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# Particular Leaf Contour-Based Feature Extraction Technique to Identify the Species when the Leaf is shrouded

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***Abstract*: A critical and challenging in pattern recognition is the identification of plant species from obstructed leaf photographs. The biggest issue at that time is to accurately identify the species of leaf when all of the leaves are identical in appearance and obscured. Shape is one of the most important visual elements and is also recognized as a fundamental attribute for conveying the content of pictures. Since it can be difficult to gauge how similar distinct forms are to one another, as well as describe the content of shapes. The two main categories of shape descriptors are region-based and contour-based shape descriptors (CBSD) techniques. Region-based approaches use the complete area of an item for shape description as opposed to contour-based approaches that only use the information contained in an image's contour. In this study, we presented a shape description approach called Particular Contour-Based Shape Descriptors (PCBSD) for the identification of the plant leaves since the CBSD recovered the low level visual properties of the pictures. This method successfully captures the local and global characteristics of a leaf shape while preserving the translation, rotation, and scaling similarity transformations. This method is also quite compact and has a low processing complexity. To evaluate our experiments, we utilized Flavia datasets of typical plant leaves. We show that our technique created the best complete leaf match when high occlusion (around 50% occlusion) occurs. We may say that our method exceeds prior state-of-the-art shape-based plant leaf recognition algorithms and it generates accuracy of 76%.Picture processing methods are used to separate the leaf-based characteristics from the leaf image. Eventually, using machine learning methods, then leaf identification was accomplished.**

***Keywords*:** Contour based, Feature extraction, Leaf Classification, Plant Species Identification, K-Nearest Neighbor Classifier**.**

## I. Introduction

Plants are divided into several categories based on morphological traits such leaf morphology, arrangement, edge, leaf apices, composition, and venation [1]. The curvature of the leaf edge, which may be used to differentiate between different genotypes, has a considerable impact on the overall shape of the leaf. The two types of shape descriptors are CBSD and RBSD, and they are both listed in [2]. The Flavia dataset was utilized throughout the testing procedure. The Flavia dataset, which was made accessible, contains images of leaves from 32 different species that date back to 1907. These images have a 1600 x 1200 resolution, a white backdrop, and are in the jpeg format. Each class has between 50 and 77 photos. There are scientific and popular names for every species of leaf [3]. The most suitable traits were then chosen for a leaf image-based plant classification after a number of aspects related to the size and form of the leaves were assessed. Provided a method to classify plants using a range of classifiers. Base classifiers were trained utilizing four distinct feature categories in order to provide a diversified pool of classifiers. A static selection was performed from the original pool of eight base classifiers to compare various classifier ensembles. Use the K-Nearest Neighbor (K-NN) Classifier to determine the results [4].The CNN feature extractor and ANN classifier outperformed other classifiers in terms of outcomes. The finest outcome of this study truly involves using the ANN as a classifier and the D-Leaf for feature extraction to obtain a pretty high accuracy [5]. The two strategies were tested using a similar dataset, and the DLNN method outperformed the SVM strategy. The suggested method had the highest degree of accuracy in the Flavia leaf database because to the utilized leaf samples' modest variances in shape and texture properties [6]. For the separate technique, the Fourier descriptor (FD) approach was the most accurate; for the four-section method, the best results came from the GLCM and colour methods. Additionally, the classification process was carried out by combining the properties of the feature extraction approaches [7]. We show how deep learning may be effectively used in agriculture, especially to identify plants based on the vein patterns in their leaves. In a cutting-edge processing pipeline, we replaced a task-specific module with a deep convolutional network and improved accuracy using a conventional deep learning model [8]. The following are some advantages of suggested integral contour angle descriptions: It has theoretically proved intrinsic invariance into group transformations including uniform scaling, rotation, and translation, and (ii) The ICA descriptors are noise-resistant. (iii) Due to its extensive usage of scales, it is remarkably adept at differentiating between different leaf kinds. The proposed ICA descriptors also only consider the area surrounding the contour point [9]. For the purpose of identifying leaf illnesses, we have looked over relevant papers in the literature and applied machine learning techniques. Using publicly available datasets from various sources, the suggested CNN was trained and evaluated. We presented a CNN model for categorizing leaves, and we developed two models by altering the network's depth using Google Net. We assessed the effectiveness of each model based on the coloration or damage to the leaves [10]. PNN is frequently used in classification and pattern recognition issues and may be a feed forward NN. Three node layers make up the PNN [11]. A method for classifying plants that can distinguish leaves. SVM was employed as a classifier. Moments are wonderful and distinguishing characteristics, but sometimes they fall short when the form of leaves from several species is quite identical. In these circumstances, we additionally applied the energy, standard deviation, entropy, mean, and histogram parameters for reliable local binary pattern resolution. The benchmark Flavia data set served as the foundation for our evaluation of our suggested approach [12]. The suggested approach may be used successfully and productively to segment individual leaves. They also include formulas for computing leaf measurements including area, length, and breadth [13]. Devices based on morphological and geometrical parameters were most often utilized [14].

The classifier of choice was K-NN for a number of reasons. Use of K-Nearest Neighbors is acknowledged as an essential machine learning technique. The application of the K-NN idea aims at predicting the collection of datasets that are most similar. Quantified requests are frequently categorized using the text region nearest to the request in question in addition to the content itself. In the publicly available datasets, there are K neighbours. The K-NN methodology is built on the similarity learning approach, which is utilized in many text classification and data analytics methodologies and domains. The category is predicted using a test document and the K-NN classifier placed next to the learned texts. The value for the respected class is then provided using the classes of the K neighbours [15]. The identification of plant species from pictures of their leaves is an important and difficult task in pattern recognition and botany. How to swiftly and properly recognize the similarities between leaf image aspects is the main challenge of this work. Triangle-distance representation (TDR), a distinct form description technique for recognizing plant leaves, is suggested in this study [16]. Using a computer vision classification system, determine the species of tree from a picture of a leaf. We compare several terms that are used to describe various leaf qualities. We will examine several classification methods and incorporate them with the descriptors to further categorise the various tree forms [17].It is a challenging issue to determine an object's shape following local deformations and no rigid transformations. By putting forth a shape identification technique based on the curvature bag of words (CBoW) paradigm, this problem is solved [18]. A technique for distinguishing plant species from a picture of a leaf with a concealed leaf was developed by authors using a database of known species of multiple leaf species [19]. The recommended Log Gabor filters approach has been extensively utilized in the literature [20] and assessed for the extraction of texture features.

The literature [21] examines a variety of methods for classifying various plant species. Zhang et al. [22] described a technique for detecting plant species that combines singular value decomposition with sparse representation. With this approach, neither the development of distinctive categorization features nor a training technique is required. This strategy is also more successful. Though not very high, this approach does have some recognition accuracy. A multi-scale fusion convolutional neural network (MSF—CNN) is proposed to detect plant leaves [23]. The two and four parts of a leaf picture are used to separately gather the characteristics. The feature vectors that make up the whole leaf picture are made using the parameters acquired from each component together. In addition, numerous aspects of leaf pictures were retrieved beyond division by using vein features. Later, the ELM technique was used to carry out the categorizing process [24]. K-Nearest Neighbor (KNN) Algorithm for Machine Learning explained by [25]. The study showcases the effectiveness of their hybrid image retrieval system, which integrates multiple descriptors, utilizes PCA for feature selection, and employs a cluster-based indexing technique to enhance retrieval speed. The comparisons with existing techniques validate the system's performance in terms of accuracy and efficiency [26]. To bridge the "semantic gap" between images by leveraging Parzen and SVM relevance feedback algorithms, focusing specifically on texture features. Notably, this research marks the first instance of employing the Parzen classifier in relevance feedback. The experimental results obtained from the study demonstrate that the performance of the Parzen classifier surpasses that of SVM and GMM, particularly within a limited number of feedback iterations [27].
Our strategy, which provides a better answer than existing methods, is built on the widely-used, public Flavia leaf image databases. The remaining sections of the paper are indicated. Methods are discussed in Part 2. In Part 3, we undertake an experiment to determine, in light of past findings, how effective our technique is. Conclusion and suggestions for improving the offered approaches are provided in Part 4.

## II. Methodology

The dataset gathering procedure is the initial stage in the approach employed in this work to identify plant leaves.

### *A. Dataset Gathering:*

The two options we have while selecting the dataset are Swedish and Flavia. The nation's leaf data repository was established as a result of a leaf categorization research carried out by Linkoping University and the Swedish Museum of Natural History. The capstone thesis of Soderknist contained this dataset [17]. It is composed of coloured pictures that were scanned at 300 dpi. There are 1125 Swedish leaf photos in all over its 15 free courses, each with 75 images [18], sample leaf images shown in below Figure 1. In the typical assessment technique, 25 photos are utilized for training and 50 images are used for testing. A shape descriptor's ability to categorise is periodically assessed using this database. Using this database of plant leaves, item recognition skills are evaluated.

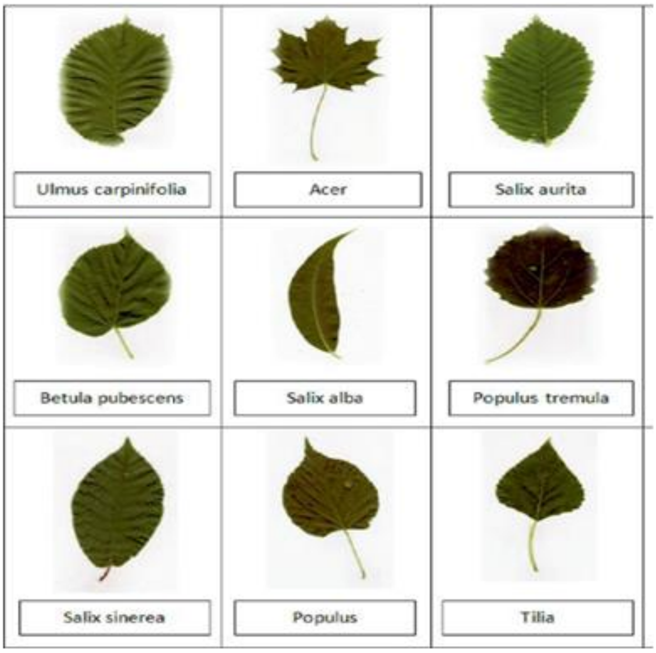


**Figure 1.** Displays examples of Swedish leaves

A second Flavia dataset with 1907 images of leaves from 32 distinct species is now available. These photographs are in the jpeg format with a white backdrop and a resolution of 1600 x 1200. There are between 50 and 77 images in each class. Every species of leaf has a name that is both scientific and common [3]. We opted to utilize the Flavia leaf dataset after comparing the two datasets in depth because it has a huge number of leaves from different species. Below Figure 2 are images of the sample Flavia leaves.

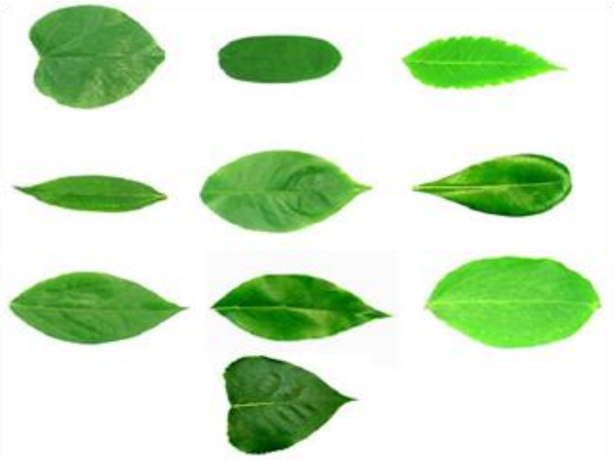

**Figure 2.** Images of the sample Flavia leaves

The approach used in this study to identify leaf species consists of a number of phases. Detail research methodology we employed in Figure 3.

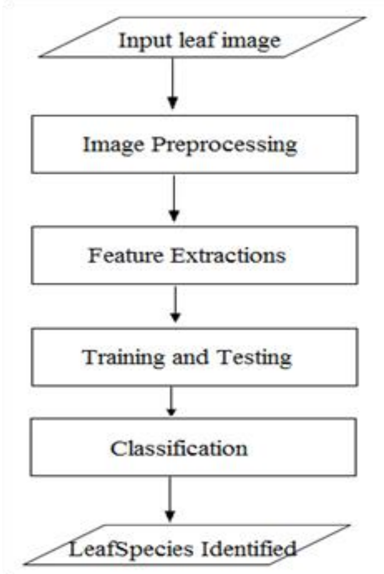


**Figure 3.** Detail research techniques we employed

*B. Input Images:*

The online Flavia leaf data collection are available, we selected the few leaves with various species. The Flavia collection yielded 380 images altogether, with 10 distinct species represented. Images are selected based on orientation, and every image that is selected has a unique pattern of orientation. We selected each of the landscape-format images. These selected images provided information to the system.

*C. Image Preprocessing:*

A colour image with an undetermined height and angle is referred to as an unedited image in the field of image processing. Prior to being cleaned up and converted to its contour, the picture is first converted to binary and gray scale formats. The method used to set up an image for pre-processing a plant leaf is shown in Figure 4 below.

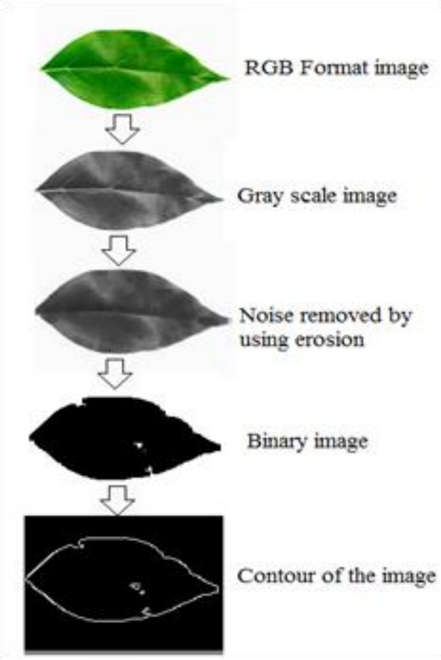


**Figure 4.** Demonstrate the technique utilized to prepare an image for pre-processing a plant leaf

*D.Feature Extractions:*

An essential aspect of the study is the extraction of features using techniques like region-based (RBSD) and contour-based (CBSD) approaches. Among the traits used in the early iterations of the contour-based feature extraction were eccentricity, extension, perimeter, solidity, equivalent diameter, and perimeter area ratio. Then, region-based feature extraction is carried out using the convex area, area, moments, euler number, and bbox parameters. Figure 5 presents a categorization of form characteristics.

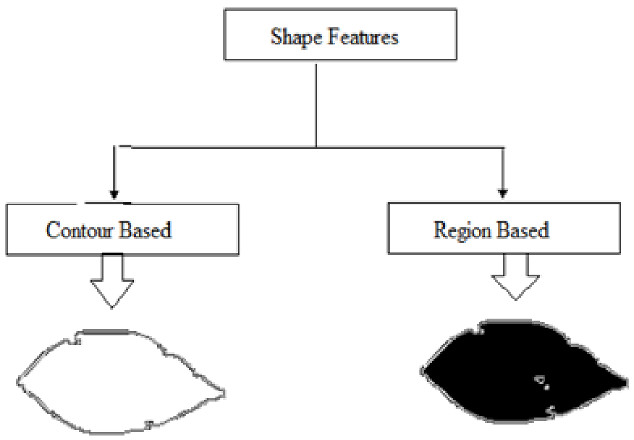


**Figure 5.** Classification of shape characteristics

***1) Contour Based:***

A contour is a curve that joins all continuous points with the same colour or intensity along the border. The contours are a useful tool for both shape analysis and item identification and recognition. For increased accuracy, use binary images. Therefore, before looking for contours, employ threshold or deft edge detection.

(a) Eccentricity

The conic section of the form where a non-negative real number should be present exhibits a pronounced eccentricity. In general, eccentricity refers to a measurement of the curve's deviance from the circularity of the defined shape.

(b) Extent

The extent is the ratio of the contour to the bounding rectangle.

Extent=Object Area / Bounding Rectangle Area

(c) Contour Perimeter

The length of a shape around its outermost extremities is referred to as the perimeter of a shape.

(d) Solidity

Convex hull area to contour area is a measure of solidity.

Solidity=Contour Area / Convex Hull Area

(e) Equivalent Diameter

Equivalent Diameter is the diameter of the circle whose area is same as the contour area.

$$\text{EquivalentDiameter} = \sqrt{\frac{(4 * Contour\ Area)}{\pi}}$$

(f) Perimeter-area ratio

The complexity of a polygon's shape is indicated by the perimeter-area ratio.

A shape's perimeter to area ratio is equal to the shape's perimeter divided by the shape's area.

The compactness ratio's opposite is the perimeter-area ratio.

***2) Region Based:***

A region in an image is a collection of related pixels that are joined together. Because they might correspond to specific objects in a picture, regions are crucial for the interpretation of an image.

(a) Convex Area

The smallest convex form that contains an object is referred to as its convex hull. An object's convex area is the portion of its convex hull that surrounds it.

(b) Area

A shape's area is the amount of two-dimensional space it takes up.

(c) Moments

A methodical approach to form analysis is represented by the examination of moments. The three low-order moments are utilized to calculate the most popular area traits. Calculating the central moments, normalized central moments, and moment invariants is possible with knowledge of the low-order moments.

(d) Euler number

The number of components minus the number of holes is known as the Euler number: – Translation, rotation, and scaling have no effect on this straightforward topological property.

Euler number = C- H

(e) Bbox parameters

In essence, a bounding box is a rectangle that encloses an item and indicates its position, class, and confidence. In the process of object detection, where the goal is to determine the location and nature of various items in a picture, bounding boxes are primarily used.

*E. Classification:*

Since classification increases the precision with which leaf species will be identified, it is a crucial step. Therefore, choosing the appropriate classification approach is essential if we want to increase accuracy. Among the several classifications that may be employed are Support Vector Machine (SVM), Convolutional Neural Network (CNN), Artificial Neural Network (ANN), Probabilistic Neural Network (PNN), and K-Nearest Neighbor K-NN. Because K-NN classification reliably separates features, has excellent generalizability, and has a surprising degree of classification resilience, it is used in the recommended technique. The only thing that has to be determined is the distance between different points based on data of different properties, and this distance may be simply estimated using distance formulae like Euclidian. It's not too difficult to implement K-NN. Since there is no training period, new data may be supplied at any moment without affecting the model.

Used single nearest neighbor technique:

Bypassing the issue of probability densities entirely, the single closest neighbor approach simply assigns an unknown sample to the same class as the most comparable or "nearest" sample point in the training set of data, often known as a reference set. The term "nearest" can be interpreted to indicate the lowest Euclidean distance, which is the typical distance between two points in n-dimensional feature space $a = a_1\ a_2 \_\_\_\_ a_n$ and $b = b_1, b_2 \_\_\_\_ b_n$ is defined by

$$d_e(a,b) = \sqrt{\sum_{i=1}^{i=n} (b_i ? a_i)^2} \tag{1}$$

Where n is the number of features.

Euclidean distance is not necessarily the optimum metric, despite being the distance function or measure of dissimilarity between feature vectors that is most frequently utilised. The characteristics for which the dissimilarity is considerable are heavily stressed due to the fact that the distances in each dimension are squared prior to summing. It could be more reasonable to utilise the total of the absolute differences between each attribute as the overall indicator of dissimilarity rather than the squares of those differences. Additionally, it would speed up computation. Then, this distance metric would

$$d_{cb}(a\ b) = \sum_{i=1}^{n} |bi-ai| \tag{2}$$

The number of features is n. The city block distance is the total of the absolute distances in each dimension.

By using a nonlinear function, such as the square root of the absolute values of the individual feature differences before summing, a metric that would downplay single large feature differences and be more impacted by several minor ones might be developed. The maximum distance measure is an extreme metric that only takes into account the most different pair of attributes.

$$d_m(a,b) = \max_{i=1}^{n} |bi-ai| \tag{3}$$

A generalization of the three distances (1), (2) and (3) is the Minkowski distance defined by

$$d_{cb}(a,b) = \left[\sum_{i=1}^{n} |bi-ai|^r\right]^{\frac{1}{r}}$$

Where r is an adjustable parameter.

The K-NN employed in picture 6 may be explained using the following algorithm

**Step1:Select the value of K, which represents the number of neighbors to consider.**

**Step2:Calculate the Euclidean distance between the new data point and all other data points in the dataset.**

**Step3:Identify the K nearest neighbors based on the smallest Euclidean distances.**

**Step4:Determine the class or category of each of the K nearest neighbors.**

**Step5:Count the occurrences of each category among the K neighbors.**

**Step6:Assign the new data point to the category that appears most frequently among the K nearest neighbors.**

**Step7:The model is now ready to classify new data points based on the majority class of their K nearest neighbors.**

**Figure 6**. K-NN Algorithm

Take into account the situation when we must categorize a new data point in order to use it, as indicated in Figure 7 below.

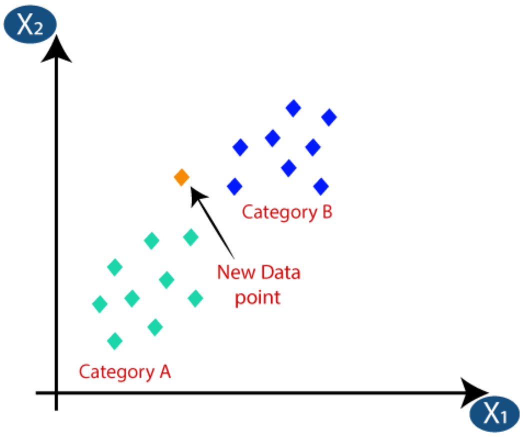


**Figure 7.** When new data point added

- We'll choose the number of neighbours first, therefore we'll pick k=5.
- Then, we will calculate the Euclidean distance between the data points. The Euclidean distance, which we have previously studied in geometry, is the separation between two points. It may be calculated in Figure 8 as shown below

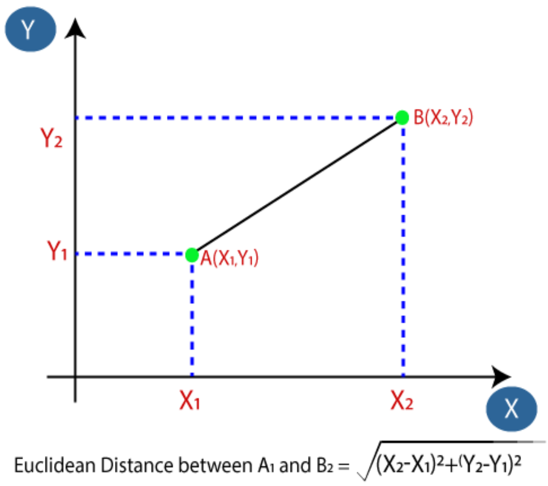


**Figure 8.** Euclidean Distance calculation method

- The Euclidean distance was calculated to identify the nearest neighbors. According to Figure 9, there were two closest neighbors in category B and three closest neighbors in category A.

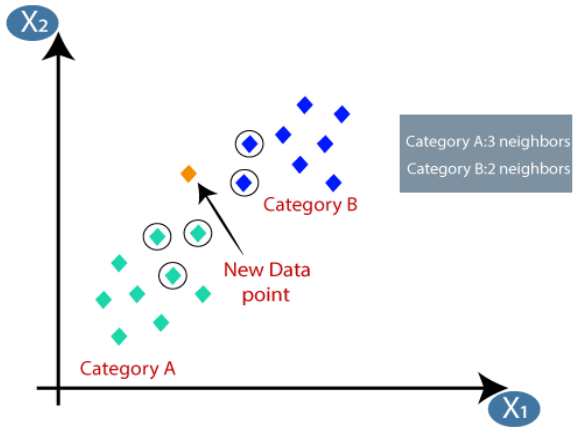


**Figure 9.** Data point added in category A

- As we can see, this new data point must be in category A as the three nearest neighbors are [25] in group A.

## III. Experimental Method, Results and Discussion

The 32 distinct species may be seen in the entire collection of 1907 leaf pictures. On the basis of the leaf orientation selected 378 leaves from 10 different species from the Flavia database for the experiments implementation. Then all images passes through preprocessing step. If any possible erosion was eliminated before the picture was transformed to a contour image in order to extract the required features. Next step is thresholding technique to turn an image into a binary form. After that the binary images converted into contour images, and extracted leaf features are shown in Table 1.The Table 1 lists the values for six contour characteristics including eccentricity, extent, perimeter, solidity, equivalent diameter, and perimeter area ratio for all sample leaves. All extracted leaves features data loaded into the systems. Then split all retrieved features data into the training and testing purposes. To choose the appropriate feature sets for the classification, 20% of the datasets are utilized for testing and 80% for training. The accuracy of the system was then assessed using K-NN classification.

| eccentricity | extent | perimeter | solidity | equivalent diameter | perimeter area ratio | Label .JPG |
|---|---|---|---|---|---|---|
| 0.66 | 0.73 | 5786 | 0.99 | 1223.5 | 0.005 | 2508 |
| 0.7 | 0.75 | 6324 | 0.984 | 1171.2 | 0.006 | 2522 |
| 0.53 | 0.73 | 7482 | 0.961 | 1151.9 | 0.007 | 3493 |
| 0.66 | 0.76 | 6012 | 0.988 | 1167 | 0.006 | 2496 |
| 0.77 | 0.72 | 5617 | 0.992 | 1162.6 | 0.005 | 2122 |
| 0.71 | 0.67 | 11012 | 0.96 | 1141.4 | 0.011 | 2034 |
| 0.7 | 0.78 | 6459 | 0.98 | 1153.1 | 0.006 | 2495 |
| 0.71 | 0.67 | 10280 | 0.965 | 1143.6 | 0.010 | 2033 |
| 0.55 | 0.7 | 7508 | 0.981 | 1150.4 | 0.007 | 2493 |
| 0.69 | 0.69 | 10170 | 0.959 | 1135.6 | 0.010 | 2492 |
| 0.65 | 0.7 | 6198 | 0.985 | 1144.3 | 0.006 | 2517 |
| 0.45 | 0.68 | 6067 | 0.955 | 1126.7 | 0.006 | 3492 |
| 0.75 | 0.71 | 6856 | 0.981 | 1141.4 | 0.007 | 2502 |
| 0.74 | 0.72 | 10467 | 0.968 | 1133.3 | 0.010 | 2022 |
| 0.78 | 0.73 | 7202 | 0.982 | 1136.6 | 0.007 | 2506 |
| 0.74 | 0.7 | 4910 | 0.991 | 1141.4 | 0.005 | 2503 |
| 0.69 | 0.76 | 5974 | 0.989 | 1137.6 | 0.006 | 2499 |
| 0.72 | 0.74 | 4473 | 0.995 | 1139.6 | 0.004 | 2490 |
| 0.73 | 0.73 | 6453 | 0.978 | 1129.8 | 0.006 | 2497 |
| 0.79 | 0.72 | 6190 | 0.977 | 1122.4 | 0.006 | 2035 |
| 0.66 | 0.73 | 5786 | 0.99 | 1223.5 | 0.005 | 2508 |

*Table 1.* Samples of features based on extracted contours

Figure 10 includes a graph of the contour features, with values of eccentricity, extent, perimeter, solidity, perimeter area ratio and equivalent diameter shown in Figure 10(a) to (f) respectively. Values for eccentricity range from 0.44 to 0.79, those for extent from 0.67 to 0.77, those for perimeter from 4472 to 11011, and those for solidity from 0.95 to 0.99. Values for equivalent diameter for the images of 2508 and 2035 have higher values, respectively. Perimeter area ratio displays lower values in the 2490 number and greater values in the 2034 picture.

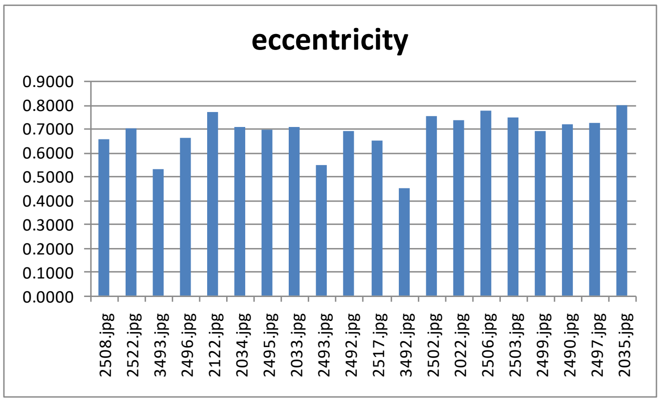


Figure 10 (a)

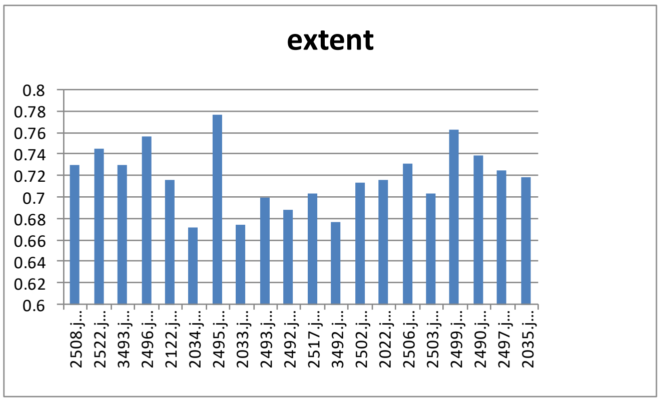


Figure 10 (b)

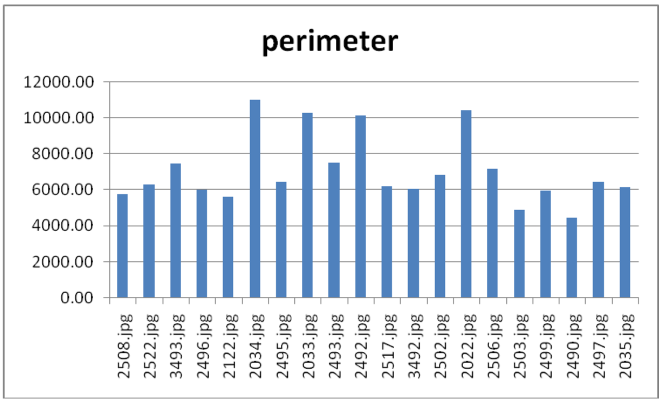

Figure 10 (c)

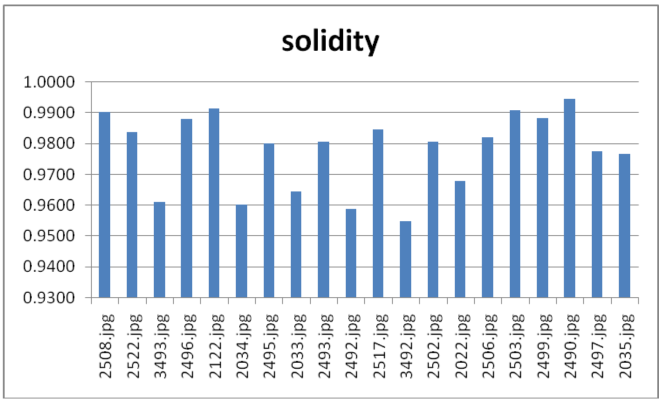

Figure 10 (d)

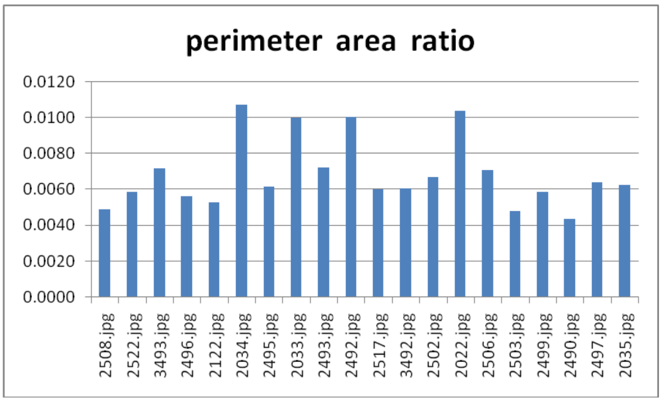

Figure 10 (e)

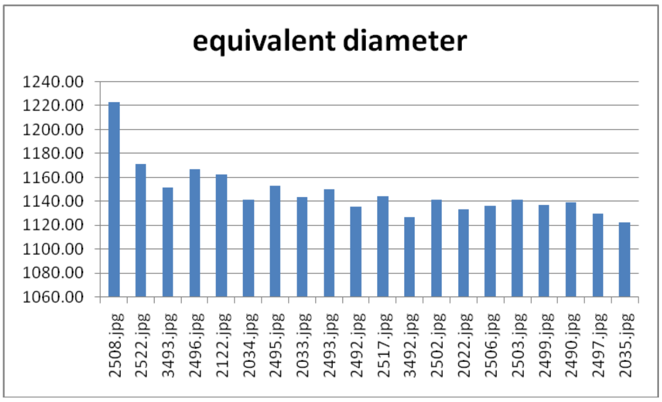

Figure 10 (f)

**Figure 10.** Contour Features (a)-(f) graphs

| Method | Contour Based Accuracy in % |
|---|---|
| [16] | 69.61 |
| [19] | 74.4 |
| [24] | 74.26 |
| [20] | 71 |
| Particular Contour-Based Shape Descriptors | 76 |

*Table 2.* Comparison of accuracy utilizing feature extraction techniques

Comparisons of the various authors' methods and the precision of leaf species identification are shown in Table 2. According to the technique suggested by [16], the mean average accuracy value is 69.61%. The accuracy of the authors' [19] suggested technique is 74.4%. Gray-Level Co-occurrence Matrix (GLCM) approaches are employed with 74.4% accuracy, according to [24], employing the bisection procedure. According to [20], with a Gabor filter accuracy of 71%, the NB classifier had the weakest performance. When compared to all prior results, our suggested mean Particular Contour-Based Shape Descriptors (PCBSD) result is 76%, and we assert that this result was improved by applying our PCBSD. The performance of the findings employing contour-based feature extraction methodologies is shown in Figure 11.The PCBSD produced higher accuracy of leaf species identification.

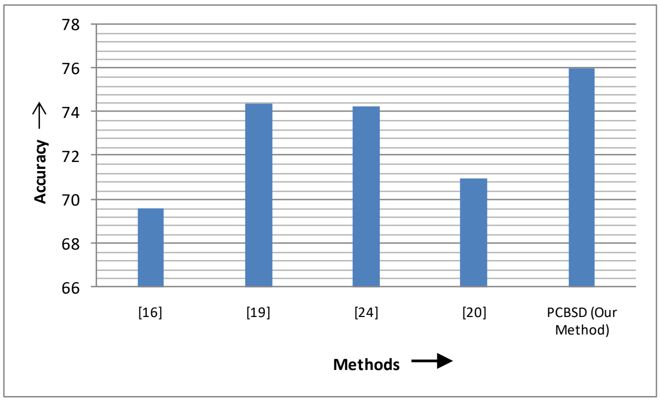


**Figure 11**. Illustrates the performance of the results using contour-based feature extraction approaches

The outcomes showed that particular contour-based feature extraction outperformed in terms of accuracy. A feature based on contours is the most reliable way to determine the species of a leaf.

## IV. Conclusion and Future Scope

We have proposed a shape description technique called Particular Contour-Based Shape Descriptors (PCBSD) for the identification of various plant species. The metrics eccentricity, extension, perimeter, solidity, equivalent diameter, and perimeter area ratio were employed in the PCBSD feature extraction implementation. The PCBSD descriptor is an efficient method for characterizing both local and global characteristics of a shape at various sizes that is invariant to similarity transformations. We performed comprehensive analyses on datasets of Flavia plant leaves. The accuracy for certain contour-based feature extraction strategies was 76% when features were extracted using K-NN classification. The results demonstrate that, in terms of retrieval accuracy and efficiency, our system surpasses the most recent cutting-edge shape-based plant species recognition techniques. Our method for recognizing wide shapes and the results of our experiments using the Flavia leaf dataset. We claim that if 50% of the veiled leaves are present, our method of selective feature extraction will also be able to identify the species of leaf since we only extracted the characteristics that were 50% related to the contour, and our finding is based on this. We employed the unique contour information of plant leaves, despite the fact that the texture and venation structure of plants are equally important traits for identifying plant species. In future study, we hope to combine our method with textures or venation cues to recognise plant leaves. We believe that the performance of our algorithm will be further enhanced when texture or venation information about plants is taken into account.

## Acknowledgment

Not applicable.

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