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Leaf classification on Flavia dataset: A detailed review

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ABSTRACT

For decades, vision scientists have contemplated the topic of plant species classification. As plants are of great importance to medicinal research, they are utilized in a wide range of medications. Plants are required in a variety of ways in order to save the species from extinction and provide an abundance of food through agriculture. Therefore,Botanists and computer scientists must conduct extensive plant species research. The plant resources are necessary for the survival of the world's nations The purpose of this paper is to examine the frequently utilized and publicly accessible dataset for plant classification in the past. We explored over 200 research papers for a deep understanding of the area. Briefly described are the procedural advancements and developments in the field of leaf classification. All the major techniques with significant advancements, the new effective approaches, and the novel techniques are discussed in this research. For the benefit of future researchers, the findings, research gap and transition, and coherence of algorithms in terms of several measurements are underlined. The hundreds of publications on a single benchmark dataset illustrate the progression of the recognition process, improvements, and innovations.

1. Introduction

Plants are indispensable to the planet and its inhabitants. They are essential to human existence. Numerous pharmaceuticals and raw materials are generated from numerous plant species [1]. They provide oxygen, absorb carbon dioxide, and return food for animals and insects. They have an impact on climate change [2] and provide a natural method of flood control. Plants are vital to ecology, as ecological awareness of the interconnectedness between humans and nature is crucial for food production, clean air and water, and biodiversity in a changing climate. In this rapidly evolving and expanding world, people are destroying their natural surroundings, so there is an urgent need to conserve and safeguard plant life. Human activities are somehow responsible for the loss of plant species [3]. Plants contribute significantly to agricultural output [4]. Moreover, the economic growth and development of the populace also depend on crop farming results. Identifying the plant and its species is the initial step in plant protection.

Taxonomists are responsible for identifying and classifying plants based on their characteristics. They are experts in classifying and organizing information according to a predetermined system. Studies conducted in the last decade [5] put the number of blooming plant species on Earth at anywhere from 220,000 to 420,000. Even with a hefty descriptive book, we cannot recognize and classify the plant species. Automation is necessary for the process due to the scarcity of taxonomist expertise and the high costs associated with hiring numerous individuals. Here comes the content-based automatic retrieval system. After the advent of portable, high-quality photographic equipment, ecological research has shifted in new directions. The automated procedure has now surpassed the manual expertise [6], decreasing time and the need to browse through long catalogs. The identification of plants is not restricted to only experts. Thus paving the way for automation in forestry, remote-sensing, precision agriculture (smart spray of herbicides), automated disease [7] or weed detection, and reducing the need for considerable manual labor. Methods involving computers can be statistically effective and reproducible. Researchers [8] considered leaf width, area, length, perimeter, diameter, shape, and color for the task of identification [9]. The content of the visual process was helpful in many ways from the beginning [10]. The research can be categorized or divided into several analyses of pairs of features, i.e., tip, base, and margin; Texture/Textons and colors and Pair of moment invariant descriptors, etc. Diversity in the inter and intra-classes of numerous leaves broadens the scope of research with no restrictions [11]. The visual content then covered recognition insights from spectral signatures to leaf venation and correlation between these with other statistical and morphology-based characteristics [12].

The fascinating thing is that the research on plant species or disease identification and classification can be easily extended to other domains.

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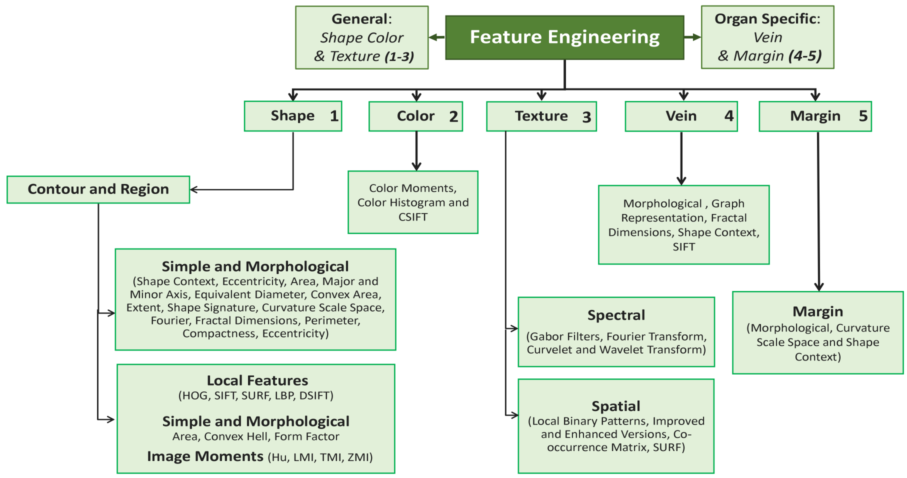


Fig. 1. Plant species identification: brief categorization of significant descriptors in the classification process.

The major contributions of this research article are as follows: We have carried out a thorough assessment of the area for plant species identification.

- Over the course of twenty years, we have carefully examined around two hundred articles. The progress in the sector is highlighted in terms of the enhancement of results.
- For future recommendations, the important experiments, creative approaches, proposed algorithms, and innovative concepts are streamlined.
- Botanists and taxonomists, in particular, can be heavily impacted by the brief overview of plant categorization by computer vision offered in our article.
- The article outlines facts that are highly effective for computer vision scientists exploring problems in different areas other than plant species as well.

Following is the order in which the sections of the paper are presented. The simple and morphological features used for leaf classification are described in Section 2. The qualitative and quantitative features, the mathematically features, and the dominant features are discussed along with the challenges. Section 3 shares the complete timeline of the plant leaf classification, the contributed datasets in the field, and algorithms and methods derived for categorization into classes. It is about the details of many classification algorithms used for the purpose, along with the feature engineering details. It further describes the research work and review papers written in the area with in past two decades. The complete timeline of major contributions to plant leaf classification considering the Flavia dataset.

Section 4 is all about the literature review and the evolved methods. In hundreds of academic publications, classifiers were fed the same 40 features, each with its own unique formula. Section 5 describes the research recommendations, research gaps, and anticipated questions with future directions. The Section 6 is about the final thoughts or the conclusion of our research. It highlights the purpose and outcomes of mainstream approaches and focused the circled pointers for upcoming researchers.

2. Taxonomy

Plant leaf identification is the process of determining the type of plant. However, classification is used to identify the species of the plant or the name of the disease that has infected it [13]. The researchers approached this process in a methodical manner. The approach employed for identification and categorization is both non-destructive and less harmful to the species of plants.

In the automated method, two different feature groups are used to tell the classes apart. Measurements such as length, height, width, and circumference are employed in the quantitative part. However, in qualitative characteristics, hue, texture, and vein patterns are used. Feature extraction is essential in the field of computer vision for describing an object in an input image. Shape, perimeter, size, color, and texture are all distinguishing characteristics of each leaf image; therefore, by extracting these features, the retrieved object is categorized into the class that applies to it the most. The significant descriptors used by researchers in the plant classification process are divided into five categories.

Shape is the most dominant feature used by researchers [14–20]. The distribution and respective names are presented in Fig. 1 as block diagram. Retrieving or classifying images on the basis of content is promising in research. In the block distribution, all the detailed features fetched from research papers are highlighted in separate blocks and under relevant branches It lies on basis of new techniques, methodologies, and ideas proposed [21]. Classifying leaves is hard because it is hard to deal with similarities between classes and differences within classes. The trends in the area are extremely diverse in multiple domains.

The traditional methods of manually crafting features for categorization have been superseded by deep learning's introduction [22]. In a number of applications, deep learning algorithms have outperformed more conventional methods of Computer Vision [23–25]. In this way, deep models automatically extract characteristics and learn them on their own. Most of the time, we consider deep learning algorithms as block boxes but the above features mentioned in Fig. 1 are learned by DL algorithms. Also, some of the researchers used the combination of features by handcrafting some mentioned in the Figure and using them with Deep Learning algorithms. The approach also helps in training the exact features for the model and making accurate predictions.

3. Timeline of research on leaf classification

The research is targeted at plant leaf species recognition, with only the Flavia dataset in observation. From 2001 to 2019, there were multiple open-source leaf and flower datasets popular in the research community, ranging from twelve to sixty thousand classes. Gajjar et al. [26] open-sourced and released a new dataset named the F2LSM dataset of imbalanced classes. The dataset is a combination of five popular datasets, namely Flavia, Folio, LeafSnap, Swedish, and MEW 2014, with data cleaning. The distinct classes are up to 374 with a total of 42420 images. The details of all fifteen datasets are shared in Fig. 2 as a flow diagram with citations and essential details.

The flavia leaf dataset released in 2007 received the highest number of citations (1095) in category of plant species. In our complete analysis

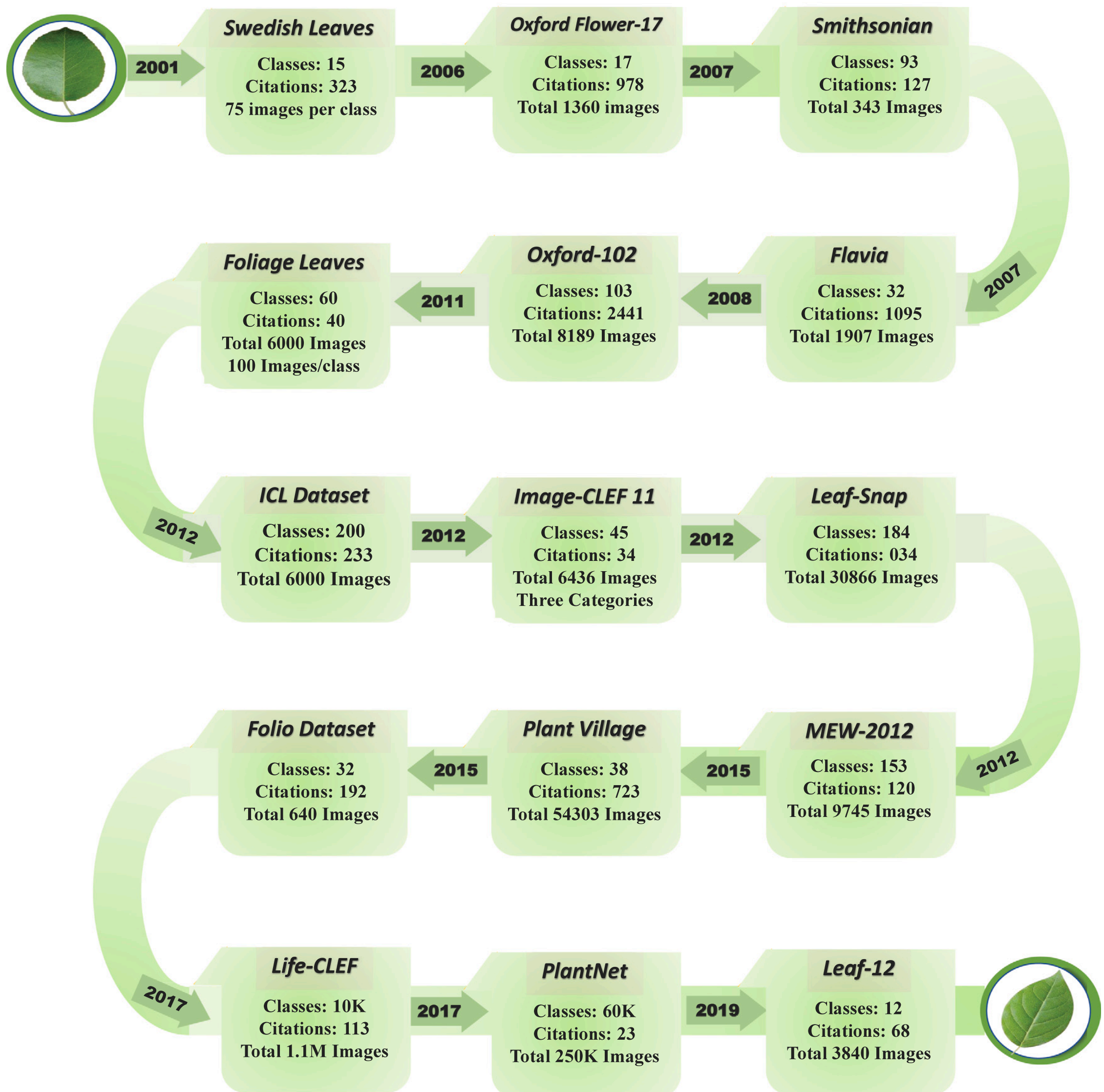


Fig. 2. 15 datasets proposed in last 20 years: significant datasets and detailed process.

of around hundreds of peer-reviewed studies, over 90 papers have cited and used the dataset for their proposed algorithms and identification techniques. The primary purpose of this research work is to examine the ongoing advancements in the classification of plant species. The evolution of the field over a period of time. The methods proposed and used to classify species in widely used datasets, the classification algorithms employed, the newly proposed features that contribute to the improvement of results, and recommendations for future research were gleaned from an in-depth analysis of over a hundred significant research papers.

In Fig. 2 Leaf-12 (2019) dataset consists of fewer classes while Smithsonian (2007) dataset contains the fewest amount of images. Hence, there is a need for balance to have a sufficient number of images for each class. The Flavia dataset is popular because of its maintained balanced between the two (classes and image count). It is worth mentioning that the datasets released before Flavia do not receive the highest citations. Moreover, the samples are both challenging and useful for testing classification algorithms. In the recent years, researchers have increased classes and image count of newly proposed datasets. Also, many researchers have not open-sourced their used datasets publicly.

If we consider citation, it is mentioned that the Oxford-102 Flower dataset has highest number but this dataset is limited to flowers, which is not taken in context for this research.

All the abbreviations used throughout the context of this paper can be viewed in Table 1.

4. Literature review

For the purpose of classification, features are necessary. Pixel-based, local-feature, region-based features [27] and derived methods are still popular in research. The idea of feature analysis and extraction dates back to 1950's. The features of an image helps in distinguishing one object from the another. Numerous features i.e. color, shape and texture features were used for Image Classification in the earlier vision solutions [28]. From medical images analysis, material sciences [29], radar or satellite imagery to field of botany (plants) features are significant for classification purposes. The trend of research starts from the basic studies of features to the advanced methods. Machine learning involved in the image classification is baseless without these features. Over the years with the introduction of deep learning and neural networks the hand-crafted or manual features are now extracted through deep learning or feature extraction algorithms. The literature review is about the

Table 1
List of the abbreviations used in research paper.

Abbreviation	Full form
SVM	Support Vector Machines
RF	Random Forest
PFT	Polar Fourier Transform
MSCM	Multiscale Sliding Chord Matching
MTD	Multiscale Triangle Descriptor
LBP-HF	Local Binary Pattern Histogram Fourier
CNN	Convolutional Neural Network
ACO	Ant Colony Optimization
HOG	Histogram of Oriented Gradients
WOA	Whale Optimization Algorithm
GA	Genetic Algorithm
ANN	Artificial Neural Network
ELM	Extreme Learning Machine
LR	Logistic Regression
DNN	Deep Neural Network
ICA	Integral Contour Angle
NB	Naïve Bayes
KNN	K-Nearest Neighbor
GPA	Generalized Procrustes analysis
BiDirP	Binary Directional Pattern
EOH	Edge Orientation Histogram
EFD	Elliptic Fourier Descriptor
RIWD	Rotation Invariant Wavelet Descriptor
MLP	Multi-Layer Perceptron
EFD	Elliptic Fourier Descriptor
DN	Deconvolutional Network
ELU	Exponential Linear Unit
ReLU	Rectified Linear Unit
2D-DWT	Two-dimensional Discrete Wavelet Transform
GLCM	Gray-Level Co-occurrence Matrices
MLBP	Modified Local Binary Pattern
ConvNet	Convolutional Neural Network
ZM	Zernike Moments
FD	Fourier Descriptor
LM	Legendre Moments
PNN	Probabilistic Neural Networks
NFC	Neuro-Fuzzy controller
LDA	Linear Discriminant Analysis
BoW	Bag-of-Words
SIFT	Scalar Invariant Fourier Transform
MSRM	Maximal Similarity Based on Region Merging
RBPNN	Radial Basis Probabilistic Neural Network
TSLA	Triangle Side Lengths and Angle Representation
PCA	Principal Component Analysis
SRVF	Squared Root Velocity Function
DMFs	Digital Morphological Features
BGLAM	Basic Gray Level Aura Matrix
SPPD	Statistical Properties of Pores Distribution
KDA	Kernel Discriminant Analysis
SOM	Self Organizing Map
IDSC	Inner Distance Shape Classification
TAR	Triangle Area Representation
ICA	Independent Component Analysis
WT	Wavelet Transform
MCC	Multiscale Convexity Concavity
CSS	Curvature Scale Space
MMNLBP	Mixed Multi-Neighborhood Weighted Local Binary Pattern
PHOG	Pyramid Histograms of Oriented Gradients

step-by-step developments in the area of leaf classification. However, for having an exact overview of the research trend we have considered one benchmark dataset [9] for our explanatory studies.

4.1. Features extraction in traditional methods

Statistical features were used extensively in the start for categorization research. Mathematical calculations and techniques with complex formulae calculations were proposed for learning unique characteristics of plant species. Zheru Chi et al. [30] used bark features for the plant classification. For the extraction process, Gabor filter banks were designed to recognize plant species. Adamek et al. [31] proposed a multiscale representation convexity concavity method (MCC) for non-rigid closed contours. The methods was tested on Flavia Dataset by Shitala Prasad et al. [32]. A new classification method Median Move Centers (MMC) with hyperspace classifier is proposed by Ji-Xiang and Du et al. [33] for the first time. Author claims that his technique is more robust and promising than the contour based features. Xiao-Feng Wang et al. [34] introduces a hypersphere classifier using the shape features of a leaf. Eight features were extracted after applying segmentation to distinguish among 20 classes of plant leaves. Plotze et al. [35] proposed a new method for extracting the morphometric characteristics of leaf structures. Experiment was tested with ten species of Passiflora plants. A limited quantity of samples were enough for structural patterns. Xiao Gu et al. [36] used the skeleton-based approach for plant species recognition. The fusion of wavelet transform and gaussian interpolation on leaf segmentation shows great improvement in recognition outcomes of species. Yunyoung Nam et al. [37] introduced a new shape representation scheme with Minimum Parameter Polygons (MPP) algorithm. By the presented scheme, the total number of points for matching the leaf are reduced and time for process is minimized. Yan Li et al. [38] applied Independent Component Analysis (ICA) for learning of linear basis functions. Antony Jobina et al. [39] used three stages of fractal refinement on leaf images for identification. The three stages used Contour, Contour-Nervure and Nervure fractal refinement respectively. Nandyal et al. [40] performed the classification of medicinal plants (with 900 leave images and 18 shapes) with base angle, apex angle and margin type of leaves. For the segmentation of leaf, Adaptive Otsu thresholding was used. Chih-Ying Gwo et al. [41] applied feature extraction on significant contour points. The Bayes classifier was applied for the identification purpose. Lavani et al. [42] implemented SIFT and edge-based contours detection for leaf recognition process. Mean Projection Algorithm is used for classification process. The method is superior over CSS methods due to lesser FP rates.

4.2. Venation based features extraction

Vein is considered as important information about plant species. In a dataset consisting of many types of leaves that are extremely similar to one another, the texture and color attributes were unable to correctly identify the specific class to which each leaf belonged. Venation extraction is applied by dividing the leaf into image patches for the retrieval of pattern maps. Also, the shape features are utilized in combination. Jin-Kyu Park et al. [43] first uses leaf venation (similar to blood veins in human) for categorization. Hong Fu and Zheni Chi [44] proposed a two-stage method, to estimate the regions of pixels of vein through segmentation and ten features were sent for fine-checking to Artificial Neural Network (ANN) based classifier. Although geometric features have major role in recognition but vein characteristics are also considered as a potential feature [45] by many of researchers [46, 47]. Shape, Color, Margin and Texture were also discarded [48] in case of Vein-based features. New venation techniques were proposed individually [49] or jointly with other characteristics of leaves. Some have also used vein features with combination of shape [50] and other characteristics.

Lei Zhang et al. [51] used stable features for plant categorization i.e, geometric features like texture venation and shape. A Neural Network SOM was implemented for the identification. Larese et al. [52] proposed an algorithm that uses only leaf vein structures for leaf identification. Segmentation of Veins was done by using unconstrained Hit-or-Miss Transform (UHMT) and adaptive threshold method. Features were reduced to few, but still it outperforms manual process. Park et al. [53] proposed efficient leaf image retrieval technique. Leaf categorization begins with leaf venation analysis. Park considered leaf shape information to discover similar leaves in a leaf database. Curvature scale scope corner detection method was applied for venation in the prototype design. Contrary to fractal dimension approach, multi-scale fractal dimension is used. Aptoula et al. [54] presented two morphological descriptors for classification of ImageCLEF12 dataset. Morphological covariance on leaf contour and circular covariance histogram were applied on vein part. Kue-Bum Lee and Kwang-Seok Hong et al. [55] utilized the vein and shape with extraction of twenty one features of leaf. The major data from the veins were transformed into frequency domain using the FFT Technique. The others were morphological and geometric features.

4.3. Shape and texture based features

Naif Alajlan et al. [56] proposed the method for shape retrieval using Triangle Area Representation (TAR) for closed contour non-rigid shapes. Their work employs Dynamic Space Warping (DSW) to ponder the similarity from the original shape. Their technique is also tested on Flavia Dataset with 867 features by Prasad et al. [32]. Ling et al. [57] proposed his new methodology Inner Distance Shape Classification (IDSC) over Euclidean distance in leaves. By combination of IDSC with different features, new and accurate leaf signatures were introduced to address part structure efficiently. The method achieves 88.11% accuracy with 12288 features on Flavia Dataset [32]. Bruno et al. [58] developed a computational program by analyzing complexity with fractal dimensions of leaf structure. Marzuki Khalid et al. [59] used two separate feature extractors and classifiers for wood species identification i.e. Basic Gray Level Aura Matrix (BGLAM) technique and statistical properties of pores distribution (SPPD) technique. Peter N. Belhumeur et al. [60] develops a prototype for botanists at the US National Herbarium. An individual snaps a picture of a single leaf against a clean background, then the system evaluates the image to determine its shape and attempts to match it to the patterns of other species leaves. The system takes a few seconds to present the most closely linked species, along with textual descriptions and more pictures of those species. Backes et al. [61] presented a novel approach in which texture is modeled as surface. The methodology surpasses traditional texture based approaches i.e., Co-occurrence matrices, Gabor filters, and Fourier descriptors. Zhaobin Wang et al. [62] introduced cortical Model for texture extraction with SVM classifier for the purpose. Harnoni et al. [63] used MSRM method for segmentation of flower with shape and color features for identification of orchid-species. Siravenha et al. [64] proposed the multi-resolution technique taking texture as feature to ANN. Hamid Laga et al. [65] proposed Riemannian elastic metric. According to the results, Metric based on shape was superior over descriptor-based metrics. The performance of the Squared Root Velocity Function (SRVF) for representing shape was studied with REM and tested over well-known databases. A novel descriptor named EAGLE was derived by Charters et al. [66] where characteristics are represented in angular relationships through histograms.

4.4. Idea of fusion

In order to achieve state of the art results consideration of individual contribution is required. Many of individual features of leaves holds significance in the final results. Therefore scientists proposed the combination approach for a set of features. Also the combined classifiers are introduced at the decision stage in desire of best results.

4.4.1. Idea of amalgamation of features

Thibaut Beghin et al. [67] used the combination of shape and texture features for classification in two stage method with a combined classifier at terminal. Using the Jeffrey-divergence measure, the signature of a contour was captured for recognition. Edge gradient orientations were then computed prior to being fed into an incremental classifier. Abdul Kadir et al. [68] (a key author with significant contributions in the field) shared the amalgamation of techniques in the hope to produce finest results. Polar Fourier Transform, color moments and features of vein are compounded. The combined model outperforms PNN, SVM and Fourier Technique used for Flavia and Foliage plants dataset. The author A. Kadir was the first to used two new techniques in field of plant classification. The Zernike Moments proposed in 1934 and Polar Fourier Transform proposed in 2002, both techniques were used for the first time in area of plant identification in his research work [69]. Kulkarni et al. [70] proposed RBPNN as classifier with Zernike moments in fusion with the shape, vein, color, texture features. The costly computation was counted as main demerit of involving Zernike moments in the categorization process. Harish et al. [71] combined Zernike moments with morphological features. PNN and SVM are used for classification and the extracted features were independent of rotation, translation and scaling. Khadije Mahdikhanlou et al. [72] used axis of least inertia and centroid distance with a PNN classifier. Zhiyong Wang et al. [73] used a combination of both local and global features for leaf identification. SIFT algorithm was implemented for local features while shape was considered as a global feature. A KNN classifier was used on ICL datasets outperforming earlier accuracy results. Yanikoglu et al. [74] proposed his work with rich variety of features on 126 species of ImageCLEF dataset. Priya et al. [75] transforms five fundamental features into twelve digital morphological features. The SVM was used for plant species identification in final stage of recognition. Abdul Kadir et al. [76] reported that the use of PCA with merger of features derived from shape, vein, color, and texture improves the final results with PNN classifier. Tsolakidis et al. [77] proposed combination of ZM and HOG with SVM as base classifier for SOTA results. The fusion of 10 morphological features were used by Uluturk et al. [78] derived from two half regions of the leaf. Using PNN Classifier by features from two halves, impact was observed in accuracy with good results reported. Vijay Satti et al. [79] took color, shape (geometric and morphological features) and tooth features as input to classifier. ANN classifier outperforms in results because of adequate feature set. A novel approach of sparse-coding based framework was introduced by [80] in comparison to general BoW approach. The sparse representation perform better with earlier methods. Chaki et al. [81] adopted a hierarchical approach with idea of strong classifiers using more than one descriptors (length, color, background, texture, shape and orientation). A new features based shape selection template was introduced to select the only required features for shape.

4.4.2. Amalgamation of classifiers

Stephen Gang Wu et al. [9] introduced a Probabilistic Neural Network (PNN) for leaf identification in Flavia dataset. The PNN algorithm receives five leaf features orthogonalized as input to PNN network. K. Singh et al. [82] put forward the idea of the combination of Support Vector Machines and Binary Decision Tree (SVM-BDT) for leaf classification with features of shape. The performance of SVM-BDT was observed superior on Flavia dataset in comparison to PNN and Fourier techniques proposed earlier. Chaki et al. [83] used two neural classifiers with texture and shape features derived from Gabor filter and GLCM.

4.5. Classifiers according to datasets

In self-collected datasets classification [84], ANN is better in comparison to many of the classifiers used earlier. Abdul Kadir et al. [85] used PNN as classifier with four features namely shape and vein, color, and texture features. The accuracy was decreased to 93.75% in comparison to his previous research based on PCA. Ali Caglayan et al. [86] used only two features (shape and color) but with a RF Classifier and Bayes Classifier. The selection of classifier lead them towards improved results. Kadir improved the accuracy to 0.01% using GLCM, Lacunarity and Shen features with a Bayesian classifier [87]. The proposed combination also reported improvements. Esraa Elhariri et al. [88] used LDA and RF classifier on self-collected dataset utilizing shape, color, texture and the margin characteristics. It is observed that using Linear Discriminant classifier with correct feature set can overcome the noisy leaf data [89].

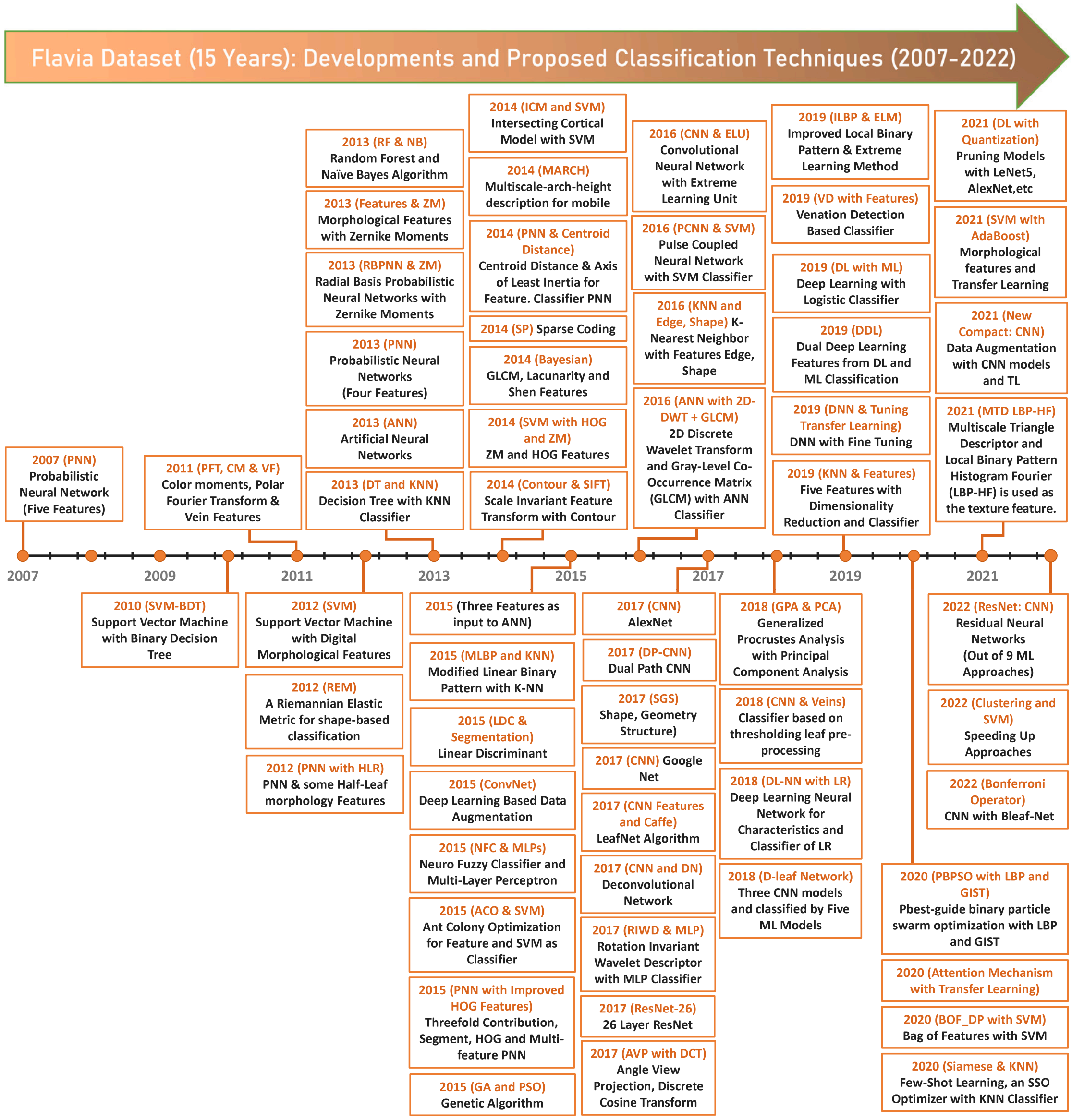


Fig. 3. Timeline diagram: representation of the development in the field of leaf classification flavia dataset only.

4.6. *Less features are cheap for faster retrieval rates*

For a low computational process specially for mobile platforms, Shitala Prasad et al. [90] used reduced shape and color features. Their algorithm have in two stages; the geometric features and then PFT before input to KNN classifier. Sangle et al. [91] also developed an Android application using shape-based features for leaf classification. Bing Wang et al. [92] generated a multiscale shape descriptor with contour of leaf shape, convexity and concavity characteristics of the arches of different levels. The prototype mobile application for consumer is developed with less retrieval time. These features are dominant for low-cost classification in terms of computation. Cihan Sari et al. [93] used combination of gross shape descriptors, Fourier descriptors, multiscale distance descriptors for leaf recognition. Pham et al. [94] developed a computer-aided identification system. The semi-automatic graphic tool and automatic identification is prepared. Similar systems and mobile-based systems [95] were also proposed for making system portable and handy. Sofiene Mouine et al. [96] introduced a new shape-based method TSLA with high retrieval accuracy. Contrary to TAR and TSL the methods work in partial occlusion and also invariant to rotation and scaling. Swedish and Flavia datasets were used for the proposed technique. Multiscale-arch-height description method (MARCH) was proposed by Bing Wang [97]. Shitala [32] implemented MARCH on different publicly available datasets with observation of significant faster retrieval speeds and low computational expense.

4.7. *Genetic algorithms in plant classification*

A genetic algorithm was proposed by Babatunde et al. [98] which used combinatorial set of 100 extracted features from leaf datasets. Babatunde in his enhanced version of research [99] added 12 more features making a total of 112 with Genetic algorithm. WOA algorithm was also used with RF later [100]. Keivani et al. [101] also used PBPSO method with LBP classifier. Ghasab et al. [102] introduced the concept of ACO for searching of the best feature with SVM classifier for comparative results.

Table 2
Research work categorization over the years in plant classification.

∑ Citation	Authors	Review details	Journal name	Years considered	∑Reference
252	MacLeod, Norman et al. [103]	Plant Recognition Algorithms and Methods	Nature	1959–2010	10
422	James S. Cope, David Corney et al. [13]	Identifying Leaf Species by Variation of Shape and Organs	Expert Systems with Applications Computers	1987–2012	113
528	Ji-Xiang Du, Xiao-Feng Wang et al. [33]	Species Recognition on Features	Applied Mathematics and Computation	1993–2004	20
41	K.K. Thyagharajan and I. Kiruba Raji [10]	Methods for Plant Features Extraction and Classification	Archives of Computational Methods in Engineering	1993–2016	200
68	Mohamad Faizal Ab Jabal, Suhardi Hamid et al. [104]	Approaches for Feature Extraction and Classification of Leaves	Journal of Computer Science	2003–2011	26
30	Oluleye Babatunde, Leisa Armstrong et al. [105]	Automatic Identification of Plants using Computer-Vision	Journal of Agricultural Informatics	2003–2012	27
307	Jana Wȁldchen and Patrick Ḿader [14]	Identification of Plant Species using Computer Vision	Archives of Computational Methods in Engineering	2005–2015	159
38	Nisar Ahmed, Usman Ghani Khan et al. [106]	Methods of Plant Identification	Science International	2006–2016	22
62	Muhammad Azfar Firdaus et al. [107]	Techniques for Recognition and Classification of Plant Leaves	Computers	2006–2019	65
1	Khaled Suwais, Khattab Alheeti et al. [11]	Plant Classification Methods in Review	International Journal of Advanced Computer Science and Applications	2006–2021	57
15	Sapna Sharma and Chitvan Gupta et al. [108]	Plant Recognition Algorithms and Methods	International Journal of Innovative Research in Advanced Engineering	2007–2013	27

4.8. A direction to be noticed

All mentioned studies on leaf identification have concentrated on feature extraction and classifier design, with some positive outcomes. Studies typically employ lab photographs or indoor images with a plain or pure background (controlled environment) as test leaves. This led to the selection of certain segmentation techniques for extracting leaf objects from color or grayscale images, such as thresholding approaches, gradient operators, morphological operators, etc. The digital photographs of leaves in the wild and outdoors will always have a complicated background, yet identifying these leaves is a primary goal of leaf classification. For instance, it is often impossible to avoid overlaps between some neighboring regions of leaves, which might lead to ambiguity about where one leaf ends and another begins. Segmentation results may be unsatisfactory if the target leaves are surrounded by interferents such as small stones, dead leaves, etc. Leaf photos taken indoors can still include unwanted elements, such as branches or other leaves, touching the desired leaves. Because of this, it is inevitable that the limits of the target leaves from conventional segmentation methods would link to the boundaries of branches or non-target leaves, rendering feature extraction inaccurate. Although the plant species recognition domain is interdisciplinary but its still segmentation techniques are separate area of research for computer vision scientists [109].

4.9. Extensive past reviews in the plant classification

The past review papers in the area of plant classification are mentioned with the significant details. The research work is categorized and distributed into the tables on the basis of years and citations. Mentioning the previous articles and their contributions will help to recognize the comprehensible details needed for this article. The innovation trends, proposed future works and achieved targets are catalysts to broaden research directions for the botanists and computer vision researchers.

Overviews, Reviews, Surveys, Opportunities, Challenges and Comparative/Competitive Analysis are examined. Our Research have a complete overview of the significant details, insights and strategies for the new researchers in the field. Table 2 discusses the year-wise developments in the research of plant classification techniques. All mentioned studies on leaf identification have concentrated on feature extraction and classifier design, with some positive outcomes. Studies typically employ lab photographs or indoor images with a plain background as test leaves. This led to the selection of certain segmentation techniques for extracting leaf objects from color or grayscale images, such as thresholding approaches, gradient operators, morphological operators, etc.

With a detailed review for the ease of understanding we have made a timeline diagram of the 61 techniques from 2007 to 2021 used on Flavia dataset by top-notch journals and highly cited papers.

The Pi Chart indicates in Fig. 4 indicates the cited datasets in the previous studies. Although it is less than 50%, still the dataset of Flavia leaves is popular among the research community due to its number of citations.

The timeline diagram 3 summarizes the outline of the evolution process in field of plant species classification. (See Fig. 5.)

4.10. Deep learning and CNN algorithms

CNN also opens the new door to ponder the problem of plant classification with improvement [110] to the results of classical approaches. Researchers used morphological and vein based features [6, 111] with CNN algorithms [112]. New derived architectures [113,114] and variants [24] with changing layers and activation functions were used [115,107,116] for the problem to achieve SOTA results [117–119]. AlexNet (variant of CNN) was used for classification of plant weeds [120]. CNN also serve for the complicated cases of categorization and recognition [121]. D-Leaf [122] derived from AlexNet achieved comparable results in relation to all other kinds of proposed CNN's. Similarly Raj et al. [123] derived DDLA algorithm with MobileNet and DenseNet architectures with fast retrieval speed. VGG-19 model of CNN was also used for plant identification and recognition [124] with competitive performance on open-source datasets. The results obtained

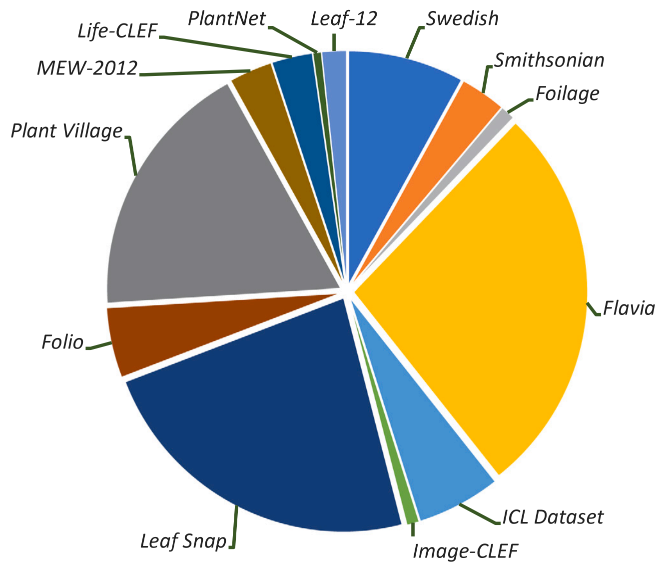


Fig. 4. Pi chart for dataset cited.

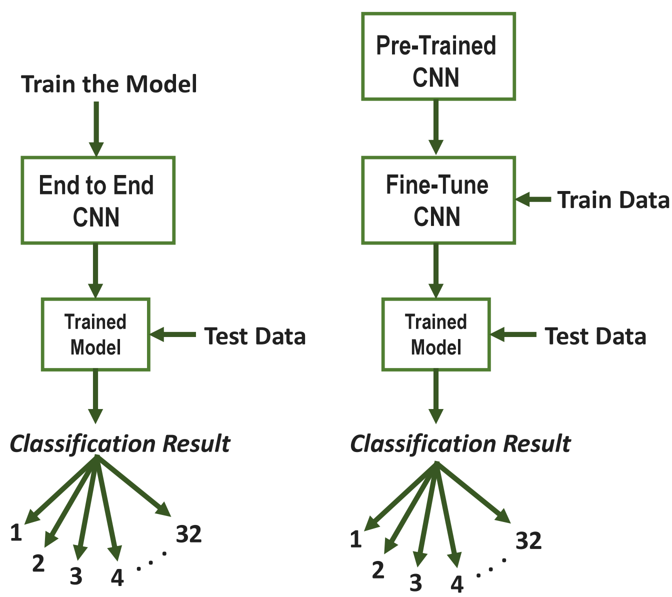


Fig. 5. End to end CNN model and concept of transfer learning.

through auto extraction of layers surpassed hand-crafted features [125] in most of cases.

The advancement in research was limited to the some initial features but analyzing the trend we came to know that the features are the same in most of the studies but new and robust methods [126] were derived with several classifiers to extract those features with a rich extraction and improved categorization outcomes. PCNN and DPCNN [127] were used for leaf [128,129] and fruit [130] recognition with BoW and entropy sequence was utilized as key feature. Yousefi et al. [131] proposed a new Rotation Invariant Wavelet Descriptor with MLP classifier based on shape features. RIWD acquires low computational cost but with a lesser performance output than proposed CNN variants. (See Table 3.)

Local Binary Patterns were also proposed for feature extraction process by Naresh et al. [136]. MLBP proposed used ANN but later Turkoglu et al. [137] improved with ELM Methods using only texture features with an improvement in base method. Keivani et al. [101] used LPB features with PBPSO method for feature minimization. The latest MTD by Yang et al. [138] outperforms all earlier LBP based approaches on benchmark datasets with combination of shape and textures. The use of transfer learning by Beikmohammadi et al. [139] with Deep Neural Networks for recognition of plant [140] fruit and vegetables [141] leaves produces surprising results. Attention mechanism was also used with Transfer learning [142] approaches in contrary of CNN. The equalization in results was achieved using encoder and decoder architecture with attention mechanism collectively with transfer learning [143]. The detailed analysis of Transfer learning techniques indicated that networks fine-tuned provided better performance as compared to available pre-trained models [5,144]. Cluster based approaches for leaf species were proposed by Goyal et al. [145] to gather plants with similar characteristics. The Fig. 6 mentions the most cited neural network

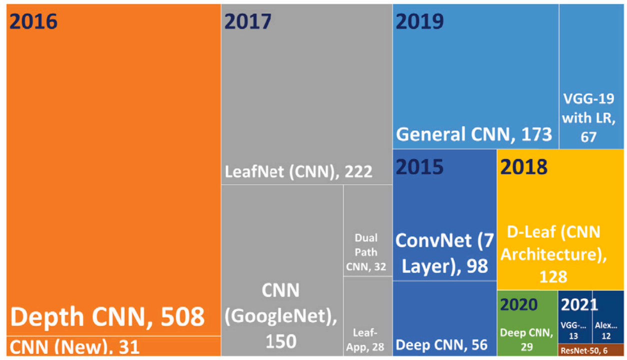


Fig. 6. CNN diagram: derived.

Table 3
CNN variants and versions derived for plant classification.

Year	Reference	Network	Citations
2015	[110]	ConvNet (7 Layer)	98
2015	[132]	Deep CNN	56
2016	[115]	CNN (New)	31
2016	[6]	Depth CNN	508
2017	[118]	Dual Path CNN	32
2017	[119]	CNN (GoogleNet)	150
2017	[125]	LeafNet (CNN)	222
2017	[117]	Leaf-App	28
2018	[122]	D-Leaf (CNN)	128
2019	[124]	VGG-19 with LR	67
2019	[133]	General CNN	173
2020	[111]	Deep CNN	29
2021	[114]	AlexNet	12
2021	[134]	VGG-16	13
2022	[135]	ResNet-50	6

based techniques in the last seven years. (See Fig. 7, Tables 4 and 5.)

5. Research recommendations

This section is organized after a descriptive overview of the research work in last 20 years. Analysis of the Pros and Cons and the development of the field uncovers various questions but for the future research will be much more structured and useful if earlier findings consolidate with some findings. After a deep dive into hundreds of future work and conclusions and their actual implementations by new researchers glorified the pathway and new directions. This section is kind of supplement to build up a pathway for accommodating new dimensions by past strategies. The ideas will sound beneficial for research community including the computer vision scientists and botanist. It will help all of us to explore innovative ways of research with the advancement in the field of vision, medicine and agriculture.

5.1. Global dataset for plants classification

Research community has been active in the field of plant classification. However, many datasets are taken into consideration till today. Several techniques and algorithms are evaluated based on selection of dataset for reaching the desirable results and classification accuracy. There are around fifteen publicly datasets available for classification of plants species namely Flavia [9], Folio [172], Leaf12 [124], LifeCLEF [173], PlantNet [174], ImageCLEF [175], Leafsnap [176], MEW2012 [177], Foliage [68], ICL [178], Swedish [179], Plant Village [180] and Oxford Flower-17 [181], Oxford Flower-102 [182] and Smithsonian Leaf [57] datasets. Many researchers have produced their own self-collected dataset [183,184] in different sizes. Among all of them, Flavia is mostly used as a benchmark by researchers for their evaluation algorithms and techniques [11]. It is observed that some classifiers and algorithms produced good results on one dataset but poor results on another. Hence there is a need for a global dataset with a large variation in features. Oluleye et al. [98] extracted 112 features only from images of flavia dataset therefore the combination of the existing datasets can lead to the preparation for a global dataset with thousands of features. In this case, the robustness and accuracy can be improved significantly through tested with enormous varying features.

5.2. Dominance of feature set in classification process

Chia-Ling Lee et al. [161] proposed region-based features over the conventional contour-based features. The features of aspect-ratio, centroid, compactness, horizontal and vertical projections feature-set were used for classification.

Region-Based Features ≫ Contour-Based Features Lee et al. [149] reported that venation orders are better representative than shape with CNN's.

5.3. Combination of features aids in correct categorization

The merger of important features ensures the finest output performance [147]. Nilsback [182] performed experiments a 103 class Oxford Flower dataset. Four attributes are calculated for each flower, each of which describes a unique aspect: the flowers local shape/texture, their boundaries, the spatial distribution of their petals, and their colors. Investigation proves that accurate selection of features. The results by Rubiyah Yusof et al. [185] indicate that increasing the amount of features by employing Gabor filters as an image multiplier and combining features from Gabor filters and GLCM feature extractors increased the accuracy rate of the wood species classification.

5.4. Shape is an important feature (leading one)

Shape [154] features has a significant position in plant recognition from the inception of the field. Humans can also perceive shape for identification of objects. The importance of shape context [186,148,187] is already recognized in the realm of computer vision problems [188,189,166,163].Wäldchen et al. [14] presents a tabular summary of all the research work that is produced by the combination of various leaf characteristics with the shape features.

The amalgamation of shape with several features are shared in Table 6 as Venn diagram with reference papers. Some other shape descriptors were also introduced [203] with other popular datasets. It is worth-mentioning that in shape-based methods of classification reducing inherent noise is extremely important for the output performance [89]. The shape descriptors used in Flavia datasets with respective accuracy are plotted in Fig. 8

Table 4
Feature engineering details and classification accuracy on flavia dataset.

Author details	Publication year	Classifiers used	Extracted features	Accuracy results
[42]	2014	Scalar Invariant Fourier Transform (SIFT) and Contour	Edge-Based Detection	87.50%
[77]	2014	Support Vector Machine (SVM)	Zernike Moments and HOG	97.18%
[87]	2014	Bayesian Classifier	Combination of GrayLevel Co-occurrence Matrix, lacunarity and Shen features	97.19%
[80]	2014	Sparse Coding (SC) and Bag of Words (BoW) separately	Feature-Vector of Image Input Patches	95.47% and 94.38%
[72]	2014	Probabilistic Neural Network (PNN)	Compute centroid distance of points and distance of sampling points from axis of least inertia	82.05%
[62]	2014	Support Vector Machine (SVM)	Shape and Texture features by Cortical Model	97.82%
[97]	2015	Multiscale-arch-height description for mobile retrieval of images (MARCH)	Global and Detailed Shape Features	96.15%
[102]	2015	Support Vector Machine (SVM)	Ant Colony Optimization (ACO) for best discriminative feature	96.25%
[146]	2015	Artificial Neural Network (ANN)	Three combined features: Morphological, Shape and Fourier Descriptors	96.50%
[89]	2015	Linear Discriminant Classifier	Segmentation-based Feature Extraction	94.00%
[110]	2015	ConvNet-based deep learning algorithm	Data Augmentation using multiform-transformations	94.60%
[83]	2015	Neuro-fuzzy Controller (NFC) and feed-forward back-propagation Multi-layered Perceptron (MLP)	Texture by Gabor Filter and Shape by Curvelet Transform	97.50%
[147]	2015	Texture Based Classifier	Improved HOG Feature Set and Segment Leaves	94.72%
[99]	2015	Genetic Algorithm Based	112 features are Zernike Moments, Fourier Descriptors, Legendre Moments, Hu's Moments, Texture, Geometrical and Color features	88.98%
[132]	2015	Deep Convolutional Neural Network (ConvNet)	Hand-crafted and DL Features	97.30%
[136]	2016	K-Nearest Neighbor (KNN)	Modified Local binary patterns (MLBP) for Texture Features	97.55%
[64]	2016	Artificial Neural Network (ANN)	Multi-Resolution 2D Discrete Wavelet Transform and GLCM	91.85%
[148]	2016	K-Nearest Neighbor (KNN)	Edge and Shape-Based Features	94.37%
[128]	2016	Support Vector Machine (SVM)	Entropy sequence obtained by Pulse-Coupled Neural Network (PCNN)	96.67%
[31]	2004	Multi-scale Convexity Concavity (MCC)	Non-Rigid Shapes Single Closed Contour	84.93%
[9]	2007	Probabilistic Neural Network (PNN)	Extracted and orthogonalized features into five principal variables	90.31%
[56]	2007	Triangle Area Representation (TAR)	Shape Features	85.03%
[57]	2007	Inner Distance Shape Classification (IDSC)	Distance Features	88.11%
[82]	2010	Support Vector Machine and Binary Decision Tree (SVM-BDT)	Distance Features	96.00%
[68]	2011	Multi-Feature Based Classification	Combination of Polar Fourier Transform, color moments and vein	93.13%
[75]	2012	12 Morphological Digital Features (DMFs)	Suppressed to Five	94.50%
[76]	2012	Principal Component Analysis (PCA) with PNN Classifier	shape, vein, color, and texture	95.00%
[78]	2012	PNN Classifier	7 Morphological + 3 Half-Leaf Features	92.50%
[41]	2013	Bayes Classifier	Shape Descriptors	92.70%
[79]	2013	Artificial Neural Network (ANN)	Color and Shape	93.30%
[85]	2013	Probabilistic Neural Network (PNN)	Shape, vein, color, and texture	93.75%

(continued on next page)

Table 4 (*continued*).

Author details	Publication year	Classifiers used	Extracted features	Accuracy results
[70]	2013	Radial Basis Probabilistic Neural Network (RBPNN)	Shape, vein, color, texture features combined with Zernike moments	93.82%
[71]	2013	PNN and SVM Classifiers	Morphological features and Zernike moments	89.10% & 88.10%
[86]	2013	Random Forest (RF) Naive Bayes	Shape and Color features	96.30% & 88.95%
[90]	2013	KNN Algorithm	Geometric feature Shape+Color with Polar Fourier Transform	91.34%
[93]	2013	Descriptor-based Matching	Combination of Gross-shape features, Fourier descriptors and multi-scale distance matrix	94.62%
[94]	2013	Support Vector Machine (SVM)	Histogram of Gradients (HOG) Descriptor with Maximum Margin Criterion (MMC)	84.6875%
[96]	2013	Classification with Multi-scale Triangular Representation	Shape-based Local Descriptors associated with Margin	93.53%
[119]	2017	GoogleNet (22 Layers)	Features by CNN Models (Two Variants)	99.60% & 99.80%
[125]	2017	LeafNet	Features by Deep Learning Models	97.90%
[149]	2017	Deep CNN	Features by CNN and Intuition by DN	99.40%
[113]	2017	ResNet-26 (DL Model)	Features by DL (ResNet26) > All available ResNets	99.65%
[122]	2018	ANN Classifier	Features by D-Leaf CNN Model	94.88%
[150]	2018	Euclidean Distance for Match	Seven Geometric Features	90% for 10-species
[5]	2019	LDA Classifier	Deep Features with AlexNet (TL)	99.00%
[142]	2020	NASNetLarge fine-grained Classifier	Attention Mechanism for features (TL)	99.72%
[114]	2021	Compact CNN and AlexNet (TL)	Features by CNN Models	99.45% & 99.65% & 99.55%
[138]	2021	Weighted Distance Measure	Text(MTD) and Shape(LPB-HF) Features	99.16%
[135]	2022	BLeafNet Classifier	Bonferroni Mean with five models (Fusion)	98.70%
[151]	2022	HerbModel (SVM Classifier)	SIFT + ORB + HOG Features	96.22%
[152]	2023	MMNLBP Classifier	LBP features fused with HOG	98.19%

5.5. Choose either a classifier or a adequate feature set for best identification

The results demonstrate that the use of combination of adequate features [148] or technique of feature extraction [136] for the recognition of leaves is on par with or superior to the state of the art [77] in accuracy. The development of LBP classifier over four years emphasizes on the selection or combination of features [138]. Elnemr [205] selected and reduced 154 features to 16 for the texture based classification. Feature space was reduced by Neighborhood Component Feature Selection method for the problem. Contour based novel methods namely GPA was introduced by Choudhury et al. [206]. The PCA was used to apply the dimensionality reduction (similar to limiting feature space). Sometimes good classifier chosen wisely produces a significant difference [122] in results [187,100,164]. We have to choose wisely between the two through trying several combinations. Hall et al. [132] proved that combining the features from hand-crafting (traditional) features and features from Convolutional Neural Network produces state of art results with major improvement in accuracy [207]. For the perfect selection or extraction of features several methods including swarm optimization, Genetic algorithm, Ant colony, Bees colony, Cuckoo search, fish, cat and Genetic algorithm were introduced [208].

5.6. Need of the hour: Computer and mobile-based portable solutions

In early times, most of the UI based solutions are proposed. Researchers developed computer programs and code algorithms to identify different plant species through captured images. Bruno et al. [58] used fractal dimensions for the purpose. Belhumeur [60] system extract and present textures and other features from leaf after removal of background and unnecessary information. The system was used by botanist at Smithsonian Institution. The semi-automatic and fully automatic tool was also proposed by Ngoc-Hai Pham et al. [94]. The semi-automatic graphical tool have the option of manually tolerate the useful information from the user feedback. The aid of assistance makes it better than previously available tools.

As world is progressing, we are moving towards the fast, handy and portable or mobile solutions for the daily requirements. The modern world is adopting portable solutions to make the things little and handy through the available IoT devices and mobile phones. Also for processing the images at the mobile end we need smart algorithms with low computational cost. In earlier systems such as CLOVER [37] few features i.e, shape are used for retrieval of images. Agarwal et al. [16] calculate similarity of shape for the process on PC and Tablet computer. Shape features for classification are used in Android by Sangle et al. [91] in his application. Kumar et al. [209] use segmentation for separating the leaf from the background and process contour features for his mobile application. Prasad et al. [90] calculated geometric features and then PFT. The strategy used is to decrease the image to aspect ratio for cutting the computational cost on mobile platform. AVP was also introduced for mobile based classification in low-vision environment [32]. Wang et al. [92] proposed multi-shape descriptor for his mobile application. The convexity and concavity of the arches at different levels are measured. The proposed methods is faster than all previous methods proposed for mobile platforms. Lin-Hai Ma et al. [188] extracted PHOG, HSV, Color and Wavelet features in controlled environment condition with NN algorithm for identification purpose. ImageCLEF dataset is used for testing and validation of categorization results.

A server-based solution with mobile platform was developed by [172]. Features used are of color, length, width, area, perimeter, centroid and distance maps. Priyankara et al. [95] adopted a distinctive approach for the application by neglecting shape-based features and

Table 5
Geometrical and morphological features: a summarized version used in two decades on Flavia dataset.

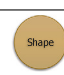
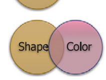
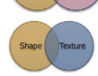
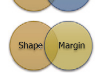
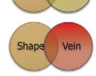
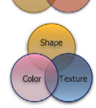
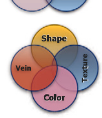
Features	Formula/Symbol	Description	Studies
Area	$A = \int_x \int_y f(x,y)dxdy$	Area of Pixels in the Region	[75,153,86,83,154,80,155,78,56]
Equivalent Diameter	$D_E = \sqrt{\frac{4\times Area}{\pi}}$	Its simply circle diameter with the organ's same area	[154]
Diameter	D	Any Two longest coordinates in the Leaf Margin	[75,153,86,156,157,9]
Perimeter	P	$\sum Distances$ of each adjoining pair of pixels	[75,86,83,102,154,156,155,9]
Convex Hull (Convex Area)	CH	Region is convex and contains region of leaf organ	[146,33,154,34]
Roundness (Form Factor)	$R = \frac{4\pi A}{P^2}$	To differentiate among big and small leaf by Area and Perimeter	[146,63,75,86,158,33,88,102,159,69,156, 157,90,34,9,160]
Circularity	$R = \frac{4\pi A}{P^2_{ConvexHell}}$	Same as roundness but Perimeter of CH (P_{CH} is taken)	[34,89]
Major Axis Length	$L = \frac{(x_1-x_c)^2}{rx^2} + \frac{(y_1-y_c)^2}{ry^2}$	Tip and Base of Leaf connected by Line Segment	[75,86,158,80,154,9]
Minor Axis Length	$W = (l(\frac{(x_1-x_c)^2}{rx^2} + \frac{(y_1-y_c)^2}{ry^2}))^{\perp}$	The maximum width ⊥ to Major Axis	[75,86,158,80,154,9]
Centroid	$g_x = \frac{\sum_{i=1}^{N} x_i}{N}, g_y = \frac{\sum_{i=1}^{N} y_i}{N}$	Geometric Center of Leaf's Organ	[161,162,78,72,163,164,144]
Slimness/Elongation (Aspect Ratio)	$AR = \frac{L}{W}$	Ratio of Major Axis to Minor Axis	[146,63,75,153,86,158,33,88,102,69,156, 161,157,90,155,34,165,9,51]
Leaf Width Factor	$LWF_c = \frac{W_c}{L}$	Leaf is divided into vertical strips made ⊥ to major axis	[154]
Area Width Factor	$AWF_c = \frac{A_c}{A}$	Same as A_c but area of each strip is computed over entire Leaf area	[74]
Perimeter Ratio of Area (Compactness)	$C = \frac{P^2}{A}, \frac{P^2}{\sqrt{A}}$	Idea about general complexity and Form Factor	[89,57,74]
Vein Features	$V_1 = \frac{A_1}{A}, \frac{A_2}{A}, \frac{A_3}{A}, \frac{A_4}{A}$	$A_1, A_2, A_3, and\, A_4$ are vein features	[9,82,87,166,46,57,60,61,66,88,50,6,167, 106,55,40,9,58,35,168,69,48,36,52,47, 54,75,167,39,37,53,43,73,102,36,83,169]
Perimeter Ratio of Diameter (Longitudinal Spread)	$P_D = \frac{P}{D}$	Perimeter Ratio to Leaf Diameter	[75,156,9]
Convexity of Perimeter	$P_c = \frac{P_{CH}}{P}$	Convex Perimeter Ratio to Origin Ratio	[33,89,160,74]
Perimeter Ratio of Major Axis Length	$P_D = \frac{P}{L}$	Perimeter Ratio to Length of Major Axis	[86,158,156]
Perimeter Ratio of Major and Minor Axis	$P_{LW} = \frac{P}{(L+W)}$	ratio of the object's perimeter to the total of the lengths of its major and minor axes	[75,86,158,156,169]
Orientation	$O = \cos m_j + \sin m_j + \sqrt{\tan(m_j \times m_i)}$	Angle in between major axis of ellipse and x-axis	[144,67]
Solidity (Area Ratio of Convexity)	$S = \frac{A}{ConvexHull(CH)}$	Leaf Fraction of Region compared to Convex Hull	[33,88,89,157,34,160]
Rectangularity	$R = \frac{A}{(L\times W)}$	Computes the Rectangular Nature of Shape	[75,86,158,33,102,154,156,9,160]
Extent (Form Factor, Roundness, Isoperimetric Factor)	$Extent = \frac{Pixels_{Region}}{Pixels_{RecArea}}$	Ratio of Organ pixels to pixels in Area of smallest rectangle	[146,63,75,86,158,33,88,102,159,69,156, 157,90,34,9,160]
Eccentricity	$E = \frac{f_{foci}}{L}$	Same second moment (moment of inertia as of region). Range 0-1	[146,33,88,154,157]
Entirety (Area Convexity)	$E = \frac{CH-A}{A}$	Ratio of Organ pixels to Pixels in Area of smallest rectangle	[74,34,89]
Narrowness Factor	$NF = \frac{D}{L}$	Ratio of Leaf Diameter over Length of Major Axis	[75,86,156,34,9]

(*continued on next page*)

Table 5 (*continued*).

Features	Formula/Symbol	Description	Studies
Dispersion/Sphericity (Irregularity)	$S = \frac{max(\sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}}{min(\sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}}$	Ratio of Radius of Max Enclosing Circle to Min Enclosing Circle	[33,69,34,160]
Smooth Factor	$SF = \frac{Area of Leaf by (5 \times 5) Averaging Filter}{Area of Leaf by (2 \times 2) Averaging Filter}$	Smoothness is defined as noise effect to image area	[75,9]
Color Features are derived	Mean (μ), Standard Deviation(σ) Skewness(θ), Kurtosis(γ)	These measures are used to computed with R, G, B channels	[86,90,63,74,101]
Mean	$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{i=1}^{N} P_{ij}$	Statistical Calculation of Mean	Derived From Color
Standard Deviation of Color	$\sigma = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{i=1}^{N}(P_{ij}-\mu)^2}$	Statistical Calculation of Standard Deviation	Derived From Color
Skewness	$\theta = \frac{\sum_{i=1}^{M}\sum_{i=1}^{N}(P_{ij}-\mu)^3}{MN\sigma^3}$	Statistical Calculation of Standard Deviation	Derived From Color
Kurtosis	$\gamma = \frac{\sum_{i=1}^{M}\sum_{i=1}^{N}(P_{ij}-\mu)^4}{MN\sigma^4}$	Statistical Calculation of Kurtosis	Derived From Color
Ellipse Variance	EV	The deviation of leaf shape to fit in ellipse with same co-variance matrix	[160,101]
Porosity (Cracks)	$PP = \frac{A-A_d}{A} \times 100$	The portion having cracks A_d is holes count in leaf	[90]
Cross-Sectional Spread	$CS = \frac{P}{L \times W}$	Constituted by both length and width	[101]
Uniformity	$U = \sum_{k=0}^{L-1} p^2(z_i)$	p is histogram, z is random variable, L is intensity-level	[166]
Entropy	$E = \sum(p \times \log_2(p))$	Histogram count measure is value of p	[170,129,51]
Hu Invariant Moments	$M(i,j) = \sum\sum(x^i)(y^j)I(x,y)$	x, y are co-ordinates i, j are changed to get moments, I is Intensity	[83,171,128]
Polar Fourier Transform for Shape	$PF2(\rho,\phi) = \sum\sum f(\rho,\phi)exp(j2\pi(\frac{r}{R}\rho + \frac{2\pi}{T}\phi))$	This capture shape and invariant to rotation and scaling	[68,85,90]

Table 6
Blend of shape and other features.

Features	Venn Diagram	Research Work
Shape		[146,190,60,191–193,32]
Shape + Color		[86,194,188,90]
Shape + Texture		[67,83,183,195,169,196,62,184,51,138]
Shape + Margin		[197–199,89,200,201]
Shape + Vein		[54,75,58,167,39,37,53,43,73,9,112,111]
Shape + Color + Texture		[202,74]
Shape + Color + Texture + Vein		[88,102]

adopting the combination of SIFT and BoW with SVM Classifier. The server-based system is used at the back end for the application. Because of low computation at the mobile end, a single feature or fusion of multiple features were used in the proposed solutions. The Venn diagrams in Table 7 highlights the feature and sets made through pairs.

5.7. Usage of simple and morphological shape descriptors

The studies shows that Simple shape descriptors should be used at high-level of classification process. According to the findings of the research, Simple and Morphological Shape Descriptors are overly simplistic and cannot discern leaves beyond those that have significant

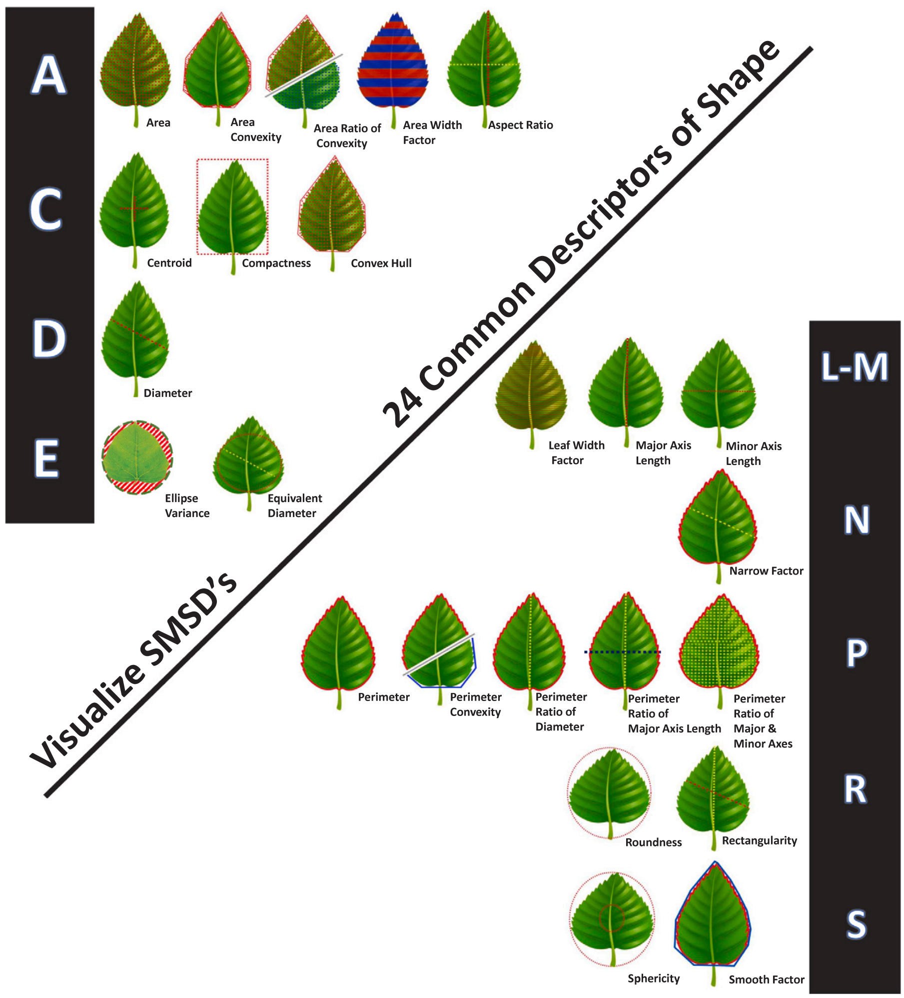
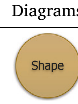
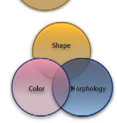


Fig. 7. Visualization directory of morphological and simple descriptors: the formulae and mathematical terms.

Table 7
Portable mobile and application based solutions.

Platforms	Diagrams	References
Computer-based (UI Solutions)		[58,60,94]
Mobile (Android) based solutions		[37,16,91,209,90,92,188,172,95,32]

variances adequately. In order to use them for complex situations having high correlation in species, they should be combined with other descriptors for the classification of leaves.

5.8. Novel CNN's and DNN's with new architectural enhancements

The introduction of CNN have completely changed research directions for plant feature extraction [133]. Studies prove that the process of auto-extraction of colors and texture features provide ease and new ways for research [210]. From compression the size of deep learning models [134] (through pruning or quantization) to the introduction of attention in the area, the redundant features are prevented to contribute in the final classification outcomes. Upon the comparison on nine machine learning algorithms over Flavia dataset, the CNN architectures proves to be the best [211]. Although, Ganguly et al. [135] tried for the fusion of many CNN classifiers with Bonferroni mean operator for getting the best output results.

6. Conclusions

In our research, we have carried out a thorough assessment of area of plant species identification. Over the period of twenty years, we have carefully examined around two hundred articles. The progress in the sector is highlighted in terms of the enhancement of results. Because of its acceptance in the research community, the dataset Flavia, which is referenced extensively, is taken into consideration for the insights. For future recommendations, the important experiments, creative approaches, proposed algorithms, and innovative concepts are streamlined. The publication examines all past research and describes

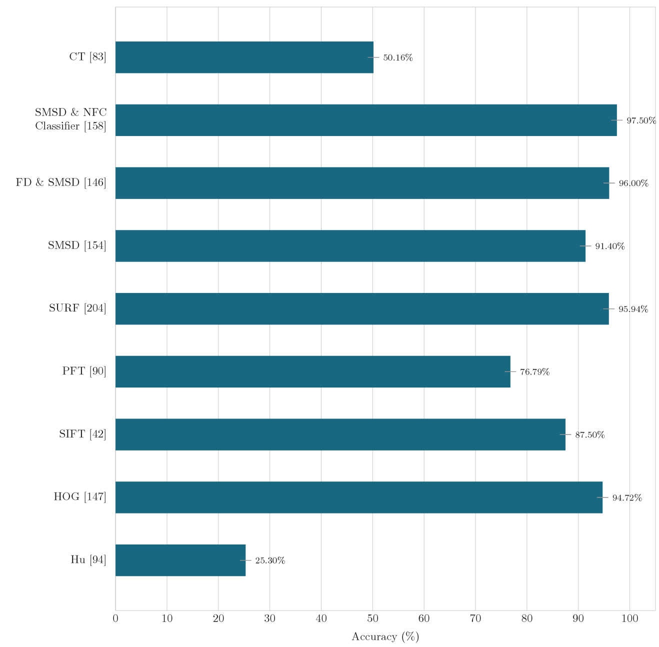


Fig. 8. Shape descriptors used with Flavia dataset (only shape) [83,158,146,154,204,90,42,147,94].

its findings in the theme of plant classification. Botanists and taxonomists, in particular, can be heavily impacted by the brief overview of plant categorization by computer vision offered here. Moreover, its highly beneficial for the vision researchers exploring problems in different areas.

CRediT authorship contribution statement

Syed Umaid Ahmed: Research and preparation of this manuscript. **Junaid Shuja:** Research and preparation of this manuscript. **Muhammad Atif Tahir:** Research and preparation of this manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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