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A REVIEW OF THE METHODS USED TO CLASSIFY AND RECOGNIZE PLANT LEAVES

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Abstract

This research aims to comprehensively analyze several techniques utilized in computer vision to automatically identify plants based on photographs of their leaf structures. It's possible that the pictures were shot with a camera attached to a mobile device or with a digital camera set on a tripod. Botanists make use of the information that was collected in order to identify various types of plants and to make use of the therapeutic or other characteristics that plants possess. As we know, plants are extremely important to the Earth's ecosystem since they provide food and shelter and assist in keeping the atmosphere pure and unpolluted. Some of these plants have medicinal properties that can be exploited. One of the most difficult challenges in computer vision is the automated recognition of plant leaves. The Ayurvedic plant leaf identification system will be useful in many areas of society, including medicine, botanical research, and others. Because of developments in image processing and pattern recognition technologies, we can instantly discern leaf pictures. This article overviews the many approaches and categories for identifying papers.

1. Introduction

The categorization of plants is an active topic of research. Plants not only provide us with air and food, but they also have various features that may be used for agriculture, the food industry, and the creation of various cosmetics and food items. Many different kinds of plants are in danger of going extinct due to human activity [1]. Botanists are the only people who can define plants with the same accuracy as they can; they accomplish this by categorizing plants based on their leaves, seeds, flowers, and germs. Consequently, individuals from all over the world are drawn to the topic, and ongoing research is being conducted to streamline the process of plant recognition. Since, most often, these people know the virtues of many plants but cannot recognize them, it is useful not only to botanists but also to ordinary people. This is because most people know the benefits of various plants but cannot recognize them [2]. Numerous research is now being conducted to assist in identifying plants based on their leaves, blooms, or other aspects. Recent developments in analytical technology, on the other hand, have provided a substantial helping hand in the identification of herbs based on scientific evidence. This makes things easier for many folks, particularly those who don't know much about medicinal plant identification. In addition, because it can be obtained in large quantities throughout the year, Leaf is often regarded as the most credible source of information [3]. Researchers have focused their attention on various aspects of leaves, including their color, structure, surface, veining, and some other morphological characteristics. However, due to the current state of the environment, all of the plants in existence today need a digital representation. The classification of plants into species that can be utilized in medicine and as food is done via agent-based systems. It is essential to create a framework for an intelligent system capable of recognizing natural species with the aid of its digital databases. Keeping in mind the ultimate objective, which is to give data on medicinal plants, this is an essential component [4]. In plant-based smart recognition, an intelligent system is a significant technique. This strategy aims to develop genuine models using plants by merging pattern categorization and object identification. Scientists have developed a new species of plant. In addition to the time-consuming processes, laboratory tests involve expertise in managing samples and interpreting findings [5]. Among the most common and non-destructive methods for identifying plants is dependent on the morphological characteristics of their leaf structures. The features of plant leaves are distinctive enough then to accurately discern between types and varieties of plants [6,7]. Plant biologists continue to be the experts in identifying different species of plants at this time. However, the development of new computing technology provides laypeople with yet another option when looking for a solution. In today's technological world, leaf morphological traits may be retrieved using a mathematical model and then entered into a software program to be recognized. This has the potential to minimize a lot of false-positive findings caused by negligence. Techniques development of computational morphometry may objectively assess the geometry of a plant to show changes in a way that is efficient, repeatable, accurate, and statistically robust. In the study of leaf morphology, some of the factors that are typically taken into consideration also include area, leaf length, breadth, perimeter, form, diameter, and color [8,9]. In the present work, we have provided a summary of an overview of biodiversity identification and an overview of the diverse graphical feature extraction methods required to recognize leaf pictures based on texture, leaf shape, and static rotation/rotation methods. In the last portions of this study, we look at the classification methods that may be used to categorize leaves and a combination of the many characteristics and classifiers necessary for efficient classification in the various leaf datasets. With the assistance of leaf photos, we have attempted to present both a fundamental foundation and an overview of contemporary approaches that have been utilized step by step in the automated identification of plants.

1. A general explanation of the different types of recognition Systems

Du et al. examined morphological traits and unchangeable moment characteristics of diverse shapes that exist in multiple plant databases Using the movable median centers (MMC) super spherical classifier. Additionally, they classified leaf types using the MMC. They utilized a leaves dataset that only included a single picture of a leaf against a blurry backdrop. They gathered a maximum of 20 distinct species of photographs with a sample size of 400 scanning plant leaves [10]. Babatunde et al. presented

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a species of plants detection approach that would apply to the wide leaves observed in Norway [11]. They discussed several feature extraction methodologies as well as leaf morphology on the basis of the DNA bar-coding technique, Macleod et al. Researched various computer-assisted systems for the identification of different species of living and nonliving items [12]. They evaluated his findings in the Digital Automated Species Identification System (DAISY), categorizing a total of thirty species based on their oceanographic-based Investigation and paleontology studies. This article reviews a variety of strategies for extracting leaves morphology and floral features, as well as the issues that arise from doing so in an agricultural setting. A survey of the significant review articles has been summarized in **Table 1**.

Table 1 survey of the significant review articles

Sr.	The subject of the review paper	No. of reviewed articles	Rf.
1	Morphological leaf analysis	20	[13]
2	Automated living and nonliving species identification	10	[10]
3	Review on the Investigation of leaf and blossom morphology, as well as analysis of texture, using digital morphometry	113	[12]
4	A computer-aided plant identification system overview	27	[14]
5	review on the extraction of features and categorization methods	26	[15]
6	Analysis of the leaf database on a local, global, and instant scale. A review study	159	[16]

Any algorithm that really is focused on differentiating between distinct kinds of plants needs to be cognizant of intra-class variance that is characteristic of botanical specimens, in addition to the relatively minor inter-class variation as shown in **Figure 1**

1.1. Leaves identification System Schematic Representation

Figure 1. Different leaves from a single sample.

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Error! Reference source not found. depicts a generic structure of a system for the identification of leaf species. This system's user receives the leaf picture. After that, the system prepares the photos by converting them to grayscale, dragging noise, segmenting them, etc. After that, the system will retrieve the general characteristics of the leaves, such as their color, shape, and texture, as well as some of the characteristics that are unique to the leaves, such as the base, Leaf's tip, apex, and border, as well as its fronds data. These characteristics are compared with the leaves that are kept in a database to determine the classification of the Leaf based on the similarities between Intra and inter-classes. The following leaf detection techniques have been published; some of them are included in

Table 2. Leaves identification techniques

Sr.	Characteristics and recognition method	Identification of the Leaves	Rf.
1	The HOG and Hu characteristics of the leaf margin Machine à vectors de soutane	a computerized method for identifying plants	[17]
2	The shape of the Leaf closest neighbor classification	Branch classification with computer assistance	[18]
3	Using classification and features as a method to identify plants	Method for plant systems depends on botanical keys	[19]

2. Modern Methodologies for Extracting Features

A characteristic is a set of data pertinent to a particular leaf picture and classified either locally or globally. Leaves patches are used to automatically extract characteristics, whereas leaf form, texture, and color are used to extract feature descriptors. The color of the leaves is constant regardless of the surrounding environment. Color, shape, and texture are all used in the process of classifying leaves [20]. The leaf manual categorizes leaves based on their level of complexity, and their available features are displayed in **Figure 2**. Cope and his colleagues examined the morphology of simple leaves [16]. These leaves may be recognized by several distinguishing characteristics, including their color, venation, shape, edge, and arrangement. Compound leaves, on the other hand, may be recognized by the number of leaflets that are attached to a single stalk and by analyzing the characteristics of a single leaflet. As a result, there is a requirement for specific characteristics that may be used to identify different species of leaves. Sharma and Gupta gave a presentation that provided an overview of the most prevalent techniques for retrieving and categorizing leaf features [21].

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2.1. Extraction properties methods

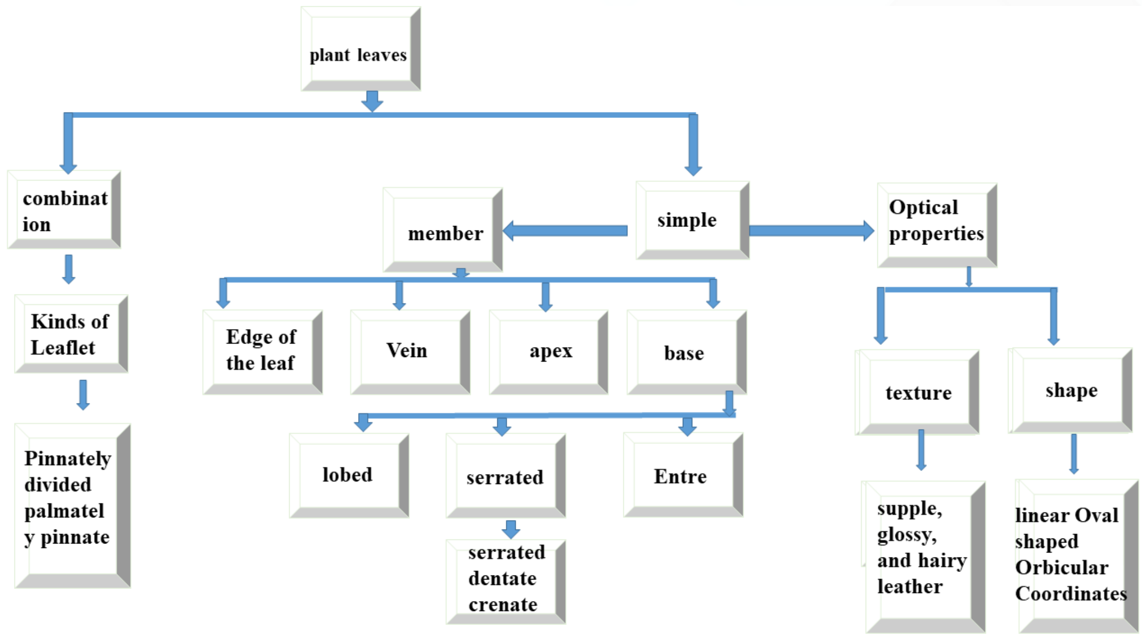

Figure 2. Kinds of leaves properties

Image classification, information processing, and object identification are all essential applications of a unique method known as visual extracting. Scientists must decide to remove beneficial traits to develop an accurate categorization system for species of plants. Roots, seeds, fruits, and flowers are the four main characteristics that botanists use to categorize plants. Because climate and camera calibration can affect it, leaf color cannot be regarded as a valid characteristic that can be used for categorization. Especially since the majority of flowers are green, it is necessary to classify them based on their shape, texture, and affine descriptors. These characteristics should remain the same regardless of how the photos are translated, rotated, or scaled. Grayscale images of leaves are utilized for identification purposes because the color is not considered [22,23].

2.1.1. Description of Curvature

CSS stands for "curvature scale space," a method for measuring the contours of forms and determining their concavity and convexity of curvature. By determining the greatest angles of the leaves, CSS may be used to locate the beginning and ending points of the venation feature points on leaves [24]. This is accomplished by analyzing the leaves. Since veins are expressed as a string for semantics, starting and terminating points aren't needed. Imperfect and overlapping leaves can't be used with these approaches. Grinblat et al. [25]employed a hit-or-miss transformation to extract foreground and background patterns. Central vein patches are extracted from leaf photos, and geometric characteristics are determined. SIFT extracts picture features. It's suitable for circular images and lighting and viewing

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situations. It retrieves local histogram characteristics. The writers retrieved corner points using MPT instead of CSS, which generates aliasing. Mean Projection Transform removes high-curvature corners to avoid difficulties. Flavia is 87.5% accurate. Chen et al. suggested using velocity to describe curvature points. This method calculates nine leaf points. CSS computes 200 junction points on the curvature, slowing down the process. Contour leaf categorization employed square root velocity representation to solve intra-class and inter-class variability. It automatically discovers similarities by estimating the geodesic distance of statistical shape features and 2D planar curves [26,27].

2.1.2. Multidimensional Descriptive Tags

Those multiresolution characteristics provide a great deal more knowledge on the curves of the Leaf. It does this by recording local and global characteristics at low to high-resolution scales and extracting picture features at various levels. Author Wang et al. developed a Multiscale Arc Height Descriptor (MARH) that is not sensitive to translation direction [28]. Souza et al. [29] came up with an idea for a new technique that they called the Multi-scale Bending Energy, or MBER for short. This technique uses energy to achieve the lowest power rate possible on a deformation signal, and it does this by being sensitive to the local characteristics of the structure shape.

2.1.3. Angle Regulation and Contour of the Centroid

The Cluster centers Curved Definition (CCD), which is invariant to translational and rotational, calculates the distance between the center and the points that define the boundaries of the contour. The Degree Code Definitions, also known as ACD, are responsible for computing the continual vector layer of leaf forms, although they only give limited data on shape [30].

3. Leaf Texture

A collection of measures meant to evaluate an image's apparent texture are used to determine whether or not a picture has texture. This provides us with information on the spatial arrangement of colors or intensities inside an image or a specified region within an image. It is possible to categorize photos based on their textures, which may either be generated artificially or discovered in the natural sceneries that were caught in an image. The characterization of areas in an image of a leaf is extracted using a method called texture-based feature extraction. This approach uses the texture content of the picture to determine characteristics of the region, such as how smooth, rough, or silky it is. Even among animals, there are variations in the Leaf's roughness.

3.1. Defined Features Derived from Geometric shapes

Topology measures the proximity of elements. The authors used pseudo-arrays of zone structures to estimate broadleaf weed texture and pixel density. They are applying a Rimani manifold to the surface of the leaf results in a smooth local consistency. The combined contrast of the leaf area is smaller than the original image. Remove edges and directions. Fractals determine the texture and roughness of the paper. Paper images were analyzed and identified using Minkowski's multiscale fractal dimension [31].

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Vijayalakshmi et al. retrieved texture by using a Filter bank with a rotation angle of 30 degrees in a 5 9 5 pixel region. As a result, they acquired thirteen distinct structural properties of a leaf. In order to classify the distinct species of Brachiaria, the Boligond–Minkowski fractal dimension approach was utilized to calculate the number of boxes that were arranged in a geometric connection with the pixels [32].

3.2. Textons

Texton dictionaries are produced utilizing spatial and frequency filter responses. To distinguish intra-class changes, the authors devised a continuous maximum response descriptor for rotation invariant databases. They created a main curvature descriptor for intra-class grouping for invariant rotation databases. These strategies are useful for interclass and intraclass leaf databases. Minu and Thyagarajan used MPEG 7 visual features to recognize floral photos. In their work, they created an ontology-based photo retrieval engine for Asteroidea flowers [33]. Guo et al. demonstrate the categorized scale-invariant material by first determining dominant orientation and then collecting anisotropy features based on this orientation. This was done to categorize curvelet material. In addition to this, they suggested two text-based statistical methodologies as a means of validating their methodology. Anisotropic pictures spin while simultaneously altering their appearance to make high-quality textures [34]. These approaches may be utilized in pitching leaf archives to categorize the leaves stored there.

4. Consistent Characteristic Detectors

Pictures may be converted into diagonal matrices using image transforms. A unit picture is represented by conversion as a group of linear composite essential pictures. Transformation also generates switch twists and scalable photos, removing edges from an image. (PHOG) is an acronym for "Ponzi Graph Elevation," and it is used to compute both the effect directly and the overall geospatial data in leaf pictures. It does this by extracting information about the edge contour and calculating histogram bins for each local bin. It functions on cells that are part of a dense grid and is invariant to alterations in geometry and photometry, except for object orientation. TSO invariance was given to the spectral via harmonic analysis. This included rotation, translation, scale, and mirroring, all based on Fourier descriptors. They did consistent affine research of something like the radii spectra for just an affine persistent transform and introduced it. Image values are used as the basis for the calculation. The identification of flux linkage is performed using redundancy wavelet transforms. It is different from other wavelet transformations in that it does not account for the fact all the source image pixels of the photo [35]. Because the spectrum produced by the Fourier-Miren transformation is unaffected by changes in rotation, translation, or scale, this transformation is a useful mathematical tool for picture recognition. The Fourier-Merren descriptors are also invariant in the location of the object. This is because they are generated from the energy centroid of the picture, which is subsequently transformed into a polar coordinate system. This is because the picture's energy centroid is translated into a system that uses fixed objects. The application of square units promotes the maintenance of direction, which,

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in turn, contributes to a phase shift in the circular harmonics that are present in the picture. The process of normalization ensures consistency in both size and intensity. As a result, the Fourier-Merren transform is invariant under a wide range of transformations, including translation, rotation, scaling, and illumination [36].

5. Modern techniques for identifying and dividing leaves

The categorization of flowering plants can be accomplished quickly and readily by botanists, but computer-aided methods are unable to do so. As a consequence of this, plants are categorized according to the veins, color, and texture of their leaves. There are a variety of categorization systems that are used to organize plant species. The classifier needs two different data sets: a labeled training and a test set. However, it doesn't consider the pictures' stratigraphic connections, lighting stability, or geographic affine. The data are transformed into a structure with a low number of dimensions. In addition, it manages noisy photos and considers the many challenges associated with lighting and orientation. Multiple learning delivers high accuracy in identifying plant species, especially when compared to the linear and guided classifiers [37]. **Figure 3** illustrates the common techniques for leaf classification.

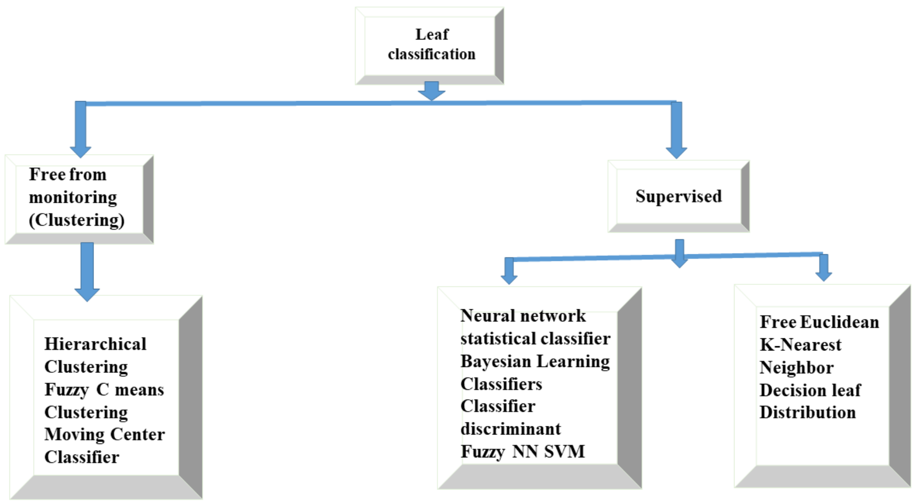

Figure 3. common techniques for leaves classification

Conclusions

In the current article, we went through various techniques for identifying different species of leaves that may be used for an experience and understanding system. It is important to remember that no one method can access a type by itself. In light of the fact that plant life varies with rocks and soils and can even be influenced by photonic and mathematical circumstances, the technique of image retrieval that is used must be chosen carefully based on the nature of the issue being addressed. The pollution, the times, and thus the length of the actual photographs may become problematic for flower images while

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they are being stored. As characteristics are crucial in machine learning to the filming of any lifeforms, we had also mentioned several different from retrieving the various features of seedlings, such as shapes, colors, fabrics, times, and also spatial and colorimetric rules. Because features are so important, we have covered many methods. Similarly, we have gone through some of the more well-known methods used in classic literature, including deep learning, manifold models, employee perception, and quadratic clustering algorithms. We chose an acceptable characteristic, the functionality of crude extract, and a powerful classifier in terms of the spacetime difficulty of pictures to assist in the identification of huge vegetation.

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