A Review on Plant Leaf Identification and Classification Using Machine Learning Techniques

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Abstract*— Leaf and plant recognition is a rapidly expanding field of study that has huge practical implications for industries as diverse as agriculture, crop rotation, horticulture and others. Image capture, including leaf image improvement, leaf segmentation, extraction of features, and classification, is the first step in the process. One widespread use of these categories nowadays is in the categorization of plants. Several methods for identifying and categorizing plant leaves are discussed in this paper. With the advent of new technologies like machine learning leaf recognition become easier and accurate. Moreover, comparative analysis of machine and deep learning based techniques for leaf recognition based on factors such as dataset used, features considered, classifier type and accuracy obtained has been executed. Apart from this the open research issues and their suggestive solutions has been highlighted in this paper.

***Index Terms*— Machine learning, Deep learning, accuracy, Support vector machine, CNN, Classification, Accuracy.**

I. INTRODUCTION

Plants play a crucial part in maintaining the planet's ecological balance by offering us air to breathe, food to eat, fuel to burn, and medicines to treat illness. However, in recent years, a number of plant species have become extinct. If we are going to save plants and keep track of all the different kinds of flora and wildlife out there, we are going to need a plant database. There are an extremely large number of plant species. To process this kind of data, researchers are actively seeking a more efficient and effective method of categorization [1]. Besides conservation, plant identification is important for using their medical value and creating bio-fuel and other alternative energy. A flower, root, leaf, fruit, or any other part of a plant may be used as a unique identifier. Recently, automatic plant identification has been achieved via the use of computer vision and pattern recognition [2]. Recognition system and image analysis approaches utilize plant pictures to create plant lists for maintaining and safeguarding current plant classes [3]. Because of their ability to offer flat, two-dimensional areas with varying features including texture, color, and form, leaves are thought to be useful for the identification and categorization of different plant species. There are several natural and biotic causes that contribute to leaf degradation. As a result, many of the properties of a damaged leaf won't be used as signals. As a result, a recognition system dependent on such features may provide inconsistent outcomes.

Conventional artificial procedures for plant species identification and categorization are currently labor-intensive since they rely on specialized botanical knowledge used by consumers [4]. There are an abundance of interesting possibilities to explore based on the automated species categorization of plants. Automated classification of plant species through the extraction of different features from images of plant leaves is a concept presented by some efficient algorithms in computer science, including recognition of patterns, processing images and some technologies, including mobile devices and digital cameras. Managing, identifying, and comprehending a plant species may now be done quickly and easily with the help of an automated system [5-6].

Botany, tea industry, cotton industry, and many others rely on a system that classifies plant leaves [7-8]. Further, leaves morphological traits are used for classifying plants and diagnosing specific illnesses in their early stages [9]. Recognizing plants is a difficult but crucial process. Whether the selected traits are stable and have a strong capacity to differentiate between different types of leaves is a major problem in leaf identification, which plays a significant part in plant categorization. Time is a major factor in the recognition process. Due to flawed models and ineffective representation strategies, computer-aided plant identification remains a formidable obstacle in the field of computer vision. Evaluation of geometrical, morphological, and Fourier- based properties of leaves is crucial to plant identification. This information is crucial for determining the different plant families.

When it comes to identifying and categorizing plants, the wide variety of leaf shapes poses a significant issue [10]. Because leaf color may fluctuate depending on environmental conditions and seasonality, it is the color trait that is more crucial in categorizing and identifying plant species. Veins and venation provide further information that informs the texture characteristics. However, there are currently only a small handful of methods for extracting leaf venation characteristics for use in species identification. Leaf characteristics such as texture, shape, and color may be used to accurately identify a plant's species [10]. Consequently, these properties of leaf images, which may remain valid and dependable for years, are relied on by the majority of current systems and techniques for plant species identification. These days, users may choose from a plethora of texture feature extraction techniques, and the most of them include parameters that can be adjusted. Finding the best feature extraction techniques and their appropriate settings for a given assignment may be challenging. On top of that, categorization performance by selecting an ideal feature classification and extraction combination is a challenging task since it is problem-specific. Machine Learning (ML) plays a crucial role in leaf recognition by enabling automated pattern recognition and classification based on extracted features, facilitating accurate and efficient species identification from leaf images. ML algorithms learn from labeled data, enabling the development of models that can generalize and make predictions on unseen leaf samples. Deep Learning (DL), which is widely utilized nowadays in image recognition and computer vision, etc., employs artificial neurons that are functionally indistinguishable from human neurons.

In this paper, we have examined many techniques for identifying and categorizing plants. The development of plant-recognition technology depends on their widespread use and successful application and that is why the comparative analysis based on factors like dataset usage, features extracted type and accuracy has been examined. The remainder of this paper organized as follows: Section 2 presents the leaf recognition general procedure using the ML. Section 3 presents work done so far by various researchers. In Section 4, comparative analysis of the state of art techniques has been done and open issues with the remedial procedures are defined in section 5.. Conclusion and future work are presented in Section 6.

II. LEAF RECOGNITION PROCESS USING ML

Leaf recognition using machine learning is valuable in several applications. It enables automated and accurate identification of plant species, aiding in botanical research, ecological studies, and biodiversity monitoring. ML-based leaf recognition can also assist in plant disease detection, crop management, and conservation efforts. By leveraging the power of ML algorithms, leaf recognition simplifies and accelerates the process of species identification, enabling efficient analysis and decision-making in various fields related to plant life.

The process of the leaf recognition using ML has been defined below

1. *Data Collection:* Collect a dataset of leaf images denoted as D = ($x1$, $y1$), ($x2$, $y2$),..., (x_n, y_n), here x_i represents the i^{th} leaf image and y_i represents its corresponding label or species.
2. *Data Preprocessing*: Perform preprocessing operations on the leaf images. This may include resizing the images to a fixed size, denoted as X = x1', x2',... xn', where x_i' represents the preprocessed image. Normalize the pixel values to a common range, typically between 0 and 1, denoted as *X_norm*.
3. *Feature Extraction:* Extract relevant features from the preprocessed leaf images. Let's assume we extract a set of features (*F*) for each leaf image. This can be represented as $F = f1, f2,..., fn$, where f_i represents the feature vector extracted from the i^{th} leaf image.
4. *Feature Selection/Dimensionality Reduction*: If the feature set *F* is high-dimensional, amount of features may be reduced via the use of choosing features or reduction in dimensionality methods.

Let's denote the reduced feature set as *F_red*.

5. *Training a ML Mo*del: Split the preprocessed and feature-selected dataset into training and testing subsets. Let's denote the training dataset as *D_train* = (*X_train*, *y_train*) and the testing dataset as *D_test* = (*X_test*, *y_test*). We can then train a ML model using the trainingdata, denoted as *M*. The model can be represented as *M.fit* (*X_train*, *y_train*), where *.fit()* represents the training process.
6. *Model Evaluation*: Calculate the trained model using the testing dataset. Predict the leaf species for the test images and compare the predictions with the ground-truth labels. Calculate performance metrics, such as accuracy, precision, recall, and F1-score.
7. *Model Fine-tuning*: If the model's accuracy falls short of expectations, one may tweak it by changing its hyperparameters, using a new algorithm, or adding more data via methodslike data augmentation.
8. *Deployment*: Once you have a satisfactory model, deploy it in a production environment. Users can provide new leaf images, denoted as *X_new*, and the model can predict the corresponding species using *M.predict* (*X_new*).

III. LITERATURE WORK

The standard procedure for identifying leaves consists of four stages: picture acquisition, pre- processing, feature extraction, and classification. Some of the prominent work that has been done in the identification and classification using the ML and associated techniques has been defined here.

In [11], an alternate approach for classifying plant leaves is proposed using the Local Binary Patterns (LBP) technique. The suggested approach for plant leaf recognition makes advantage of previously extracted textural information. Swedish, Flavia, Foliage, and the ICL datasets are used in this system. In order to demonstrate that the suggested approach can distinguish between noiseless and noisy pictures, the acquired results are compared. In [12], a fully automated and very precise segmentation technique is suggested. The authors have developed a powerful encoding strategy for extracting depth information from features. After that, they utilize Mask R-CNN to train on the gathered RGB-D information. The suggested method is shown to automatically recognize leaves with a precision of around 89.3% by comparing trial data.

Using an optimized Deep Neural Network (DNN), the Jaya Algorithm was proposed in [13] as a method for identifying illnesses in rice leaves. To separate healthy and sick samples, RGB pictures are first transformed to HSV images, and then binary images are retrieved. Clustering is used to separate healthy tissue from infected tissue and healthy tissue from background. Using Multiscale Triangle Descriptor (MTD) and Local Pattern Histogram Fourier (LBP-HF), the authors of [14] devised a technique for classifying plant leaves. Both techniques are used to describe form and texture. However, there are restrictions to the approach. Due to the lack of an automatic learning mechanism, the leaf characteristics must be developed by hand. Generalized Procrustes Analysis (GPA) is used to give an alternate recognition approach in [15]. The approach relies on form categorization using contour characteristics. Calculating the distance between a collection of contour points and the contour's center after applying specific alignments is fundamental to the procedure.

In [16], the Multiscale Sliding Chord Matching (MSCM) identification technique is introduced. Soybean cultivar identification based on joint leaf patterns is the goal of this technique. Extracting form characteristics using the MSCM method. Soybean cultivars may be distinguished from one another based on leaf characteristics. Furthermore, the descriptions of leaves from various areas of soybean plants are not included into the joint leaf pattern. Leaf image recognition algorithms were suggested using leaf contour and centroid in [17]. The suggested approach intended to use image processing methods in addition to Support Vector Machine (SVM) used as a classifier. Seventy shapes and geometrical characteristics were extracted from the Flavia dataset and used as patterns. In [18], the authors evaluate leaf identification and classification systems side-by-side. SVM was employed for classification, and a shape detector was used to isolate 14 unique characteristics of the leaves. Sixteen unique plant species were originally provided by the Flavia database for use in the training dataset.

Using Artificial Neural Network (ANN) as a classifier, as shown by the system described for recognizing leaf patterns in [19], is effective. Researchers found that one additional dataset improved identification accuracy to 98.6 percent. As shown in [20], the results for recognizing and identifying the leaves of medicinal plants may be enhanced by using ANN as a classifier. The leaf photos were used to train an ANN classifier on the extracted color, shape, and texture. In [21], a cotton growth identification system is developed using CNN. The accuracy of a CNN model has been shown by adjusting training/test sets using the k-fold test. High accuracy, low cost, and real- time performance are all indicators that this approach works well for the recognition problem. In [22], the authors suggest a system that uses CNN to automatically categorize medicinal plants. High-level characteristics for categorization are extracted using a 3-layer Convolution Neural Network (CNN). A data augmentation strategy is used to aid the method's effectiveness. In [23], a practical approach is offered to the issue of disease similarity. This issue is caused by the simultaneous presence of two different diseases in a single leaf and the effect of environmental light. They started with a dataset of diseases found on cucumber leaves, and then used EfficientNet to create a classification model for those four categories. CNNs were utilized to extract aspects of rice leaf diseases in [24]. The SVM approach is then used for disease categorization and prediction. The best SVM parameter is found by their cross-validation procedure. Using field pictures, researchers in [25] trained a deep CNN to automatically classify and recognize different types of biotic and abiotic stress on rice crops. Five distinct types of rice crops are represented by 30,000 field pictures in a dataset with 12 stress classifications. In [26], the authors tried to use a conventional CNN for disease detection in leaves by combining an inception structure with a pooling layer. This model has fewer parameters and higher identification accuracy of 91.7%. The model in [27] also employed a CNN classifier to identify diseases in maize leaves. Diseases may be divided into three categories using this strategy. CNN has been shown to be an efficient means of disease categorization and identification in plants. For classification purposes, the approach described in [28] combines DL and CNN. A smaller number of characteristics had no effect on identification accuracy, as shown by the study's findings. The works done by other researchers in the same aspects has also been noteworthy [29-30].

Also many researchers has used DL to the problem of identifying plants. With PCA, Hu's moment invariant approach, and morphological traits, the authors of [31] were able to divide leaves into sixteen distinct categories for categorization purposes. A plant recommender strategy based on 2D visual pictures of plants is proposed by the authors of [32]. Attribute fusion and multilabel categorization were used in their system. The experimental results showed that compared to standalone applications, the accuracy of the function fusion approach was much greater.

In [33], the authors propose a CNN architecture for determining plant types using data collected from smart agro-stations camera feeds. The layout is a preprocessing step used to get rid of the photo attributes. Because of their effect on the neural network's recognition skills, the configuration of the CNN design and width need special attention. In [34], the authors provide a method for gathering leaf images using leaf features as input to CNN, which is then used to recognize patterns for each plant's depth data. In this case, CNN is used primarily to better depict the properties and conduct efficient research of leaf creatures.

In [35], the authors analyze the factors that affect the architecture and effectiveness of DNNs used in plant pathology. The authors of [36] employ CNNs to identify individual plant leaves. The sample-normalization founding V2 used in the developed approach improves region CNN's precision. The method was hypothesized to be quicker than the standard CNN. The authors of [37] proposed using DL for plant classification using the notion of Transfer Learning (TL). This research compares the results of four different transference training methods for four different datasets to show how each affects DNN-based plant classification deals. At the end of their theoretical investigation, they find that TL provides a foundation for autonomous estimation and analysis in plant categorization.

In [38], the authors offer BLeafNet, a DL and Bonferroni fusion learning-based model for classifying images of leaves for use in identifying plants. They started by creating five distinct classification models using the ResNet-50 architecture and five distinct inputs. In another work [39], the authors propose a very effective approach of maximum behavioral similarity created using three DL based models to represent a botanist's behavior in leaf identification, making the system more interpretable and dependable. The botanist's behavior is correctly depicted by seeing different levels of the three models. Grapevine leaf varieties may greatly affect both cost and

flavor. Images of grapevine leaves are used for categorization in another study [40] that use DL. The categorization was done using a highly-advanced CNN model called MobileNetv2.

IV. COMPARATIVE ANALYSIS

In this section the comparative analysis of the techniques expressed in the state of art work has been done in context of leaf identification and classification using the ML and DL based techniques. The main factors that are being evaluated are the dataset (flavia) whether used or not, type of classifier used for the work, what type of features are extracted (color, shape and texture) along with the accuracy of the method. The analysis has been depicted in Table 1.

Table 1: Comparative evaluation of ML and DL based methods for leaf identification and classification

ference Work	Flavia Dataset Usage	assifier Used	Color Extraction	Shape Extraction	Texture Extraction	ccuracy (%)
[11]		LBP				98.9
[12]		R-CNN				89
[13]		DNN				90.5
[14]		LBP				99.1
[15]		GPA				98.4
[16]		MSCM				72.4
[17]		SVM				72.4
[18]		SVM				97.7
[21]		CNN				93.2
[22]		CNN				71.3
[23]		CNN				96
[24]		SVM & CNN				96.8
[25]		CNN				92.8
[26]		CNN				91.7
[27]		CNN				92.8

It may be deduced that several approaches exist for classifiers as per the derivations from table 1. According to inference drawn from table 1, CNN-based classifiers are receiving more attention. When CNN is combined with other classifiers, such SVM or LBP, the results are often improved. CNN-based approaches have been shown to have the highest accuracy ratio. It is also inferred that most researchers have already created testing datasets for their models and tested the methods on that only. Very few work extensively use widely-used standard datasets like Flavia. In terms of classification strategy, recent studies have focused on topics like CNNs and DNNs. CNN and SVM have received more attention in leaf classification due to their effectiveness in image-based tasks and non-linear classification, respectively. CNNs excel at automatically extracting features from leaf images, while SVMs provide robust classification.

It has also been noticed that more work has been done by using the color-based feature for leaf recognition other than shape and textual information. Color-based features in leaf recognition are favored due to their ability to visually discriminate plant species, non-invasiveness, robustness to variations, intuitive interpretation, and computational efficiency. While shape and texture information are valuable, combining them with color features can enhance classification performance in leaf recognition tasks, and this is one of the prominent works to peruse in the time to come. As far as accuracy is concerned, ensemble models are more accurate at leaf recognition. Ensemble models are more accurate in leaf recognition due to their ability to combine the predictions of multiple individual models. By leveraging diverse classifiers, ensemble models can capture a wider range of leaf characteristics and make more robust predictions. They reduce bias, improve generalization, and effectively handle the complexity and variations in leaf data, resulting in higher accuracy.

V. OPEN ISSUES AND SUGGESTIVE SOLUTIONS

Plant leaf identification and classification using machine learning techniques is an active area of research with several open issues. Here are a few recent research challenges and potential remedial solutions:

1. Limited Dataset and Class Imbalance: The availability of a comprehensive and diverse dataset is crucial for training accurate models. However, obtaining labeled leaf images for all plant species can be challenging. Remedial solutions include crowd-sourcing initiatives to collect data, leveraging TL from pre-trained models, and using data augmentation techniques to artificially increase the dataset.
2. Robustness to Variations: Leaves exhibit variations due to factors like lighting conditions, angles, deformations, and diseases. Developing robust models that can handle these variations is essential. Solutions involve incorporating data augmentation techniques so to expose the model to diverse leaf variations during training.
3. Inter-class Similarity: Some plant species may have leaves that are visually similar, leading to classification difficulties. Handling inter-class similarity requires the development of advanced feature extraction techniques that can capture subtle differences. Additionally, exploring multi-modal approaches, such as combining leaf images with other data sources like texture, venation, or spectral information, can enhance classification accuracy.
4. Explainability and interpretability: ML models often lack transparency, making it challenging to understand the reasoning behind their predictions. Developing interpretable models or techniques to provide explanations for leaf classification decisions is crucial for gaining trust and facilitating adoption in practical applications.
5. Scalability and Efficiency: As the size of leaf image datasets grows, scalability and efficiency become significant concerns. Exploring techniques like model compression, low-resource learning, or designing lightweight models can help address these issues, making leaf classification algorithms more practical for deployment on resource-constrained devices or in real-time applications.
6. Generalization to Unseen Species: Extending leaf recognition models to identify previously unseen plant species is an ongoing challenge. TL, where models are pre-trained on large-scale datasets, can aid in generalizing knowledge across related species. Fine- tuning or domain adaptation techniques can then be applied to adapt the pre-trained models to specific target species.

Addressing these research issues would advance the field of plant leaf identification and classification using ML, leading to more accurate, robust, and applicable solutions for various botanical and environmental applications.

VI. CONCLUSION AND FUTURE WORK

This paper aims to review and assess recent developments in the literature on leaves categorization and identification. It is explained that how to categorize leaves based on their many characteristics is useful for better classification. These characteristics are extensively examined and studied, and their effectiveness in facilitating the identification and categorization procedure is shown. Features, classifiers, and datasets all play a role in this process of leaf identification and classification. Multiple feature combinations improved classification accuracy, as inferred from the work done by the researchers. Nonetheless, further study is needed to determine which aspects work best together. For instance, not a single study has analyzed veins in conjunction with other features like color, form, and texture. It has also been inferred that CNN and SVM are the widely used methods so far for the leaf categorization. There is a need for further research on the relationship between accuracy and the best quality characteristics that should be employed in SVM-based classification algorithms, since SVM classifiers have been gaining popularity in recent years. The vast majority of academics have only evaluated their approaches on user-defined datasets, making direct comparisons of the various proposals difficult at best. It has been determined that a new strategy based on DL methods and the incorporation of TL in the form of ensemble models will be superior for automatically identifying and recognizing plants from images of their leaves. Future studies might increase the dataset's size by collecting more data samples and include more kinds of plant leaves. Also, data augmentation and hyper-parameter tuning will be one of the crucial aspects to work upon while implementing the ML models for leaf recognition.

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