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Leaf Recognition Based on PHOG and COA-LBP Features

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Abstract: ***Leaf can be characterized by its color, texture, vein structure, and shape. The vein can be an important morphological characteristic of the leaf. Plants can be seen in different places, including roads, mountain paths, and fields, which have many different kinds where recognizing them can be useful in various applications. In this paper, a feature level fusion scheme is presented using PHOG and COA-LBP features. It gives result as 80.95% rank one recognition rate on Indian leaf database.***
Keywords: ***Indian leaf data samples, PHOG, LBP, Post processing.***

I. INTRODUCTION

Plants occur everywhere we live, as well as places without us. Most of them carry substantial information for the development of human society. The crucial situation is that many plants are at the risk of extinction. So it is central image processing step to set up a database for Indian plant protection. There are several ways to recognize a plant, like fruit, root, flower, leaf etc. And they are three dimensional objects and have complex with the exclusion of leaf. Leaf classification and recognition is a significant component of automated plant recognition system, because leaf features often contain important information that can help in plant species recognition and we can find a great number of leaves easily. A leaf can be categorized by its self-color, glaze texture, internal vein structure, and geometric image shape. The type of the vein is an important morphological characteristic of the leaf. Plants can be seen in many places, including roads, mountain paths, and fields, which have many different kinds where recognizing them can be useful in various applications. For example, the institutes discovering new plant species need a process and method for plant recognition or management of botanical gardens. So far, this process is performed based on using leaves, and they should be examined with expert humans manually, where this operation is a time-consuming via a low-efficiency process. In order to cope with the limitations of the introduced process which is done manually, current paper tries to design a system based on machine vision algorithms for improvement of result accuracy and reduction of process time. As the performance of such a recognition system depends on good feature selection, it is very important to select a set of features which can describe leaf characteristics very well. In this case, the other including leaf shape, vein structure, teeth and color for recognition. Compared with other methods, such as cell and molecule biology methods, classification based on leaf image is the first choice for leaf plant classification. Sampling leaves and photonic them are low-cost and convenient. Researcher user can catch the leaf image into a computer and a computer can extract features. Some systems employ descriptions used by botanists. But it is not easy to extract and transfer those features to a computer automatically. It is also a long discussed topic on how to extract or measure leaf features. That makes the application of pattern recognition in this field a new challenge. Shape is one of the most important features of an object. Shape plays a key role in object recognition tasks, in which specific objects are illustrious by shape. Shape recognition approaches are alienated into two classes, i.e., contour based and region-based, correspondingly. Plant recognition based on leaf images is very important and necessary to agricultural information, ecological protection, and automatic plant recognition system. It is well known that the way to validly extract classification features is central to the plant recognition based on leaf images.

II. LITERATURE SURVEY

Du et al. [1] formulated the problems by classifying leaf image sets rather than single-shot image, each of set contains leaf images pertaining to the same class. They extract leaf image feature and compute the distance between two manifolds modelled by leaf images. Specifically, they apply a clustering procedure in order to express a manifold by a collection of local linear models. Then the distance is measured between local models which come from different manifolds that constructed above. Finally, the problem is transformed to integrate the distance between pairs of subspace. Experiment based on the leaves (ICL) from intelligent computing laboratory of Chinese academy of sciences, which shows that the method has a great performance. Wang et al. [2] stated that pulse coupled neural network is a powerful tool for image processing. It is widely applied in the field of image segmentation, image fusion, feature extraction, etc. Support vector machine is an excellent classifier, which can finish the complex task of data exploration. Based on these two techniques, a novel plant recognition method is proposed in their paper. The strategic feature is the computed entropy sequence gained by pulse-coupled neural network. Other ancillary features can be computed directly by mathematical and morphological methods. Both key feature and ancillary features are employed to represent the unique feature of one plant. Support vector machine in our method is taken as the classifier, which can implement the multi-class classification. Experimental results show that the proposed method can finish the task of plant recognition effectively. Compared with the existing methods, our proposed method has better recognition rate. Chaki et al. [3] modeled the leaf shape using the Curvelet transform Coefficients and statistical Invariant Moments. The glaze texture is modeled using a Ridge Filter and some subsequent statistical measures derived from the available filtered image. As the topographies are subtle to geometric orientations of the leaf image, a pre-processing step is accomplished to extract features invariant to geometric transformations. To categorize images to pre-defined explicit classes, a Neuro fuzzy classifier is used. Experimental results spectacle that the method achieves acceptable recognition rates for images varying in glaze texture, original shape and varied orientation. Zhang et al. [4] proposed a dimensionality reduction method based on local discriminative tangent space alignment LDTSA is introduced for plant leaf recognition based on leaf images. The proposed method can encirclement part based optimization and whole actual image specific alignment and encapsulate the geometric and image discriminative information into a local patch. Lukic et al. [5] proposed an algorithm based on tuned support vector machine as a classifier and Hu moments and uniform local binary pattern histogram parameters as features. Their proposed algorithm was tested on leaf images from standard benchmark database and compared with other approaches from literature where it proved to be more successful (higher recognition percentage). Pradip et al. [6] presented a leaf recognition system using orthogonal moments as shape descriptors and Histogram of oriented gradients (HOG) and Gabor features as texture descriptors. The shape descriptors captures the global shape of leaf image. The internal vein structure is captured by the texture features. The binarized leaf image is pre-processed to make it scale, rotation and translation-invariant. The Krawtchouk moments are computed from the scale and rotation normalized shape image. The HOG feature is computed on rotation normalized gray image. The combined shape and texture features are classified with a support vector machine classifier (SVM). Al-Kharaz et al. [7] presented a concept of distinctive hybrid descriptor is proposed consisting of both global and local features. HSV Colour histogram (HSV-CH) is extracted from leaf images as the global features, whereas Local Binary Pattern after two level wavelet decomposition (WavLBP) is extracted to represent the local characteristics of leaf images. A hybrid method, namely “Hybrid Descriptor” (HD), is then proposed considering both the global and local features. The proposed method has been empirically evaluated using fourdata sets of leaf images with 256 × 256 pixels. Experimental results indicate that the performance of proposed method is promising. It outperformed typical leaf image recognizing approaches as baseline models in experiments. The presented work makes clear, significant contribution to knowledge advancement in leaf recognition and image classification.

III.SYSTEM DESIGN AND OVERVIEW

A. PHOG features

PHOG is a spatial shape descriptor applied to image classification recently. It represents the spatial distribution of edges and is formulated as a vector representation. This descriptor is mainly inspired by two sources: (1) the use of the pyramid representation, and (2) the Histogram of Orientation Gradients (HOG). The PHOG features are extracted from the region of mouth to stress the contribution of features related to the mouth motions. Smile and non-smile samples were represented by its local shape and the spatial layout of the shape around mouth. Here local feature was captured by the distribution over edge orientation within a region, and spatial layout by tiling the image into regions at multiple resolutions. The details of extracting PHOG features are as follows.

Step 1: Extracting edge contours. Giving a sample image, edge contours of the image are extracted first for further processing. As shown in Fig. 1(b), the information of edge contours is a description of shape. In this study, the edge contours were extracted using the Canny edge detector.

Step 2: The image is divided into cells at several pyramid level. As shown in Fig. 1(a), the grid at level L has 2^L cells along each dimension.

Step 3: The HOG for each grid at each pyramid resolution level was computed. The Local level intrinsic shape is represented by a grayscale histogram of internal edge orientations within an available image subregion quantized into K bins. Edge contours were located in step 1, and the orientation gradients were computed at edge contours in the original image. The orientation gradients were computed using 3x3 Sobel mask without Gaussian smoothing. The contribution of each edge was weighted according to its magnitude with a soft assignment to neighboring bins in a manner similar to SIFT [8]. Each bin in the histogram represents the number of edges that have orientations within a certain angular range.

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Step 4: The final PHOG descriptor for an image is a concatenation of all the HOG vectors at each pyramid resolution. The concatenation of all the HOG vectors introduces the spatial information of the image. Each HOG is normalized to sum to unity taking into account all the pyramid levels. .

B. Co-occurance of Adjacent Linear Binary Patterns

A new Local Binary Pattern (LBP)-based feature by introducing the spatial co-occurrence of adjacent LBPs. LBP-based features, such as LBP histograms, have recently attracted attention as a fundamental technique in the applications of texture recognition, face recognition, and facial expression recognition owing to their high robustness to changes in illumination and their efficient computation. The basic idea of the LBP histogram, the focus of this paper, is the representation of entire images as a composition of numerous LBPs, where each LBP is extracted from a local region. LBP was originally designed as a texture description for a local region, called a micropattern [6]. LBP is a pixel level pattern that represents the magnitude geometric relation between the center pixel its neighboring pixels. LBP is obtained by thresholding the image intensity of the surrounding pixels with that of the center pixel. In the LBP histogram, the obtained binary patterns are converted to a decimal number as a label, and a histogram is generated from the labels of all the local regions of the whole image. Since LBP considers only the magnitude relation between the center and neighboring pixel intensities, LBP is invariant to uniform changes of image intensity over the entire image, making it robust against changes in illumination. This characteristic of LBP has led it to become a standard feature for face recognition and facial expression analysis [7]. Unfortunately, however, spatial relations among the LBPs are mostly discarded during the LBP histogram generation process, because the LBPs are forcedly packed into a single histogram, resulting in the loss of global image information. This suggests that there is still a room for further improvement to the performance of LBP-based features, while retaining invariance to changes in illumination. To consider the spatial relation among LBPs, we introduce the concept of cooccurrence. Although co-occurrence of LBPs can be obtained as a heuristic problem, we introduce a more sophisticated way to obtain the co-occurrences of all combinations of LBPs by using auto-correlation matrices calculated from two considered LBPs. The calculation process will show that the proposed feature is a natural extension of the original LBP in that the proposed feature consists of both the original LBP and the co-occurrence of LBPs. The co occurrence of adjacent LBPs is defined as an index of how often their combination occurs in the whole image. In the proposed feature, the number of possible combinations of LBPs is significantly greater than that of the original LBPs. It is therefore difficult to use a rule-based program to compute the co-occurrence of all combinations when there are many types of LBPs. Instead of using a heuristic program, we introduce an auto-correlation matrix as an effective method of calculating the co-occurrence of LBPs. First, although the original LBP uses eight neighbor pixels of a given center pixel, we modify the LBP configuration to consider two sparser configurations, thereby reducing computational cost. One configuration is LBP(+), which considers only two horizontal and two vertical pixels.

C. System

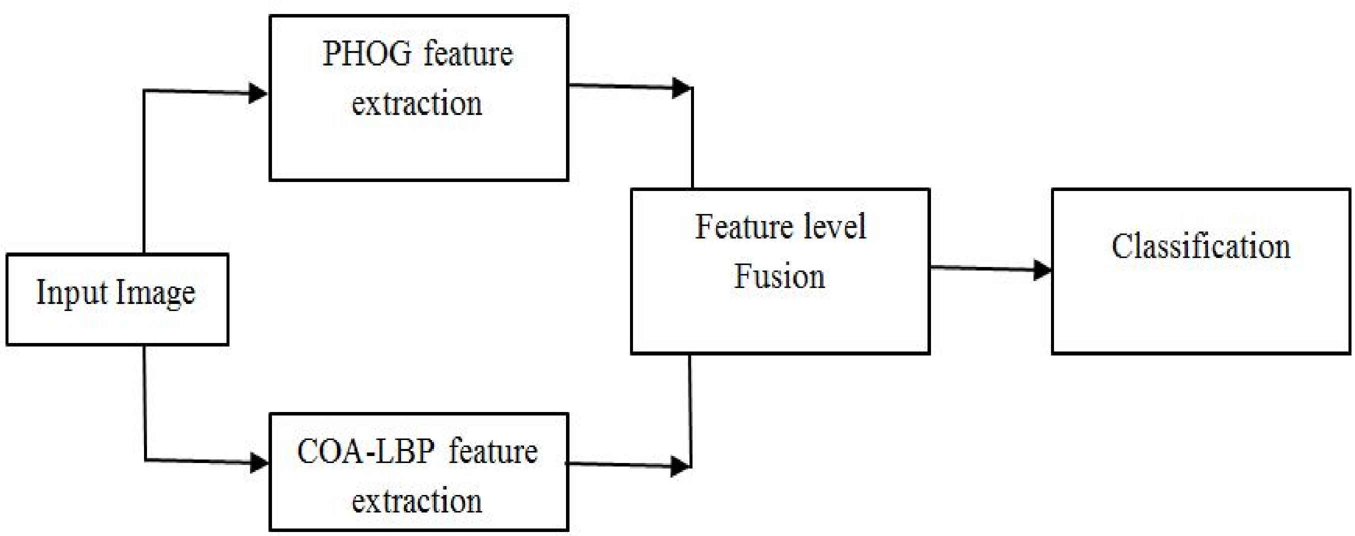

Fig.1. Indian Leaf Recognition system

The presented system consists of pre-processing the input image for noise removal. Subsequently, the PHOG features are extracted

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from the input image. The feature vector from PHOG is temporarily stored. The input image is processed in the COA-LBP block to obtain another feature vector. These two feature vectors are fused to obtain a combined feature vector which represents the train image.

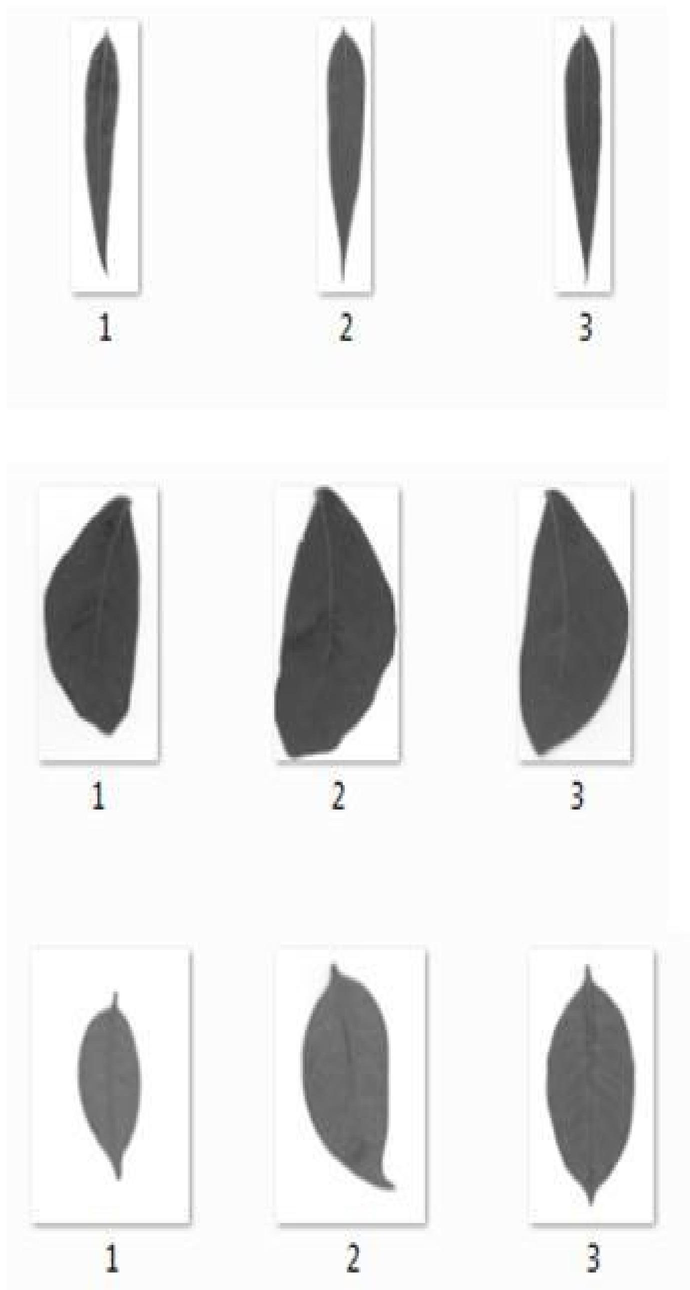

Fig.2. Sample Images from Indian Leaf databases

The same process is repeated for test images. The feature vectors are submitted to the principal component analysis subspace to obtain reduced feature vector. These vectors are matched with other training feature vectors to obtain the classification rates. The following diagrams show sample images from Indian leaf image dataset. Total seven different classes of leaves are considered for the experimentation. The rank one recognition rate for this experimentation is 80.95%. The performance curves are as shown in Fig.3.

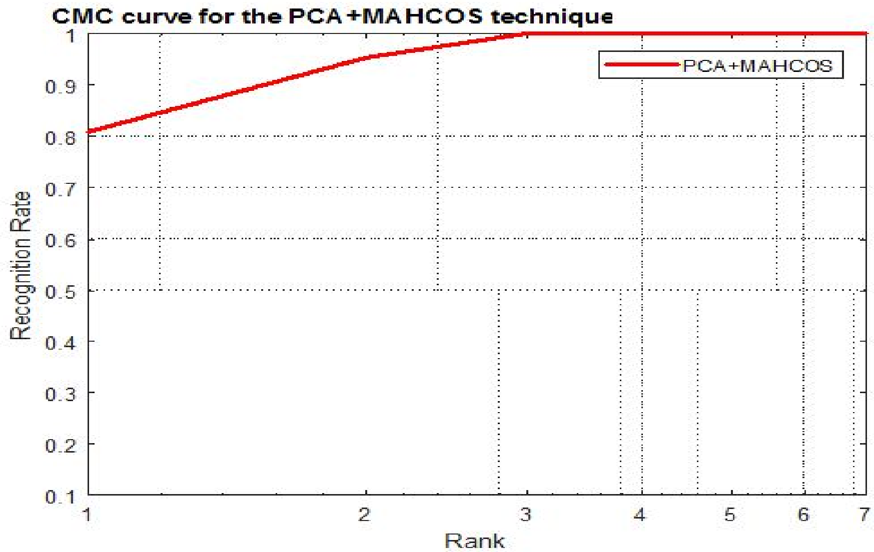

Fig.3. CMC curves characteristics for the experiment

IV. CONCLUSIONS

A leaf can be characterized by its color, texture, vein structure, and shape. The type of the vein is an important morphological characteristic of the leaf. Plants can be seen in many places, including roads, mountain paths, and fields, which have many different kinds where recognizing them can be useful in various applications. In this paper, a feature level fusion scheme is presented using PHOG and COA-LBP features. It yields 80.95% rank one recognition rate on Indian leaf database.

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REFERENCES

[1] J-X. Du, M.-W. Shao, C.-M. Zhai, J. Wang, Y. Tang, and C. L. P. Chen, "Recognition of leaf image set based on manifold–manifold distance," Neurocomputing, vol. 188, pp. 131-138, 5/5/ 2016.

[2] Wang, X. Sun, Y. Zhang, Z. Ying, and Y. Ma, "Leaf recognition based on PCNN," Neural Computing and Applications, vol. 27, pp. 899- 908, 2016

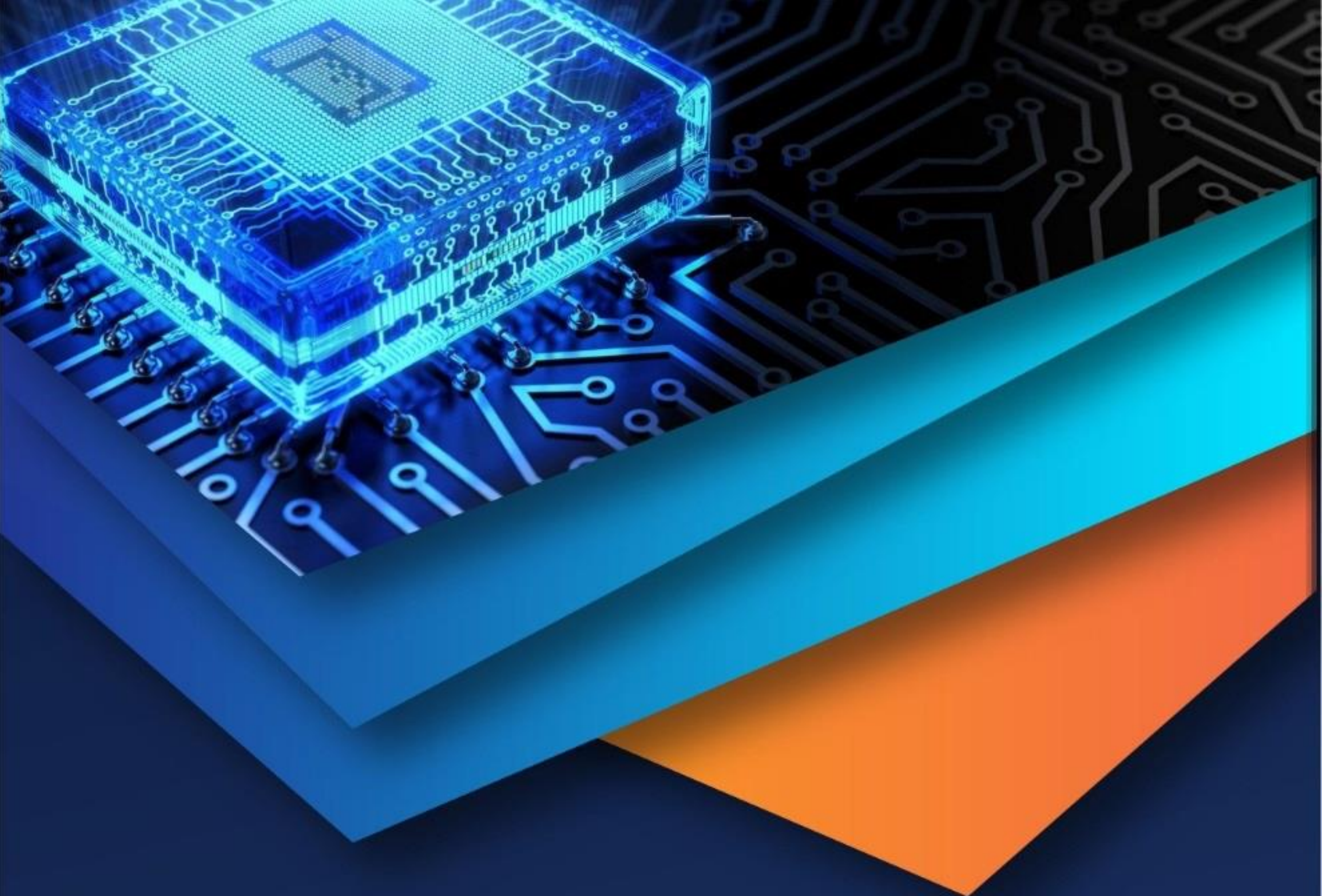
[3] J. Chaki, R. Parekh, and S. Bhattacharya, "Plant Leaf Recognition Using Ridge Filter and Curvelet Transform with Neuro-Fuzzy Classifier," in Proceedings of 3rd International Conference on Advanced Computing, Networking and Informatics: ICACNI 2015, Volume 1, A. Nagar, D. P. Mohapatra, and N. Chaki, Eds., ed New Delhi: Springer India, 2016, pp. 37-44.

[4] Zhang, S. Zhang, and W. Fang, "Plant Leaf Recognition through Local Discriminative Tangent Space Alignment," JECE, vol. 2016, p. 9, 2016.

[5] M. Lukic, E. Tuba, and M. Tuba, "Leaf recognition algorithm using support vector machine with Hu moments and local binary patterns," in 2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2017, pp. 000485-000490.

[6] T. Pradeep Kumar, M. Veera Prasad Reddy, and P. K. Bora, "Leaf Identification Using Shape and Texture Features," in Proceedings of International Conference on Computer Vision and Image Processing: CVIP 2016, Volume 2, B. Raman, S. Kumar, P. P. Roy, and D. Sen, Eds., ed Singapore: Springer Singapore, 2017, pp. 531-541.

[7] A. Al-kharaz, X. Tao, J. Zhang, and R. Lafta, "Adopting Hybrid Descriptors to Recognise Leaf Images for Automatic Plant Specie Identification," in Advanced Data Mining and Applications: 12th International Conference, ADMA 2016, Gold Coast, QLD, Australia, December 12-15, 2016, Proceedings, J. Li, X. Li, S. Wang, J. Li, and Q. Z. Sheng, Eds., ed Cham: Springer International Publishing, 2016, pp. 219-233.



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