. The automatic identification and classification of medicinal plants is a problem that must be solved for the benefit of humankind as a whole. Therefore, automatic medicinal plant identification and classification is useful for image processing research. One important step in the identification of medicinal plants is feature extraction.

A. *Transfer Deep Learning*

Among the many applications of medicinal plant classification is the identification of the appropriate species of medicinal plants for the associated disease. Plant identification by hand takes a lot of time and requires professional assistance. The automatic identification and classification of medicinal plants is a problem that must be solved for the benefit of humankind as a whole. Therefore, automatic medicinal plant identification and classification is useful for image processing research [1] One important step in the identification of medicinal plants is feature extraction. You will need high-quality photos for this.

CNN is the most well-known architecture for classifying images based on visual information. Convolutional layers are used in deep learning techniques to automatically extract features. The identification and classification of medicinal plants is done through computer vision, machine learning, and image processing methods. [1]

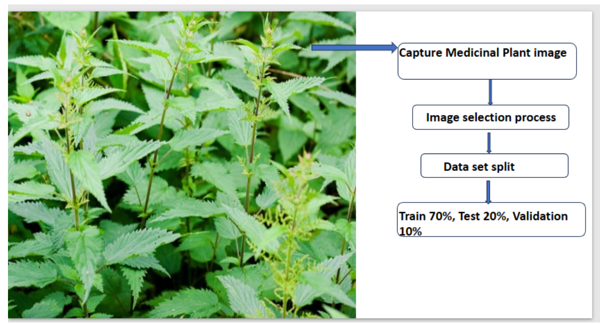

Fig. 7. Image processing steps

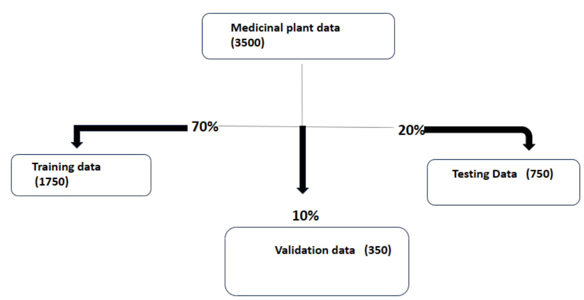

Fig. 8. Data distribution

1) *method Recognition Phase:*

2) *Data Collection and Dataset Preparation:* The Plant dataset which consists of 3600 species of Medicinal plants in Vietnamese herbal plant, can be used in this work.

3) *Training: :* Plant recognition model built by ResNet will be trained by the stochastic gradient descent (SGD) algorithm with the categorical cross entropy loss function as optimization objective.

4) *Evaluation Measures::*

```
Assuming you have a test set
(test_images, test_label_indices)
test_loss, test_acc = model.evaluate
(test_images, test_label_indices)
print(f'Test accuracy: {test_acc}')
32/32 [==============================] -
1s 35ms/step - loss: 2.4379 - accuracy:
0.6170
```

```
Test accuracy: 0.6169999837875366
```

Model Evaluation:

This little piece of code computes the test accuracy and loss, applies the trained machine learning model to a test set, and outputs the test accuracy to the console. The test accuracy provides a measure of the model's ability to generalize to new, untested data.

VIII. Challenges and Future Directions

Diversity and Accessibility of Data: Problem: There may not be as many varied and properly labeled datasets available for herbal medicinal plants. Solution: Create extensive datasets covering different species of herbal plants and environmental conditions by working with botanists, herbalists, or organizations.

Discreet Recognition: Challenge: Differentiating between closely related species of herbal plants can be difficult due to their subtle differences.

Solution: To increase accuracy, create more complex models or integrate image recognition with other data sources, like chemical composition analysis.

Low Level of Public Awareness:

Problem: Fewer photos of some species may be available due to a lack of public awareness regarding the diversity of herbal plants.

One potential solution could be to implement outreach programs, engage the community, and promote image submissions through citizen science initiatives.

Changing Environmental Factors: Problem: Models trained on one set of conditions may not generalize well because environmental factors can influence the appearance of herbal plants. Solution: To improve model robustness, add more photos to the dataset that were shot in various lighting, weather, and soil conditions.

Gaps in Ethnobotanical Knowledge: Challenge: Inaccurate or unclear dataset labeling may result from a lack of knowledge about regional names and applications for herbal plants. The answer is to work together with local communities and ethnobotanists to make sure that herbal plants are properly labeled and documented.

IX. Conclusion

Because CNN's convolutional layers utilize the inherent qualities of images, it is far more effective at processing images and videos than traditional neural networks. Inputs to simple neural feed forward networks don't show much structure. [2] The neural network will function equally well when trained on non-shuffled photos if all the images are combined in the same manner. However, it also maximizes the coherence of the local spatial picture. By applying convolution to adjacent pixel patches, they can ensure that processing an image will require a significantly smaller number of operations because adjacent pixels have meaning when combined. [2] In summary, the model shows a moderate level of success in accurately predicting the classes within the dataset, with an accuracy of 0.61. But it's important to keep the bigger picture and potential problems like class disparity in mind. To obtain more insight into the model's performance, additional evaluation metrics such as the confusion matrix, precision, and recall should be investigated. Improvements may be investigated by fine-tuning the model, modifying the hyperparameters, or gathering more data, particularly for underrepresented classes, depending on the application. [3] Understanding the model's consistency across various data subsets can be gained through cross-validation. Overall, in order to satisfy the particular demands of the task at hand, a comprehensive approach to model evaluation and possible refinement is advised.

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