Review Paper on Plant Recognition Using Machine Learning

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***Abstract*— Identification of plants is a crucial issue, particularly for biologists, chemists, and environmentalists. Manually conducted by human specialists, plant identification is a time-consuming and inefficient operation. Automation of plant identification is a crucial step for plant-related fields. In this research we studied methods for plant identification based on leaf photos.[1] Shape and colour data taken from leaf photos are utilised by various machine learning techniques such as k-Nearest Neighbor, Support Vector Machines, Naive Bayes, and Random Forest classification algorithms, etc., to identify plant species.[2] The proposed framework comprises acquiring image, pre-processing, feature extraction, and classification.[1] The experiments are carried out on the Swedish Dataset, the Flavia dataset and the ICL dataset that contains 1800 images belonging to twenty different plant species.**

Keywords: Leaf recognition, machine learning, image dataset

I.INTRODUCTION

Plants are an essential component of life on Earth. They provide us with air to breathe, food, medicine, and numerous other things that make life worthwhile. They are the foundation of life. The accurate identification of plants, however, is beyond the ability of the average individual since it takes specialist knowledge; only those with a botanical background are capable of doing this work. One of these challenges is the extraction of features of plant leaf and their representation so that accurate classification of plant species could be made.[3] Out of many features, leaf shape is a conspicuous element that most algorithms rely on to perceive and describe a plant. In addition, leaf shading, surface, and vein can also be considered for more accurate classification. Furthermore, even botanists do not know all plant species in the world, as there are an infinite number of plant species. Thus, the duty of plant identification is restricted to a small number of individuals.[4] However, knowledge of plant species is required for a variety of reasons, including recognizing new or uncommon species, balancing the environment, therapeutic uses, the agricultural business, etc.

A computerized plant categorization system can utilize different plant traits, including leaves, flowers, fruits, branching types, and appearances.[5] Using leaves to identify plants is an efficient and precise method. Numerous research on leaf image retrieval based on shape, venation, and texture information have been undertaken in computer-aided plant identification systems due to the importance of leaves in species identification. The objective of this study is to establish a method for classifying plants based on leaf characteristics. Classification based on leaf pictures has the benefit that sampling leaves (obtaining photographs) is inexpensive and convenient.[6] The performance of a leaf recognition system is dependent on the feature selection and recognition algorithm used. We expanded the approach and investigated additional categorization features and methods.

In this paper, we examined techniques for Feature Extraction and Classification algorithms. In addition to form features, color features of leaf photos were also used. k- Nearest Neighbor, Support Vector Machines, Naive Bayes, and Random Forest are used to categorize both form and color data. We also studied some other techniques such as TDR(Triangular Distance Representation),[7] Hidden Naïve-Bayes,[8], [9] Curvelet Transformation, and AdaBoosting.[5] For classification results, several datasets such as the Swedish leaf dataset, the Lavia dataset, the ICL dataset etc. are used. According to our understanding, the results are cutting-edge for such a huge number of plant species.[10]

II.BASIC METHODOLOGY

The proposed framework consists of different stages, specifically, data acquisition, digitization, pre-processing, feature extraction and classification based on the extracted features.The flow of operation of the proposed system is shown in figure 1. The details of each step are discussed in the subsequent sub-sections.

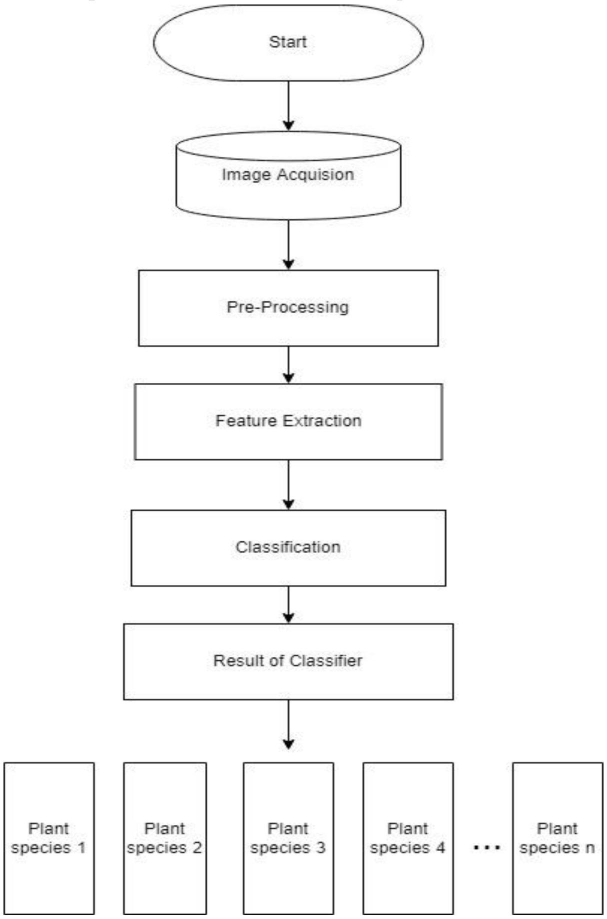

Figure 1: Different steps taken in methodology

1. Image Acquision: Getting a picture of the plant is the first step in the identification procedure. The complete plant, a leaf, a flower, a stalk, or even the fruits might be included in the image. The Swedish dataset (15 species of leaves), the Flavia dataset (32 species of leaves), the ICL dataset (220 plant species), and others are some of the standard datasets that are readily available.[11] Images from these three datasets have been used in the majority of studies (refer table 1). In our investigation, we used the Swedish dataset [19], which includes 1,125 photos altogether, 75 photographs of each of 15 different plant species.[12] The dataset may be obtained from (http://www.cvl.isy.liu.se/en/research/datasets/swedishleaf/) and is in the public domain. It includes.tiff-formatted pictures of plant leaves.

Species	Image	Species	Image
Acer		Salix aurita	
Alnus incana		Salix sinerea	
Betula pubescens		Sorbus aucuparia	
Fagus silvactica		Sorbus intermedia	
Populus		Tilia	
Populus tremula		Ulmus carpinifolia	
Quercus		Ulmus glabra	
Salix alba (sericea)			

Figure 2: Swedish dataset leaves

2. Pre-Processing: Pre-processing is a vital step since it enhances the image's quality for further processing. This step is crucial since noise is a natural component of photos, which might result in less precise classification.[13] It is carried out to eliminate the noise that interferes with handling the degraded data and the identification procedure. A variety of actions are taken to enhance the reputation of the leaf, such as transforming the RGB picture to binary after transitioning from grayscale to binary filtering, filtration, etc.[1] The processing mechanism employed in this article includes noise management as well as improvement of the photograph and resizing.

3. Feature Extraction:

3.1. Texture Features:

Texture analysis is particularly important in many fields, including image retrieval and medical imaging. In image processing, the term "texture" refers to a variety of visual characteristics, including smoothness, coarseness, regularity, etc. It depicts the neighbourhood-level spatial distribution of a digital image's pixel's grey levels.[14] There are four ways to extract texture features: structural, model-based, transform-based, and statistical.[15] We employed a statistical approach in our work that defines texture using the statistical characteristics of the grey-level picture. There are three levels of statistical methods: first order (one pixel), second order (two pixels), and higher order (three or more pixels).[16] No matter how closely a pixel is related to its neighbours, first order statistics (or histogram-based features) compute texture characteristics from the particular pixel.[17] The pixels' positions in relation to one another are taken into consideration using second order statistics.[18] For the extraction of texture features, we employed the GLCM (Grey-Level Co-occurrence Matrix), one of the most researched second order statistics. By calculating how frequently a pixel with the grey-level value I appears in a certain spatial connection to the grey-level value "j," GLCM takes into account the spatial relationship of pixels and extracts texture information.[19] In other words, it takes into account the relationship between the reference pixel and neighbour pixel, two pixels, at a time.

Feature	Formula
Contrast	$\sum_{1=1}^{N}\sum_{j=1}^{N}(i-j)^2\ P_{i,j}$
Correlation	$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{(i,j)(P_{i,j}-\mu_i\mu_j)}{\sigma_x\sigma_y}$
Energy	$\sum_{i=1}^{N}\sum_{j-1}^{N}P_{i,j}^2$
Entropy	$-\sum_{i=1}^{N}\sum_{j=1}^{N}P_{i,j}*Log_b P_{i,j}$
Homogeneity	$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{P_{i,j}}{1+(i-j)^2}$

Table 1: Formulas for Texture Features

3.2. Colour Features:

The input image was split into three separate colour channels during the segmentation stage. All three photos created as an ensemble have their distinct colour attributes removed. segmentation phase's result.[20] The extracted colour features can also be referred to as colour-based texture in this article. characteristics that we have retrieved (mean, standard deviation, kurtosis, skewness) derived from a coloured picture using first order statistics instead of the standard grey-scale.[21] The calculations for these Table 4 lists the characteristics, with "xi" standing for the a single pixel, while 'N' denotes the total number of pixels.

Feature	Formula
Contrast	$\sum_{1=1}^{N}\sum_{j=1}^{N}(i-j)^2\ P_{i,j}$
Correlation	$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{(i,j)(P_{i,j}-\mu_i\mu_j)}{\sigma_x\sigma_y}$
Energy	$\sum_{i=1}^{N}\sum_{j-1}^{N}P_{i,j}^2$
Entropy	$-\sum_{i=1}^{N}\sum_{j=1}^{N}P_{i,j}*Log_b P_{i,j}$
Homogeneity	$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{P_{i,j}}{1+(i-j)^2}$

Table 2: Formulas for Colour Features

4. Classification:

In our study, classification generally refers to ascribing a particular plant species to the picture based on the feature set collected. In other words, classification is the process of determining a new input image's class label based on previously learned information (training dataset).[22] To classify the new data input for our investigation, we employed a supervised classification approach in which the labels of the classes (in this case, plant species) were previously known.[10]

One of the best and most reliable techniques for classification is support vector machine.[2] It uses supervised learning methods that are used for classification and regression. Due to its capacity to maximise predicted accuracy and inclination to prevent over-fitting of data, SVM,[23] which was first created by Vapnik, has been extensively used by researchers in the field of image processing.

SVM typically divides data into two classes using a binary classifier. Building a hyperplane (or group of hyperplanes) in an n-dimensional space (where "n" is the number of features) that clearly classifies input data points is how the SVM performs classification.[24] The largest margin between positive and negative classes is what defines an ideal hyperplane.[25] A hyperplane that best divides two classes is created by using a kernel function to translate the input data into a higher dimensional feature space. This is how an SVM classifier is generated. We chose Multiclass SVM because there are more than two classes (plant species) in our investigation (MSVM). Typically, binary SVMs are combined to create MSVMs. The MSVM utilised in this study employs a "one-vs-all" strategy, in which the i th SVM is trained to specify that the samples of the i^{th} class are "positive" and the remaining samples are "negative.

III.LITERATURE SURVEY

Sr no	Title	Year	Author	Algorithm	Advantages	Limitations
1	Automatic Plant Species Recognition Technique using Machine learning approaches	2015	Suchit Purohi, et al.	Support Vector Machines	SIFT features pooled with SPM approach gives better accuracy than combined vocabulary and pixel-based approach, best being 98% accuracy for leaf scan images.	Low accuracy in sub-categories leaf and fruit with 69.17% and 67.33 % respectively.
2	A Plant Recognition Approach Using Shape and Color Features in Leaf Images	2013	Ali Caglayan, et al.	k-Nearest Neighbor, Support Vector Machines, Naive Bayes, and Random Forest classification algorithms	The average accuracies were above 89%	Classification accuracy can be improved by using shape and color features together
3	Plant Species Recognition Using Morphological Features and Adaptive Boosting Methodology	2019	Munish Kumar, et al.	Multilayer Perceptron with Adaboosting	The AdaBoost methodology is considered to improve the precision rate of the proposed system.	Computations with MLP are time consuming
4	Improved Deep Learning-based Approach for Real-time Plant Species Recognition on the Farm	2020	Chung-Liang Chang,Sheng-Cheng Chung	YOLO-v3 model with Darknet-53 network framework	The results illustrate that the use of image pre-processing method can faster achieve a average loss than the method of not using pre-processing.	It has difficulty in meeting the requirement of real-time processing.
5	Plant Species Recognition Using Triangle-Distance Representation	2019	Chengzhuan Yang and Hui Wei	Triangle-distance representation (TDR)	The approach exceeds existing shape-based plant species recognition approaches on the aspects of retrieval accuracy, efficiency, and storage space. Therefore, it is is very effective for real-time application.	More information about the plants should be added
6	Plant Identification Using Leaf Specimen	2020	Gurdit Singh, et al.	VGG-CNN-F and VGG net 16	Presents an easy and computationally environment-friendly technique for plant identification, training and testing requires less space and time.	Comparatively Low generalization potential
7	Leaf plant identification system based on hidden naive bays classifier	2015	Heba F. Eid, et al.	Hidden Naïve Bayes	Robust, computationally efficient and doesn't require as much training data.	Naive Bayes assumes that all predictors (or features) are independent, rarely happening in real life
8	A Multiscale Fusion Convolutional Neural Network for Plant Leaf Recognition	2018	Jing Hu, et al.	MSF-CNN	Better results and accuracy than multiple state-of-the-art plant leaf recognition methods.	Lot of training data is needed
9	Plant species identification based on leaf venation features using SVM	2020	Agus Ambarwari, et al.	SVM	Notable correctness with less computation power, good speed which gets better with higher specifications.	Training time is comparatively longer, identification using the feature of leaf venation requires quite a long time
10	Plant leaf recognition using shape features and colour histogram with KNN classifiers	2015	Trishen Munisami, et al.	KNN	Simple to use system, fast and highly scalable with a good accuracy of 87.3%	Accuracy decreases when more species of plants were taken into account.

11	Comparison of Plant Leaf Classification Using Modified AlexNet and Support Vector Machine	2021	Shivali Wagle and Harikrishnan Ramachandran	Alexnet, Support Vector Machines	The proposed model based on AlexNet performed well with an accuracy of 91.15% as compared to SVM giving 88.96% and 89.69% for radial basis function kernel.	The time required for training and testing the deep learning network is comparatively higher.
12	Plant Recognition using Watershed and Convolutional Neural Network	2019	N Manasa, et al.	AlexNet	AlexNet is a powerful model capable of achieving high accuracies on very challenging datasets.	Takes more time to achieve higher accuracy results.
13	Plant Species Identification based on Plant Leaf Using Computer Vision and Machine Learning Techniques	2019	Surleen Kaur and Prabhpreet Kaur	Multiclass-support vector machine	Proposed method is easy to implement and efficient, with an accuracy of more than 90%,	Training time is comparatively longer
14	Plant Leaf Species Identification using Curvelet Transform	2011	Shitala Prasad, Piyush Kumar, R. C. Tripathi	SVM	Notable correctness with less computation power, high accuracy rate of around 95.6% with 624 leaf dataset.	Training time is comparatively longer.
15	Leaf Analysis for Plant Recognition	2016	Aparajita Sahay and Min Chen	Weighted KNN	Simple to implement and intuitive to understand, fast since there is no training time.	Accuracy still lacking in comparison to other state of the art classifiers.
16	Multiscale Distance Matrix for Fast Plant Leaf Recognition	2012	Rongxiang Hu, et al	Multiscale distance matrix (MDM)	Significantly fewer parameters to tune, Very easy to implement since it is based only on the distance matrix of the shape	The metric selection is critical, and the discriminability highly depends on it
17	Plant Recognition Based on Intersecting Cortical Model	2014	Zhaobin Wang, et al.	SVM	Easy to implement, with less computation power, high accuracy rate up to 97.8%	Training time is comparatively longer.
18	Recognition of Leaf Images Based on Shape Features Using a Hypersphere Classifier	2005	Xiao-Feng Wang, et al	Moving center hypersphere classifier	Proposed method can not only save the storage space but also reduce the time consumed without sacrificing the classification accuracy, average recognition rate is up to 92.2 percent.	Accuracy not much better than other state of the art classifiers.
19	Recognition of Leaves Based on Morphological Features Derived from Two Half-Regions	2012	Caner Uluturk and Aybars Ugur	PNN	Easy in implementation and fast in execution, with a recognition accuracy of 92.5%	Because there's one hidden node for each training instance, more computational resources (storage and time) during inference.
20	Leafsnap: A Computer Vision System for Automatic Plant Species Identification	2012	Neeraj Kumar, et al	KNN	Simple to implement and intuitive to understand, fast since there is no training time.	Knn doesn't work well with a large dataset or a high number of dimensions
21	A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network	2007	Stephen Gang Wu, et al	Probabilistic Neural Network(PNN)	Fast in execution and easy in implementation, with an accuracy greater than 90%.	because there's one hidden node for each training instance, more computational resources (storage and time) during inference.
22	DEEP-PLANT: Plant Identification With Convolutional Neural Networks	2015	Sue Han Lee, et al.	CNN	CNN can provide better feature representation for leaf images. Performance of 99.5%, which outperforms conventional solutions.	Lot of training data is needed.
23	Leaf recognition of woody species in Central Europe	2013	Petr Novotny and Tomas Suk	KNN	Simple to implement and intuitive to understand, fast since there is no training time.	Accuracy still lacking in comparison to other state of the art classifiers.
24	Leaf shape based plant species recognition	2007	Ji-Xiang Du, et al	Move median centers (MMC) hypersphere classifier	MMC classifier can not only save the storage space but also reduce the classification time under the case of no sacrificing the classification accuracy.	Accuracy not much better than other state of the art classifiers.

25	A Combined Color, Texture and Edge Features Based Approach for Identification and Classification of Indian Medicinal Plants	2010	B. S. Anami, et al	SVM, radial basis exact fit neural network (RBENN)	Less computation power with good accuracy, which is improved to 90% with combined color and texture features.	Classification accuracy is better with SVM classifier than neural network classifier. The methodology has not performed well for the images of herbs and shrubs
26	An Efficient Leaf Recognition Algorithm for Plant Classification Using Support Vector Machine	2015	ArunPriya C., et al.	Support Vector Machines	The proposed approach produces very high accuracy of 94.5% in Flavia dataset and takes very less execution time.	Training time is comparatively longer.
27	In Situ Leaf Classification Using Histograms of Oriented Gradients	2015	Alex Olsen, et al.	PNN, Gaussian SVM	The proposed classifier achieves high accuracy (86.07%) in reasonable time and is thus viable for real-time detection.	More computational resources (storage and time) during inference.
28	Automatic Recognition of Medicinal Plants using Machine Learning Techniques	2017	Adams Begue, et al.	Random Forest	With an accuracy of 90.1%, the random forest classifier performed better than other machine learning approaches	requires much more computational power and resources
29	Recognition of plant leaf image based on fractal dimension features	2013	Ji-xiang Du, et al	KNN	Simple to implement and intuitive to understand, fast since there is no training time.	Accuracy still lacking in comparison to other state of the art classifiers.
30	Plant Species Recognition Using Triangle-Distance Representation	2019	Chengzhuan Yang and Hui Wei	Multi-layered perceptron, NFC	Provides a robust system with a high overall accuracy of 97.6% by NFC and 85.6% by MLP	Disadvantage of a neural network is that it imposes strict classification i.e. a data sample must belong to only one class.

IV.DISCUSSION AND FUTURE SCOPE

This section presents experimental results reliant on the suggested framework. Experiments are conducted using a public dataset obtained from http://flavia.sourceforge. net/. This dataset comprises 32 distinct plant leaf types. This collection contains leaf photos of 32 common Chinese plants, including Phyllestachys Pubescens, Aesculus Chinensis, Berberis Ferdinandi-coburgii Schneid.[26] It has 1907 photos 720 × 960 pixels across all 32 categories. The dataset's size is around 1 GB. In this experimental work, the authors have considered 10 images from each category. Three distinct assessment methodologies were utilised. First, an 80-20 approach is used, wherein 80% of images are considered randomly as training dataset and the remaining 20% as testing dataset.[27] Threefold and fivefold cross-validation are an alternative method. In three-fold cross-validation, the entire dataset is arbitrarily divided into three groups.[28] The training of two groups is followed by testing of the third group. Fivefold cross-validation employs a similar methodology.[29] The Python platform is utilised for experimentation on an Intel i3 machine with 8GB RAM.

V.CONCLUSION

Plant species detection aims to identify plants automatically. Although many factors including leaf, flowers, fruits, and seeds could influence the decision, leaf characteristics are the most significant.[30] In this paper, we investigated the effect of various machine learning algorithms on plant recognition. The research was conducted in phases that included image pre-processing, image segmentation, feature extraction, and finally image classification. Support Vector Machines, k-Nearest Neighbor, Naive Bayes, and Random Forest classification algorithms are investigated. Experiments demonstrated that using only shape features to classify leaves with similar shapes is ineffective. The accuracy of classification can be enhanced by combining shape and colour features.

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