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Detection and Analysis of Local, Global and Texture Features of the Pumpkin Leaf Images Using Cv Algorithms to Improve the Productivity Rate of Pumpkins

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ABSTRACT

In Image Processing algorithms, the feature extraction stage is one of the most important step to detect and extract the features of an input image. Normally, these features are classified into three main categories such as local, global and texture features. Each feature can contain the relevant information according to the particular images. The extraction of these features can be performed by means of feature selection and feature extraction steps. In recent decades, there are lots of computational algorithms were developed to extract the features. This paper mainly represents the Computer Vision (CV) based algorithms such as MSER, QTD, WHT, HHT, RT and CZT for extracting the local, global and texture features of the pumpkin leaf images. By extracting these features, the classification process will be performed more efficiently to detect the downy mildew, powdery mildew, gummy stem blight diseases in the pumpkin leaf images. Based on these computations, the productivity rate of the pumpkins will be improved significantly. The above-mentioned feature extraction algorithms are tested and validated by using the MATLAB supporting platform.

Keywords:
Feature extraction, CV algorithms, Dimensionality Reduction, PCA, LDA, KNN, MSER, Unitary Transformation.

Introduction

In human life, the plants are fundamentally important. The important research areas of plant science are plant species identification, weed classification using hyper spectral images, monitoring plant health and tracing its leaf growth, and semantic interpretation of leaf information. Botanists can easily identify plant species by discriminating between the shape of the leaf, tip, base, leaf margin and leaf vein as well as the texture of the leaf and the arrangement of leaflets of compound leaves. There is a need for intelligent systems that recognize and characterize leaves so as to scrutinize a particular species, the diseases that affect them, the pattern of leaf growth and so on by the reason the increasing demand for experts (Thyagharajan, K.K.and Kiruba Raji, 2019) [1]. Hence, the Image processing algorithm is an emerging technique to perform the above-mentioned tasks by h1andling the three most important steps like preprocessing, feature extraction and classification and is clearly shown in Fig.1.

The first stage performs the image resizing, enhancement and filtering processes, the Secondary stage performs the extraction of the features those that are related to the particular image set and finally classification state. It classifies the diseased images in the given image database from the three states of processing. This paper mainly focuses on the second stage of image processing technique (i.e.) feature extraction stage. This technique is helpful in various image processing applications like character recognition, medical image processing and leaf pattern recognition and etc. In this paper, the different feature extraction algorithms are applied to extract the Global, Texture and local features in the pumpkin leaf images.

Global feature extraction technique is branched into several categories. Statistical method is one of the examples of basic category which defines the texture of the images based on spatial distributions of gray level value in an image. It's based on statistical orders by means of the first-order static finds the value and extracts the properties of each level based on those values. While, the second-order findout the value which relating two gray-level with a few geometrical relationships and it indicates the important features of an image.The higher order statics depends on find the values of compound properties of an image (Bataineh B et al 2011) [2].

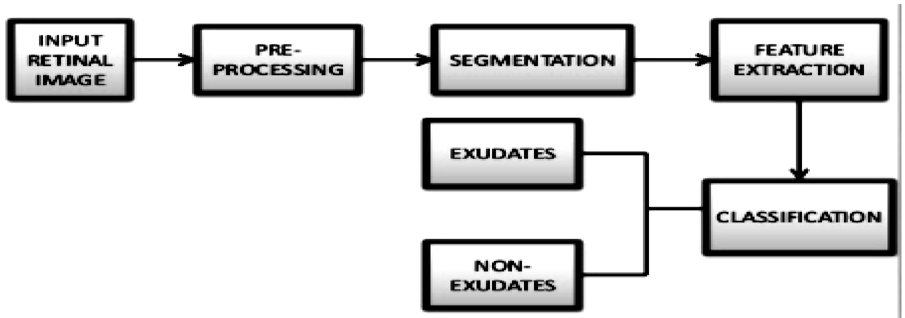

Fig. 1 Generalized Block Diagram for Image Processing Algorithm

The local features allow an application to find local image structures in a repeatable fashion. This also allows to encode them in a representation that is invariant to a range of image transformations, such as translation, rotation, scaling, and affine deformation. The resulting features form the basis of approaches to recognize specific objects. Local invariant features are to provide a representation that allows to efficiently match the local structures between images.

Finally, the texture gives us an information about the content of an image, inside objects, background context, and so on. This analysis in most areas of image processing, especially in the process of learning and extracting the feature is being discussed when the images such as Medical image analysis, Vegetation and Product quality diagnostics are to be compared (R. M. Haralick et al 1973) [3], (Laleh Armi and Shervan Fekri-Ershad et al 2019) [4]. So, the paper mainly discusses the global, local and texture feature extraction of the pumpkin leaf images. In this paper, Section 2 describes the literature Review, Section 3 describes Image Processing algorithms which are used for performing the extraction of the pumpkin leaves and results are tabulated in Section 4. Finally, Section 5 ends with the corresponding Conclusion and Future Implementation.

Literature Survey

Zhao et al 2017 [5] described the Medial Axis Transformation (MAT) used to convert the complex shapes of leaves into graph structures by describing the topological skeleton of the leaves and utilization of the topological skeleton to extracting the image. C. Arrasco et al 2018 [6] Presented a method to enhance the Pattern of nerves over the leaf area, beneficial to improve the texture feature extraction in pits areas in the plant species identification. U. Suttapakti and A. Bunpeng 2019 [7] gives the different color feature and texture extraction of potato leaf images based on the three different categories such as Segmentation, feature extraction and Image classification. C. U. Kumari et al 2019 [8] identified the diseases leaf spot using an image processing technique. For images, segmentation is done with help of K-means clustering algorithm and other features are calculated from disease affected area. The extracted features of an image from disease affected area are given to classifier inputs to classify the diseases. The Neural network (NN) classifier is used in this paper.

R. R. Isnanto et al 2016 [9] developed a system for herbal plants identification. It's mainly focuses on the shape of the herbal plants' leaves. Early the preprocessing stages can be performed such as conversion to grayscale image, conversion to binary image and image segmentation using Otsu's method. In this System which is simply using one kind of region-based invariant feature extraction, Hu's seven moments invariant and the Euclidean or Canberra distance as a recognition Feature extraction method. D. Li et al 2020 [10] represents a five-stage framework that includes multi view point reconstruction, preprocessing, stems removal in outer layer of the leaf, leaf segmentation and leaf phenotypic feature extraction. In leaf phenotypic carries on two types of ornamentals-Maranta arundinacea and Dieffenbachia picta. The properties of phenotypic such as the leaf area, leaf length, width and leaf inclination angle for each single leaf are calculated and compared with ground truths. S. Adinugroho and Y. A. Sari 2018 [11] created a framework to know plant species based on leaf characteristics. In that first identify the 31 features of leaves from 13 species are extracted that shows color, texture and shape of the leaves. Next the features are selected according to their correlation of class label.

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D. Venkataraman and N. Mangayarkarasi et al 2016 [12] discussed regards the formation of feature set which is the most important step in recognizing any plant species. In that, a Vision based approach is being employed to create an automated system. Which recognizes the plants and gives its medicinal values thus helping the common man to be aware of the medicinal plants around them. C. Sari et al 2013 [13] have evaluated with varies type of images and shape descriptors on the automatic leaf recognition problem. The results of gross shape descriptors, Multiscale distance descriptors, Fourier descriptors and the combination of these on the leaf recognition performance were obtained. A. Sujith and R. Neethu 2021 [14] describes a methodical hybrid feature extraction using the PHOG, LBP, and GLCM feature extraction techniques. The feature vector is normalized and reduced in size by using Neighborhood Components Analysis (NCA). The efficient feature extraction and feature selection techniques are helped to improve the classification performance and reduced the model complexity

N. Nandhini and R. Bhavani et al 2020 [15] investigated the proficiency of the Leaf Image classification performed based on following extraction techniques as Support Vector Machine, K- Nearest Neighbor and Decision trees. Kan et al 2017 [16] describes an automatic classification method based on leaf images of medicinal plants. It addresses the constraint of manual classification method in identifying medicinal plants. They approach first preprocess the leaf images then compute the 10 Shape Feature (SF) and 5 Texture characteristics (TF); lastly, Support Vector Machine (SVM) classifier is used to classify the 12 different Medicinal Plant images.

M. Lv et al 2020 [17] explained about a novel maize leaf disease recognition technique. In this technique, they first constructed a maize leaf feature enhancement framework with enhancing the features of maize under the system circumstances. After, they designed backbone Alexnet architecture named DMS-Robust Alexnet for analysis.

Background Methodology

A part of the dimensionality reduction process is called as Feature extraction, in which an early part of the raw input data is separated and reduced to more manageable sets. The important features of data sets is that they need large number of variables and these variables requires a lot of computing resources to process them The feature extraction is used to help to get the best feature from the big data sets. In those data set, they select and combine variables into features and effectively reducing the amount of data. These feature techniques are easy to process, but able to describe the actual data set with the accuracy and originality. The overall sequence of this process is simply done by two manners, (i.e.) Feature selection and Feature Extraction Process.

A) Feature Selection Process

Feature selection is about choosing a subgroup of features out of the novel features in order to reduce model complexity, enhance computational efficiency of the models and reduce generalization error introduced due to noise by irrelevant features. The following represents some of the important feature selection techniques:

- **Regularization techniques** such as L1 norm regularization which results in most features' weight to turn to zero.
- **Feature importance techniques** such as using estimator such as Random Forest algorithm (Akar et al 2012) [18] to fit a model and select features based on the value of attribute such as feature importance.
- **Greedy search algorithms** such K-nearest neighbors, K-NN (Guru et al 2010) [19]) where regularization techniques are not supported.
    - Sequential forward selection
    - Sequential floating forward selection
    - Sequential backward selection
    - Sequential floating backward selection

B) Feature Extraction Process

Feature extraction is about extracting or deriving data from the original features set and to create a new feature subset. The primary idea behind feature extraction is to compress the data and maintaining most of the related information. These techniques are also used for decreasing the number of features from the original data set

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to reduce model complexity, model overfitting, enhance model computation efficiency and reduce generalization error. The following are different types of feature extraction techniques:

- Unsupervised data compression using Principal component analysis (PCA)
- A supervised dimensionality reduction using Linear Discriminant Analysis (LDA) for maximizing class separability (E. Hidayat et al 2011) [20].
- Nonlinear dimensionality reduction using Kernel Principal Component Analysis (KPCA) (Z. Huibo et al 2009) [21].

1. Proposed CV based Feature Extraction algorithms

Feature extraction is an important factor of the computer visualization system. A reality of the techniques is that deep learning works around the idea of extracting useful information and which clearly define the objects in the pumpkin leaf images. Here the feature is an individual measurable property or characteristic of a phenomenon being observed. These features are the input data that feed into the machine learning model to get an output prediction or classification. A feature potentially a definite color in an image or a specific shape of a line, edge, or an image segment. A good feature is used to distinguish objects from one another. Hence, this section mainly discusses some of the CV based feature extraction algorithms for extracting the local, global and texture features of the pumpkin leaves.

A) MSER for Pumpkin Leaf Feature Extraction

Maximally Stable Extremal Regions (MSER) is a feature detector. This algorithm extracts a sum of co-variant regions from an input pumpkin leaf image I. An MSER is a constant linked element of some level sets of the pumpkin leaf image I. MSERs can be individually recognized by (at least) one of its pixels x, as the connected component of the level set at level I(x) which contains x. Such type of pixel is called as seed of the region. Originally, MSERs are controlled by a single parameter Δ, it controls the way the stability is calculated. The stability of an extremal region R.

R is the inverse of the relative area variation of the region R, when the intensity level is increased by Δ. Formally, the variation is defined in Equation (1).

$$\text{Variation} = |R(+\Delta) - R| / |R| \qquad \text{----------------------- (1)}$$

where |R| means the area of the extremal region R, R(+Δ) is extremal region. The +Δ is going to up which contains R and |R(+Δ) - R| is the area difference of the two regions. If the System is stable region, it has a small variation. Suppose the algorithm finds a region which is "maximally stable" means that, they have a lower variation in the regions one level below or above. The region below / above may be coincident with the actual region, in which case the region is still deemed maximal, due to the discrete nature of the image. Generally, MSERs are extracted into two regions (ie) dark-on-bright regions and bright-on-dark regions. However, even if an extremal region is maximally stable, it might be rejected if: However, even if an extreme area is maximally stable, it can be discarded:

- It is very large (Max Area)
- It is very small (Min Area)
- It is very unstable (Max Variation)
- This is very similar to its parent MSER (Min Diversity)

B) QTD for Pumpkin Leaf Feature Extraction

Quadtree decay is based on the subsequent subdivision of the image block depending on the complexity of the set. If a subset is not a homogeneous volume, it is again divided into four equal subunits until all the byproducts are in the same volume. A subset is called a uniform structure of block if the gray-state of each pixel in the block varies by a certain constant. The gray-level f (x+ i, y+j) of each pixel in a block in the (x, y) position is 0 ≤ i, j <n, and n is called block size. Say that the mean gray-level of this block, the mean (x, y) is defined by an equation (2).

$$Avg(x,y) = \frac{\sum_{j=0}^{n-1}\sum_{i=0}^{n-1} f(x+i,y+j)}{n^2} \qquad \text{----------------------- (2)}$$

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Given a specific error tolerance ε, if all the pixels in the module meet the following equation (3), the module is defined as a homogeneous module.

$$Avg(x,y) - f(x+i, y+j)| \le \varepsilon \qquad \text{---------------------- (3)}$$

C) Walsh-Hadamard Transformation based Pumpkin Leaf Feature Extraction

The WHT different from the Fourier Transform and Cosine Transform in the simple functions that are non-sinusoids. The WHT is used for data compression techniques. The fundamental equations are based on rectangular square or waves with peak value of ±1. Here, the rectangular wave represents any function of this shape, where the width of the pulse may vary. A primary advantage of transform is that the calculations are much simpler. When an image is programmed into basic functions, each pixel is multiplied by ± 1 and the N × N image is considered in the WHT equation (4). The basic function for using WHT in pumpkin leaf image extraction is based on the use of transformation functions based on Equation (4). The WHT is applied in squared size of gallery space images, it generating M×M blocks from each pumpkin leaf image, $N = 2^n$. The layer of (-1), and p (r) is found by finding the ith bit to treat r as a binary number.

$$WH(u,v) = \sum_{r=0}^{n-1}\sum_{c=0}^{n-1} I(r,c)(-1)^{\sum_{i=0}^{n-1} b_i(r)p_i(n)+b_i(c)p_i(c)} \qquad \text{---------------- (4)}$$

D) Hilbert Transformation based Pumpkin Leaf Feature Extraction

In the Hilbert transformation, the input pumpkin image is distorted over time and the length of the IMF's (intrinsic mode function) is equal to the original signal, meaning that HTT preserves different frequency characteristics. This presents an important advantage to HTT because many causes occur at different causal intervals. In HTT, time and frequency resolution are not regulated by uncertainty and frequency resolution is better than Fourier or DWT. HTT has two levels; The first is spectroscopic analysis using the Empirical Mode Decomposition (EMD) and the second stage of the decomposition process using Hilbert Spectral analysis. Fig. 2 illustrates the HTT feature extraction procedure of the pumpkin leaf images.

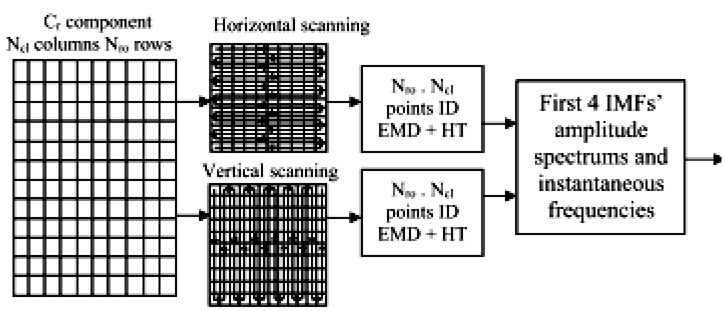


Fig. 2 HTT for Feature Extraction

Mathematically, the decomposed signal I(t), can be represented by finite sum of the IMFs as a function of time t and the final residue $R_n(t)$ as in Equation (5).

$$I(t) = R_n(t) + \sum_{j=1}^{n} IMF_j(t) \qquad \text{---------------- (5)}$$

In the second stage, Hilbert transform of image G(t) used to calculating the instant frequencies and amplitudes is defined as in Equation (6).

$$H[G(t)] = \frac{1}{\Pi} PV \int_{-\infty}^{\infty} \frac{G(t)}{t-\tau} d\tau \qquad \text{---------------- (6)}$$

Where PV denotes Cauchy's Principal Value integral. Since the frequency and amplitude of the Hilbert spectrum are expressed as functions, they can show energy or amplitudes. The spectrum is calculated by summing the time field from 0 and T as in (7).

$$E(\omega) = \int_0^T H(\omega, t) dt \qquad \text{---------------- (7)}$$

E) Radon Transformation based Pumpkin Leaf Feature Extraction

Radon transformation is based on the parameterization of straight lines and the evaluation of the coordinates of the input pumpkin leaf image with these lines. The directional features of an image can be captured easily, Due to inherent properties of Radon transform. The Radon transform of a two-dimensional function f(x, y) in (r, y) plane is represented as in Equation (8).

$$R(r,\theta)|f(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\delta(r - x\cos\theta - y\sin\theta)dxdy \qquad \text{---------------- (8)}$$

where δ (.) is the Dirac function, r $\in (-\infty,\infty)$is the vertical distance of a stripe from the basis and yA[0,p] is the angle formed by the distance vector. It refuses to reconstruct the image from its programs (or authentication may reach the maximum value of accuracy). The minimum (N_{smin}) and maximum (N_{smax}) numbers required for the reconstruction are expressed in Equation (9).

$$Nsmin = \pi N \quad and \quad Nsmax = 2\pi N \qquad \text{---------------- (9)}$$

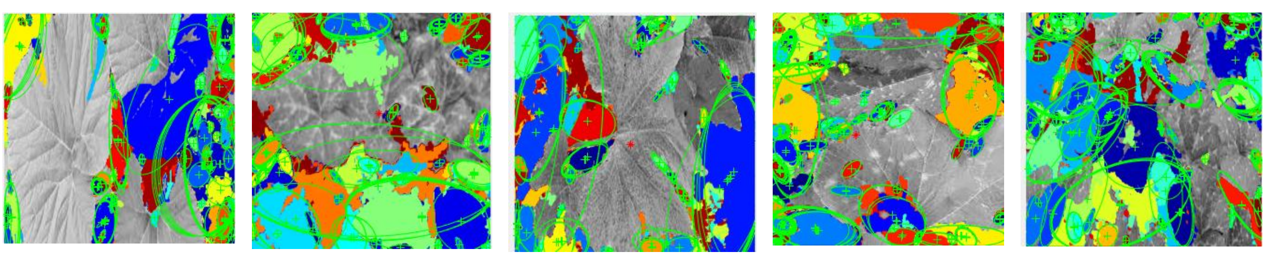
Radon transformation is widely used to extract local features in edge detection and texture features in pumpkin leaf images. In these approaches, the images are subdivided into sub-modules and the minimum number of radon projections as specified by Equation (9), which is used to obtain local features.

F) Chirp Z-Transformation based Pumpkin Leaf Feature Extraction

CZT calculates the Z transform at M points on a Z-plane. The Goertzel method is most useful when calculating an N point DFT using a small number of coefficients. The CZT algorithm converts the image into a Z Transform. When the Goertzel algorithm is used for this modified image, it acts as a reconstruction mechanism for the image. Reconstruction creates an image upside down in relation to its original.

Results and Discussions

This section presents an implementation of six different feature extraction algorithms used in extracting the features of the pumpkin leaf images. The overall implementation is performed in MATLABR2019 platform. Fig. 3 (a-h) shows the Local and Texture feature extracted by the MSER algorithm and its feature set is tabulated in Table 1. Similarly, Table 2 represents the local and texture features of pumpkin leaf images by Quad-Tree Decomposition algorithm. The global features of the pumpkin leaf images are measured by unitary transforms such as Walsh-Hadamard, Hilbert, Radon, and Chirp-Z transforms and its feature parameters are tabulated in Table 3-6 respectively.



(a) Image 1 **(b) Image 2** **(c) Image 3** **(d) Image 4** **(e) Image 5**

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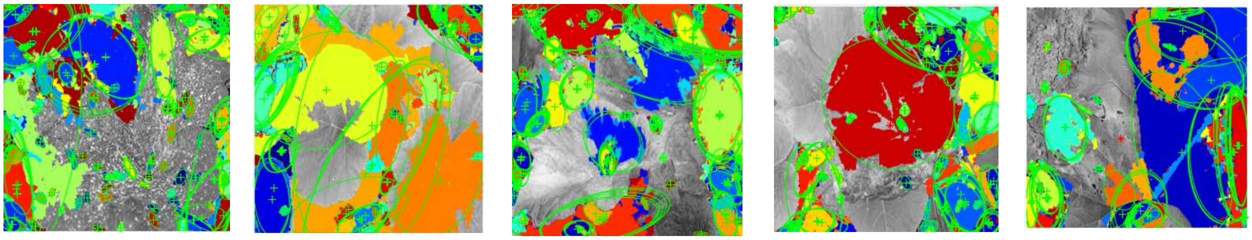

(f) Image 6 (g) Image 7 (h) Image 8 (i) Image 9 (j) Image 10

Fig. 3 (a-h) Feature extracted images of 10 pumpkin leaf images

Table 1. Local and Texture Features Extracted by MSERF Algorithm

Features/ Image	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
X Gravity Pt	0.0018	0.0014	0.0012	0.0009	0.0012	0.0012	0.0013	0.0011	0.0013	0.0011
Y Gravity Pt	0.0014	0.0011	0.0014	0.0014	0.0010	0.0013	0.0009	0.0012	0.0013	0.0015
Area	0.0002	0.0002	0.0001	0.0001	0.0002	0.0002	0.0002	0.0002	0.0002	0.0001
Orientation Mean	0	0	0	0	0	0	0	0	0	0
Axes Mean	0.0003	0.0003	0.0004	0.0003	0.0003	0.0003	0.0004	0.0003	0.0003	0.0004
Axes STD	0.0003	0.0004	0.0005	0.0003	0.0003	0.0003	0.0004	0.0003	0.0003	0.0004
Axes Sum in X Pts	0.1121	0.0788	0.0667	0.0998	0.1008	0.1009	0.0727	0.1106	0.0955	0.0638
Axes Sum in Y Pts	0.0447	0.0387	0.0276	0.0461	0.0461	0.0427	0.0344	0.0516	0.0458	0.0281
Pixel Length	2.0526	1.8369	1.5235	1.6001	1.4969	1.5526	1.5700	1.9638	1.7205	1.4236
Pixel Mean in X Pts	0.0019	0.0012	0.0011	0.0009	0.0014	0.0016	0.0014	0.0014	0.0016	0.0017
Pixel Mean in Y Pts	0.0015	0.0015	0.0014	0.0014	0.0012	0.0012	0.0013	0.0010	0.0011	0.0014
Pixel STD in X Pts	0.0007	0.0008	0.0009	0.0008	0.0008	0.0009	0.0008	0.0008	0.0007	0.0008
Pixel STD in Y Pts	0.0007	0.0008	0.0007	0.0009	0.0007	0.0008	0.0008	0.0008	0.0009	0.0007
Pixel STD Difference	0	0	0.0002	0	0.0001	0.0001	0	0.0001	-0.0002	0

Table 2. Local and Texture Features Extracted by QTD Algorithm

Features/ Image	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Sum of Blocks	0.0002	0.0002	0.0003	0.0003	0.0002	0.0003	0.0002	0.0003	0.0003	0.0002
QTD length	6.5505	6.5522	6.4956	6.5351	6.5523	6.5471	6.5422	6.5489	6.5445	6.5530
Mean_R	0.0288	0.0270	0.0464	0.0561	0.0252	0.0525	0.0270	0.0246	0.0264	0.0240
Mean_C	0.0262	0.0202	0.0571	0.0337	0.0280	0.0490	0.0255	0.0365	0.0305	0.0242
Non Zero Elements	6.5437	6.5494	6.3820	6.4978	6.5494	6.5362	6.5182	6.5419	6.5287	6.5518

Table 3. Global Features Extracted by Fast Walsh-Hadamard Transformation

Features/ Image	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Strongest Co-efficient_ Max	210.027	147.199	152.050	167.687	155.351	173.476	191.914	174.125	205.902	165.535
Strongest Co-efficient_ Min	-55.355	-30.070	-27.695	-60.449	-34.199	-40.418	-36.851	-48.011	-52.652	-43.335
Average	0.4645	0.4437	0.3815	0.2484	0.3950	0.2651	0.5359	0.3883	0.4909	0.5189
Standard Deviation	9.1051	7.3448	6.8139	7.1665	6.9830	8.0829	8.3734	8.0368	9.6335	7.7620
Normalized Non Zero Elements	0.9968	0.9972	0.9977	0.9984	0.9981	0.9986	0.9975	0.9983	0.9983	0.9980

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Table 4. Global Features Extracted by Hilbert Transformation

Features/ Image	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Strongest Co-efficient_Max	2.2200	2.4300	1.1300	2.5400	1.8400	1.9600	2.2700	2.0300	2.1700	2.1500
Strongest Co-efficient_Min	0	0	0	0	0	0	0	0	0	0
Average	1.3201	1.0974	0.9831	1.0058	0.9988	1.1658	1.2290	1.1506	1.4354	1.1581
Standard Deviation	0.7536	0.5671	0.6115	0.7140	0.6516	0.7018	0.6653	0.7817	0.7520	0.5750
Normalized Non Zero Elements	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100

Table 5. Global Features Extracted by Radon Transformation

Features/ Image	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Strongest Co-efficient_ Max	39.4666	29.8581	39.7132	41.9465	40.6016	67.0738	41.9840	34.2136	33.7700	103.714
Strongest Co-efficient_ Min	0	0	0	0	0	0	0	0	0	0
Average	4.8468	4.1893	4.8242	5.6024	5.1902	13.3956	5.1131	4.9940	5.9083	11.8288
Standard Deviation	5.4408	3.5886	4.4403	4.7233	4.4287	11.5300	4.4753	4.4199	4.9856	9.2688
Normalized Non Zero Elements	0.7577	0.8329	0.7862	0.8472	0.8253	0.8208	0.7979	0.8226	0.8369	0.8656

Table 6. Global Features Extracted by Chirp Z Transformation

Features/ Image	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Strongest Co-efficient_Max	4.7479	3.3724	3.7274	3.6705	3.4666	4.2661	4.1310	4.2880	4.8834	4.0911
Strongest Co-efficient_Min	0	0	0	0	0	0	0	0	0	0
Average	0.0137	0.0127	0.0103	0.0075	0.0117	0.0079	0.0153	0.0104	0.0137	0.0143
Standard Deviation	0.2586	0.2017	0.1774	0.2033	0.1972	0.2180	0.2383	0.2160	0.2612	0.2138
Normalized Non Zero Elements	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

Conclusion

In this paper we have proposed Local, Global and Texture feature extraction Methods. In this work we have considered five different Computer Vision (CV) based algorithms like MSER, QTD, WHT, HTT and Radon Transformation used for extracting the Pumpkin leaf images. Also, we created data base for ten images, based on the performance the productivity rate of the pumpkin leaf has been improved using CV algorithms. The important thing to note in this work is that only the extraction of features has given a good classification accuracy compared to other results available in the literature. Our future work will Study various classifier and implementing the results of pumpkin leafs with different images.

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