Analysis of Morphology Based Horticultural Features through Clustering Methods

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Abstract: Cluster analysis is a prime Pattern Recognition method used to categorize sample patterns in a population by means of forming different clusters by assigning cluster memberships to the sample patterns depending on the feature similarity relationship among different patterns. Patterns displaying dissimilar feature values are assigned different cluster memberships whereas patterns carrying similar feature values are placed into same cluster. Searching the relationship among horticultural data has become a major research area in Pattern Recognition. In this paper we have used the morphological features for describing the characteristics of Tomato leaves and fruits belonging to different classes. Morphological feature values are extracted from different tomato leaf and fruiting habit samples to analyze through K-Means and Two-step clustering techniques to segment leaf and fruit samples into separate clusters according to their species owing to categorize them. Our experimentation also compares and discusses about the importance of the features which are obtained through K-Means and Two-step Clustering technique, may be useful for leaf and fruit species categorization.

Keywords: Cluster analysis, K-Means Clustering, Two-step clustering, Pattern Recognition, Horticulture, Morphological Feature.

1. INTRODUCTION

Economic growth of a nation depends highly on its agricultural and horticultural development. As different cultivars may need specifically different cultivation processes for better growth and quality development hence it is very much needed to identify the horticultural cultivars belonging to different classes independently, so that appropriate cultivation means can be applied for specific cultivar. Thus horticultural species categorization is a very important task for cultivation. This task of categorization is easy to perform for the crops with small number of species variations, but the task becomes a tough one if huge numbers of crop species are to be dealt with. Horticultural vegetable like tomato have large variety of species found all around the globe. The high variation of morphological feature values of tomato leaf and fruit among different tomato species is a prominent indicator of species diversity upon which cluster analysis would be applied to form different tomato-species clusters and thus categorizing the tomato species depending on their cluster memberships. This automatic method of species categorization through clustering exhibits high level of accuracy and requires trifle time compare to manual process. Cluster analysis also produces some distinguishing results through which the feature importance of leaves and fruits could be predicted which may be of very useful while classifying the particular plant species.

2. BASIC CLUSTER ANALYSIS

Cluster analysis is an important analytical procedure used for the purpose of analysing data. Cluster analysis is widely used in different research areas like machine learning, pattern recognition, market research, digital image processing, Biology etc. Basically, clustering divides the sample entities into different groups called clusters depending on similarity present between entities. Entities placed into same cluster, bear great deal of similar features where as entities belonging to different clusters don't have that much of feature similarity like same cluster entities. All the member entities of a cluster can be represented by the cluster centre of that cluster. Now with the compact cluster formation, obtaining information from the original entity set can be sufficiently reduced to collecting information about a small number of clusters. Information obtained from the clusters can be very effective for purposes like entity classification, identification etc.

Clustering algorithms can be classified into categories such as: Partitional Clustering and Hierarchical Agglomerative Clustering. We discuss these two clustering techniques briefly in the following-

Partitional Clustering starts with some initial clusters. For each of the initial clusters, a cluster center is calculated by fulfilling the optimality condition. Sample objects are placed in different clusters depending on the smallest distance criterion i.e. a sample object is placed in that cluster whose cluster center is minimum distance away from the sample object. Sample input data are partitioned into the initial clusters. In the next step, cluster centers are recalculated and objects are again placed in different clusters depending on the new calculated cluster centers. This process of cluster center recalculation and placing the objects in clusters continues unless the placement of the objects in the clusters remains unaltered between two successive rotations.

Hierarchical Agglomerative Clustering algorithm starts with some single clusters depending on the size of the input data set. Number of initial single clusters is equal to the size of the input data set and each of the input patterns belongs to different cluster. Now as the algorithm moves, at each of the successive steps, merging of the cluster pairs having highest level of attribute similarities is performed.

3. APPLIED CLUSTERING METHODS

3.1 K-means Cluster Analysis

K-Means cluster analysis falls into the category of partional clustering algorithm. K-Means cluster analysis is used for analysing the feature data set.

Let's assume that P number of sample patterns is to be clustered. A pattern set $D=\{d_1, d_2, .., d_P\}$ represents the sample patterns .The characteristics of each sample pattern is represented by Z number of features, which constitute the feature set $F = \{f_1, f_2, \dots, f_Z\}$. Now for each of the Z features, P different feature values are obtained from each of the P sample patterns. The feature values associated to a feature f_x forms the individual feature value set IFV_X={ ifv_{1X} , ifv_{2X} ,..., ifv_{NX} ,..., ifv_{PX} },of size P, where ' ifv_{NX} ', an element of the set $\ensuremath{\mathrm{IFV}}_X,$ denotes the feature value of N th sample pattern with respect to feature f_x. K-Means cluster analysis is done on each IFV, to place P patterns in k(user given value) different clusters depending on the values of the elements of the IFV. K-Means clustering initially selects k patterns out of P patterns as initial clusters. Each cluster is represented by a cluster center. The value of each initial cluster center will be one of the elements of the IFV chosen randomly with uniqueness condition that same IFV element can't be placed into more than one initial clusters. Also the cluster membership of a particular IFV element remains same till the end of the clustering process.

Let's consider that K-Means clustering is applied to IFV_x. This will lead to the formation of k clusters each having a cluster center. Let's consider that the cluster center of 'i' th cluster is denoted by CC_i. Let's denote the value of cluster center CC_i by VCC_i. Now 'M' th data pattern d_M will be placed into the 'i' th cluster by satisfying the condition $Dis(d_M, CC_i) < Dis(d_M, CC_j)$, for all $j \neq i$, where $Dis(d_M, CC_i)$ is the distance between the data pattern d_M and the 'i' th cluster center CC_i and $Dis(d_M, CC_j)$ is the distance between d_M and another 'j' th cluster center CC_j. Now, $Dis(d_M, CC_i)$ can be calculated as per the following equation-

$$Dis(d_M, CC_i) = | ifv_{MX} - VCC_i |$$
(1)

The values of k cluster centers will be recalculated again and again unless no new member is placed in clusters. The updated value of a cluster center is the calculated average of the values member elements of the cluster. So VCC_i is updated as -

 $\begin{array}{ll} \bar{VCC}_i = (vme_{1i} + vme_{2i} + + vme_{li} + + vme_{si}).(1/s) \quad (2) \\ \text{, where `vme_{1i}` denotes the value of `l' th member element of `i' th cluster having `s' number of member elements of the `i' th cluster. Basically value of each member element is an element of set IFV_X. \end{array}$

In the following, we summarize different steps of K-Means algorithm done on the set $\ensuremath{\text{IFV}}_X$ -

1) Randomly choose k number of initial cluster centers out of P elements of the IFV_X set.

2) Place each pattern from pattern set D in the cluster whose cluster center is closest to it by calculating the pattern-cluster distance as per equation (1).

3) Recompute cluster centers as per equation (2), depending on the recent placement of the elements into the cluster and reassign the elements to its closest cluster based on the newly computed centers.

4) Repeat step 2 and 3 until there is no alteration in the cluster memberships.

3.2 Two step Cluster Analysis

Two-step cluster analysis belongs to the class of Hierarchical Agglomerative Clustering. Consider the pattern set D of size P and feature set F of size Z as mentioned in section 3.1. Values of Z features are extracted from each pattern. Hence values related to Z features, extracted from I th pattern d_I, forms the values of features set VF_I={vf_{I1},vf_{I2},....,vf_{IJ},....vf_{IZ}},where vf_{IJ} is the value of J th feature extracted from I th pattern. Each pattern is represented by its VF set. Now the values of all features extracted from all P patterns build a set of all values of features AVF={ VF_1 , VF_2 ,..., VF_1, VF_P }. Two-step cluster analysis is performed on the set AVF .Two-step clustering initially forms some sub-clusters and places P patterns into them. Each pattern is described by its VF values, so each subcluster contains the VF value of the member pattern. Let's consider that sc_A and sc_B are two sub-clusters containing pattern d_I and d_K respectively. Now the distance between sc_A and sc_B is calculated by calculating the Euclidean Distance between VF_I and VF_K , denoted by $ED(VF_I, VF_K)$, in the following equation-

 $ED(VF_{I}, VF_{K}) = ((vf_{I1} - vf_{K1})^{2} + (vf_{I2} - vf_{K2})^{2} + ... + (vf_{IZ} - vf_{KZ})^{2})^{1/2}$ (3)

The Two-step algorithm operates on AVF set in the following manner-

1) Place all the P sample patterns into different sub clusters depending on the values of the features set (VF) of each pattern. So each sub-cluster contain the VF set of a pattern.

Calculate the distance between sub clusters using equation
 Merge two nearest sub-clusters(clusters with minimum distance between each other) into one cluster to form new clusters.

Repeat the process of nearest cluster merging between the new clusters until desired number of clusters are formed.

4. EXPERIMENTAL RESULTS

In this paper we have used the best selected morphological features^[1] to perform K-Means and Two-step clustering with the help of IBM SPSS statistics 20 data mining tool and there by comparing the cluster building abilities of these features. This comparison will give better visibility about the impact of the features in machine vision solutions. The morphological features used in our experiment are listed below -

Leaf Features

- 1) Major Axis
- 2) Minor Axis
- 3) Aspect Ratio
- 4) Eccentricity
- 5) Area
- 6) Rectangularity

Area

- 7) Diameter
- 8) Compactness
- 9) Perimeter Ratio of Major Axis-Minor Axis
- 10) Perimeter Ratio of Diameter
- 11) Concavity
- 12) R-Factor

Fruit Features

- 1) Branch Length
- 2) Branch Width
- 3) Length Width Ratio
- 4) Area
- 5) Perimeter
- 6) Equivalent Diameter
- 7) Rectangularity
- 8) Diameter
- 9) Perimeter Ratio of Branch Length-Branch Width
- 10) Perimeter Ratio of Diameter
- 11) Convexity
- 12) Solidity
- 13) On Pixels
- 14) Narrow-Factor

4.1 K-Means Clustering Results

K-Means clustering is performed individually on feature values, related to each individual leaf and fruit features, extracted from all sample leaf and fruit patterns.

K-Means process starts by randomly selecting 15 and 14 initial cluster centers of individual leaf features (Table 1) and individual fruit features (Table 2) respectively.

Table 1- Randomly chosen Initial cluster centers for individual leaf features

Initial Cluster Centers

	Cluster								
	1	2	3	4	5	6	7	8	
Major Axis	479	390	419	339	370	435	587	503	

Initial Cluster Centers

	Cluster							
	9	10	11	12	13	14	15	
Major Axis	599	533	519	575	621	654	557	

nitial	Clu	ster	Cen	ter

		Cluster							
	1	2	3	4	5	6	7	8	
Minor Axis	167	321	216	197	254	182	279	291	

Initial Cluster Centers									
				Cluster					
	9 10 11			12	13	14	15		
Minor Axis	150	303	366	404	266	230	245		
	Initial Cluster Centers								
				Cluster					
	1	2	3	4	5	6	7		
Aspect Ratio	2.523810	2.795276	3.086207	3.264000	3.175000	2.081340	3.462264		

Initial Cluster Centers									
		Cluster							
	8	9	10	11	12	13	14		
Aspect Ratio	1.912371	2.939850	4.360000	1.602459	1.423792	2.642336	2.410072		
	Initial Cluster Centers								

	Cluster
	15
spect Ratio	2.260116

Initial	Chue	torl	Cont	0.00
initiai	Cius	ter i	cen	en

	Cluster								
	1	2	3	4	5	6	7	8	
Eccentricity	.933819	.837966	.943856	.803081	.924178	.874209	.957381	.852387	

Initial Cluster Centers

	Cluster								
	9	10	11	12	13	14	15		
Eccentricity	.885553	.824524	.781392	.711832	.893455	.914260	.973342		
Initial Cluster Centers									

Cluster							
	1 2		3 4		5	6	
	279909.125	321362.000	315217.375	337626.625	343288.250	330031.62	

Initial Cluster Centers

		Cluster								
	7	8	9	10	11	12				
Area	298127.250	301354.125	271183.500	276812.625	290063.875	262710.500				
Initial Cluster Centers										

	Cluster					
	13	14	15			
Area	285034.125	304995.625	295351.000			

Initial Cluster Centers

	Cluster							
	1	2	3	4	5	6	7	8
Rectangularity	.525200	.252211	.287069	.202822	.320442	.369372	.551564	.426617

Initial Cluster Centers

		Cluster						
		9	10	11	12	13	14	15
Rectangulari	ty	.621876	.586994	.792047	.883636	.504833	.463316	.403556

Initial Cluster Centers

		Cluster						
	1	1 2 3 4 5 6 7 8						
Diameter	414	316	398	441	356	492	470	614

Initial	Cluster	Centers

		Cluster	
	13	14	15
Perimeter Ratio of Diameter	10.257154	9.872329	6.920409

			Initial	Cluster (enters				
	Cluster								
1		2	3		4		5	6	7
91802.87	5 50	350.000				:	28423.750	41680.37	5 73584.75
T			Initial	Cluster (enters				
				0	luster				
8		9		10		11		12	13
70357	.875	100528.5	00	94899.37	5 8	1648	3.125	108918.500	86677.87
Initial Cluster Centers									
Cluster									
				14				15	
					66716.	375			76361.00
			Initial	Cluster C	enters				
				Clu	ster				
1		2		3		4		5	6
897.85507	2 1	176.303797	933	3.949749	1143	.729	231 1	044.134831	745.87951
			Initial	Cluster (enters				
				CI	uster				
7		8		9		10		11	12
791.1565	550	571.89838				9.04	3478	658.595745	842,28571
			inicial	ciuster (ar.			
		13			14				15
	91802.87 91802.87 8 70357 1 897.85507 7	91802.875 50 8 70357.875 1 897.855072 1	91802.875 50350.000 8 9 70357.875 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 100528.5 1176.303797 1176.303797 7 8 791.156550 571.898383	1 2 3 91802.875 50350.000 56494. Initial Initial 8 9 Initial 70357.875 100528.500 Initial 1 2 Initial 8 9 Initial 1 2 Initial 1 2 Initial 1 2 Initial 1 2 Initial 7 8 Initial 7 8 Initial 7 8 Initial 1 2 Initial 1 1176.303797 933 1 571.888383 6 Initial Initial Initial	1 2 3 91802.875 50350.000 56434.625 34 Initial Cluster C Initial Cluster C C 8 9 10 70357.875 100528.500 94899.37 70357.875 100528.500 94899.37 70357.875 100528.500 94899.37 100528.500 94899.37 Initial Cluster C 114 14 14 114 14 14 114 14 14 114 14 14 114 14 14 114 14 14 114 14 14 114 14 14 115 1176.303797 933.949749 1161 11838383 622.190856 117 1838383 622.190856 1181 11838383 622.190856 1181 11838383 622.190856	1 2 3 4 91802.875 50350.000 56434.625 34085.375 91802.875 50350.000 56434.625 34085.375 8 9 10 10 70357.875 100528.500 94899.375 8 9 100528.500 94899.375 8 100528.500 94899.375 8 111111111111111111111111111111111111	I 2 3 4 91802.875 50350.000 56494.625 34085.375 3 91802.875 50350.000 56494.625 34085.375 3 8 9 10 11 70357.875 100528.500 94899.375 81644 Initial Cluster Centers Initial Cluster Centers <	Cluster 1 2 3 4 5 91802.875 50350.000 56494.625 34085.375 28423.750 Initial Cluster Centers 8 9 10 11 70357.875 100528.500 94899.375 81648.125 Initial Cluster Centers Initial Cluster Center	Cluster 1 2 3 4 5 6 91802.875 50350.000 56434.625 34085.375 28423.750 41680.37 Initial Cluster Centers Initial Cluster Centers 8 9 10 11 12 70357.875 100528.500 94899.375 81648.125 108918.500 Initial Cluster Centers I

Table 2- Randomly chosen Initial cluster centers for individual fruit features

726.193548

703.500000

682.181818

R-factor

Initial Cluster Centers

	Cluster						
	1 2 3 4 5 6					6	
Branch Length	508.861407	631.948827	484.844350	654.464819	574.908316	691.991471	

	Initial Cluster Centers							
		Cluster						
	7	8	9	10	11	12		
Branch Length	447.317697	598.925373	586.916844	537.381663	553.893390	615.437100		

Initial Cluster Centers							
	Cluster						
	9	10	11	12	13	14	15
Diameter	597	650	584	564	545	515	530

Initial Cluster Centers

				Cluster			
	1	2	3	4	5	6	7
Compactness	1.530433	2.035084	1.588200	1.205719	1.857097	1.249416	1.063003
			Initial Cluste	r Centers			
Cluster							

 8
 9
 10
 11
 12
 13
 14

 Compactness
 1.350639
 .982277
 1.284001
 1.439500
 1.319113
 1.104743
 1.375947

 Initial Cluster Centers

	Cluster
	15
Compactness	1.157990

Initial Cluster Centers

			Clu	ster		
	1	2	3	4	5	6
Perimeter Ratio of Major Axis-Minor Axis	6.694405	7.195364	7.080442	5.983089	7.969643	7.500000

Initial Cluster Centers Cluster 7 8 9 10 11 12 Perimeter Ratio of Major 5.771539 5.629520 5.404010 6.914864 5.087829 4.831944 Axis-Minor Axis Initial Cluster Centers Cluster 13 14 15 Perimeter Ratio of Major Axis-Minor Axis 6.293952 6.139844 6.528949 Initial Cluster Centers Cluster 1 2 3 4 5 6 Perimeter Ratio of 12.536517 8.997152 8.718986 13.753165 11.278894 13.200000 Diameter Initial Cluster Centers Cluster 7 8 9 10 11 12

Perimeter Ratio of Diameter

7.576137

7.902203

8.465625 9.509748

8.228941

10.629945

Initial Cluster Centers

	Clu	ster		
	13	14		
Branch Length	520.869936	673.978678		

			Initial Cluste	r Centers								
		Cluster										
	1	1 2 3 4 5										
Branch Width	411.29211	1 358.7	54797 475.8	37953 321	228145	382.771855	295.710021					
Initial Cluster Centers												
Cluster												
	7	8	9		10	11	12					
Branch Width	447.31769	7 496.8	52878 460.0	327292 25	6.682303	424.801706	340.742004					
Initial Cluster Centers												
Cluster												
	13 14											
Branch Width			235.66	57377		306.2174	84					
			Initial Cluste	er Centers								
				Cluster								
	1	2	3	4	5	6	7					
Length width Ratio	2.491228	1.78440	4 1.017065	2.039409	1.4918	157 2.19230	8 1.206790					
			Initial Cluste	er Centers								
				Cluster								
	8	9	10	12	13	14						
Length width Ratio	1.414894	55 1.57706	1 1.926471									
			Initial Cluste	er Centers								
			(Cluster								

		Cluster											
	1	2	3	4	5	6	7	8					
Area	175316	207688	186587	240592	292808	269369	200254	227813					

	Initial Cluster Centers											
		Cluster										
	9	9 10 11 12 13 14										
Area	248800 134572 256387 193219 160739 213099											
			Initia	l Cluster Ce	nters							
				Clu	ster							
	1	1 2 3 4 5 6 7 8										
Perimeter	4396	4808	4946	5793	5720	6427	5205	4603				

Initial Cluster Centers

		Cluster											
	9	10	11	12	13	14							
Perimeter	5056	5475	3815	5319	4530	5569							

Initial Cluster Centers											
			Cluster								
	1	2	3	4	5						
Equivalent Diameter	472.461197 514.234433 487.411966 553.472282 610.585559										

Initial Cluster Centers											
			Cluster								
	6	7	8	9	10						
Equivalent Diameter	585.637892	504.946683	538.572670	562.834324	413.934674						

						Initial (Cluster Cen	ters						
		Cluster												
					11		12			1	3			14
Equivalent (Diam	neter	r		571	.350950	495	.9982	216	45	2.3933	34	5	20.889542
						Initial (Cluster Cen	ters						
							CI	uste	r					
			1	2		3	4		5		6	7		8
Rectangular	ity	1.	51555	.988	69	1.35499	.56056		.74742		89254	1.250	91	1.46348
	Initial Cluster Centers													
Cluster														
9 10 11 12 13 14										12 13		13		14
Rectangular	ity		1.	06472	472 1.12193				1.2)264		2.47732		1.41198
						Initial C	Cluster Cer	iters	5					
							Clu	ster		_				
		1	1		2		3		4		5			6
Diameter	4	21.	799574	483.	.3432	84 52	2.371002	5	70.40511	7	639.4	54158	6	75.479744
						Initial (Cluster Cer	iters						
							Clu	ster						
		1	7		8		9		10		11			12
Diameter		597.	.424307	619	9.9402	299 5	80.912580	(661.9701	49	505.8	359275	6	97.995736
						Initial (Cluster Cer	ters						
									Cluster					
						1	3					14		
Diameter	Diameter 609.432836 447.317697													

Initial Cluster Centers										
			Clu	ster						
	1	2	3	4	5	6				
Perimeter Ratio of Branch Length-Branch Width	4.430537	4.718868	5.148424	4.235480	5.946467	5.038155				

					Initia	al Clust	er Ce	nters						
									uster		_		_	
			i	1		8		9		10		11	4	12
Perimeter R Length-Bra		anch	4.8	80447	3	8.996112	-	5.74539	9	5.2860	98	6.16060)9	3.301852
					Initia	al Clust	er Ce	Centers						
							┢				Clus	ter		
							╉		13				14	
Perimeter R	atio of Bra	inch Lei	ngth-Bi			h al Clust	or Co	ntors		5.4150	92			5.539335
			Г		innue	il ciusi					_		_	
				1		2		3	luste	4 4		5		6
Desimates D	ation of Di-		40.4	-			,	s 8.15591	0		07	9.6869	14	
Perimeter F	catio of Dia	ameter	10.4	22011		9.08549 al Cluste			9	8.4478	91	3.6663	51	7.963229
					an R K	ar orusu	.r oe		uctor					
		7 8							uster		Τ	44	Т	40
Device of the	-010 ¹	an de la				8		9	,	10		11		12
Perimeter R	atio of Dia	meter	9.3	72221	_	.772676 al Clust		3.70354 nters	(7.39736	10	8.89411	2	6.618560
							Γ			(lust	ter		
								13				14		
Perimeter R	latio of Dia	meter						7.7	0739	3		11.	890	878
					nitia	l C lust	er Ce	nters						
		Cluster								_				
	1		2 3					4		5		6		7
Convexity	84.556	87	79.527	60	77.3	1115	72	58582	64	4.13240		57.8360	0	70.96449
					Initia	al Clust	er Ce	nters						
							Clu	ister			_		_	
	8		9		1()		11 12				13		14
Convexity	82.055	563	80.741	26	68.1	10407	66	66.74663 69.29754			L	87.08688 74.88155		
					Initia	al Clust	erCe	nters						
							Clus	ster				1		
	1	2		3		4		5		6		7		8
Solidity	.471645	.558	735	.5019	968	.647	254	.787	728	.724	672	.5387	34	.612875
	1				Initi	al Clust	er Ce	nters						
							CI	uster						
	9			10		11			12			13		14
Solidity	.6	69336		.40070	4	.6	39746		.519	809		.434213		.573290
					Initia	il Clust	er Ce	nters						
						1	Clu	ster					_	
	1	1 2 3 4						5		6		7		8
On-Pixels	175227							292	731	269	295	2001	73	227711
	_				Initia	al Cluste	er Ce	nters						
	\vdash				Т			uster						
	9			10		11			12			13		14
On-Pixels		248725		1345	14	2	5631	3	193	144		160675		212979

Initial Cluster Centers

				Cluster			
	1	2	3	4	5	6	7
Narrow-Factor	.891534	.819477	1.250774	.927954	.953964	.986842	1.00000
			Initial Cluster	Centers			

		Cluster								
	8	9	10	11	12	13	14			
Narrow-Factor	1.146341	1.015284	1.065491	1.038560	.974359	1.094017	1.111959			

Table 3 and Table 4 represent the iteration history of the K-Means clustering on individual leaf and fruit features respectively. Iteration history shows the number of times the clustering iterates before completion. Clustering algorithm completes when there is a small change or no change in the cluster centers, there by achieving the convergence.

Table 3- Iteration History of clustering on 12 individual leaf features

Table 3.1- Iteration History of clustering on Major Axis

	a Iteration History												
Iteration		Change in Cluster Centers											
	1	1 2 3 4 5 6 7 8											
1	.000	.000 .000 2.150 .000 .000 .000 .530 2.5											
2	.000	.000	.000	.000	.000	.000	.000	.000					
3	3 .000 .000 .000 .000 .000 .000 .000												
	a Iteration History												

Iteration		Change in Cluster Centers										
	9	10	11	12	13	14	15					
1	.000	3.002	.000	4.203	4.003	.000	4.000E-007					
2	.000	1.128	.000	.000	.000	.000	1.334					
3	.000	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 12.009.

Table 3.2- Iteration History of clustering on Minor Axis

lte	ration Histo	ry		
(Change in Cl	uster Centers	3	
		-		

Iteration

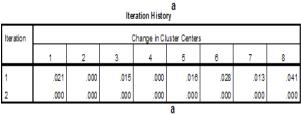
	1	2	3	4	5	6	7	8	
1	.375	.000	.790	.461	1.501	.375	1.001	.000	
2	2.377	.000	.000	.000	.000	.000	.000	.000	
3	.000	.000	.000	.000	.000	.000	.000	.000	

a Iteration History

Iteration		Change in Cluster Centers										
	9	10	11	12	13	14	15					
1	3.753	.000	.000	.000	3.002	1.876	3.002					
2	1.751	.000	.000	.000	.000	1.876	1.501					
3	.000	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 9.006.

Table 3.3- Iteration History of clustering on Aspect Ratio



Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14	15				
1	.000	.000	.053	.000	.023	.005	.001				
2	.000	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is .089.

Table 3.4- Iteration History of clustering on Eccentricity

	a Iteration History										
Iteration	Iteration Change in Cluster Centers										
	1	1 2 3 4 5 6 7 8									
1	.002	.002 .001 .002 .001 .002 .002 .002 .004									
2	.000	.000	.000	.000	.000	.000	.000	.000			

a Iteration History

_	;											
It	eration		Change in Cluster Centers									
		9	10	11	12	13	14	15				
1		.002	.000	.000	.000	.003	2.325E-005	.000				
2		.000	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is .008.

Table 3.5- Iteration History of clustering on Area

a Iteration History

Iteration		Change in Cluster Centers										
	1	1 2 3 4 5 6 7 8										
1	1280.688	804.875	561.531	.000	.000	1761.583	92.188	605.896				
2	.000	.000	.000	.000	.000	.000	473.604	.000				
3	.000	000. 000. 000. 000. 000. 000. 000.										

Iteration History

Iteration		Change in Cluster Centers										
	9	10	11	12	13	14	15					
1	109.938	.000	477.083	.000	.000	49.875	788.925					
2	.000	.000	.000	.000	.000	.000	513.044					
3	.000	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 2776.250.

Table 3.6- Iteration History of clustering on Rectangularity

	a Iteration History											
Iteration		Change in Cluster Centers										
	1	1 2 3 4 5 6 7 8										
1	.007	.007 .002 .004 .001 .003 .001 .000 .008										
2	.000	000. 000. 000. 000. 000. 000. 000.										

Iteration History

Iteration		Change in Cluster Centers								
	9	9 10 11 12 13 14 15								
1	.004	.000	.000	.000	.008	.000	.007			
2	.000	.000	.000	.000	.000	.000	.000			

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is .020.

Table 3.7- Iteration History of clustering on Diameter

	Iteration History										
Iteration		Change in Cluster Centers									
	1	1 2 3 4 5 6 7 8									
1	.000	4.500	.000	4.503	.000	1.629	6.004	3.002			
2	.000	.000 .000 .000 .000 .000 1.329 1.501 .000									
3	.000	.000	.000	.000	.000	.000	.000	.000			

a Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14	15				
1	.000	.000	4.878	1.001	.429	.500	1.876				
2	.000	.000	1.128	4.003	.000	.000	.000				
3	.000	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 13.510.

Table 3.8- Iteration History of clustering on Compactness

	a Iteration History											
Iteration		Change in Cluster Centers										
	1	1 2 3 4 5 6 7 8										
1	.000	.009	.000	.001	.000	8.000E-006	.005	.000				
2	.000	000. 800. 000. 000. 000. 000. 000.										
3	.000	000. 000. 000. 000. 000. 000. 000.										

Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14	15				
1	.017	8.050E-005	.000	.004	.001	.000	.002				
2	.000	.000	.000	.000	.007	.000	.000				
3	.000	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any

center is .000. The current iteration is 3. The minimum distance between initial centers is .025.

Table 3.9- Iteration History of clustering on Perimeter Ratio of Major Axis-Minor Axis

Iteration History

Iteration		Change in Cluster Centers									
	1	1 2 3 4 5 6 7						8			
1	.034	.000	.000	.018	.020	.025	.039	.007			
2	.000	.000	.000	.000	.000	.000	.000	.000			

a Iteration History

Iteration		Change in Cluster Centers								
	9	10	11	12	13	14	15			
1	.044	.000	.023	.000	.012	.027	.058			
2	.000	.000	.000	.000	.000	.000	.000			

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is .115.

Table 3.10- Iteration History of clustering on Perimeter Ratio of Diameter

a Iteration History

Iteration		Change in Cluster Centers									
	1	2	3	4	5	6	7	8			
1	.014	.000	.004	.000	.000	.080	.072	.013			
2	.040	.000	.000	.000	.000	.028	.000	.000			
3	.000	.000	.000	.000	.000	.000	.000	.000			

Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14	15				
1	.034	.008	.009	.000	.048	.028	.086				
2	.000	.000	.000	.000	.000	.000	.000				
3	.000	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is .237.

Table 3.11- Iteration History of clustering on Concavity

a Iteration History

Iteration		Change in Cluster Centers									
	1	1 2 3 4 5 6 7 8									
1	1280.688	804.875	561.531	.000	.000	1761.583	92.188	605.896			
2	.000	.000	.000	.000	.000	.000	473.604	.000			
3	.000	.000	.000	.000	.000	.000	.000	.000			

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Iteration	H	iđ	1

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14	15				
1	109.938	.000	477.083	.000	.000	49.875	788.925				
2	.000	.000	.000	.000	.000	.000	513.044				
3	.000	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 2776.250.

Table 3.12- Iteration History of clustering on R-Factor

	Iteration History											
Iteration	Change in Cluster Centers											
	1	2	3	4	5	6	7	8				
1	.000	.000	.000	.000	.000	1.634	3.755	.000				
2	.000	.000	.000	.000	.000	.000	.000	.000				
3	000. 000. 000. 000. 000. 000. 000.											
					а							

	Iteration History												
Iteration		Change in Cluster Centers											
	9	10	11	12	13	14	15						
1	3.273	1.387	7.984	8.423	.602	3.522	4.450						
2	5.889	.000	2.004	.000	.000	.000	.000						
3	000	000	000	000	000	000	000						

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 19.686.

Table 4- Iteration History of clustering on 14 individual fruit features

Table 4.1- Iteration History of clustering on Branch-Length

Iteration History

na zna z											
Iteration		Change in Cluster Centers									
	1	2	3	4	5	6	7	8			
1	.000	1.501	.000	5.004	3.753	4.503	.000	1.501			
2	.000	.000	.000	1.376	.000	.000	.000	.000			
3	.000	.000	.000	.000	.000	.000	.000	.000			

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Iteration		Change in Cluster Centers								
	9	10	11	12	13	14				
1	.563	.000	2.502	3.002	3.002	3.002				
2	.000	.000	.000	.000	.000	1.501				
3	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 12.009.

Table 4.2- Iteration History of clustering on Branch-Width

	Iteration History										
Iteration		Change in Cluster Centers									
	1	2	3	4	5	6	7	8			
1	5.254	4.003	3.333E-007	4.503	3.377	.000	3.603	6.004			
2	.000	.000	3.753	.000	.000	.000	3.603	1.876			
3	.000	.000	.000	.000	.000	.000	.000	.000			

Iteration History									
Iteration			Change in Cluster Centers						
	9	10	11	12	13	14			
1	1.501	.000	.751	3.377	.000	1.501			
2	1.501	.000	1.951	.000	.000	.000			

.000

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a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 10.507.

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Table 4.3- Iteration History of clustering on Length-Width Ratio

Iteration History											
Change in Cluster Centers											
1	2	3	4	5	6	7	8				
.000	.021	.013	.004	.010	.000	.025	.023				
.000	.000	.000	.000	.000	.000	.007	.000				
.000	.000	.000	.000	.000	.000	.000	.000				
	.000	.000 .000	1 2 3 .000 .021 .013 .000 .000 .000	Change in Cl 1 2 3 4 .000 .021 .013 .004 .000 .000 .000	Change in Cluster Centers 1 2 3 4 5 .000 .021 .013 .004 .010 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000	Change in Cluster Centers 1 2 3 4 5 6 .000 .021 .013 .004 .010 .000 .000 .000 .000 .000 .000 .000	Change in Cluster Centers 1 2 3 4 5 6 7 .000 .021 .013 .004 .010 .000 .025 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000				

Iteration History

Iteration		Change in Cluster Centers								
	9	10	11	12	13	14				
1	.000	.000	.019	.004	.016	.021				
2	.000	.000	.009	.000	.000	.000				
3	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is .074.

Table 4.4- Iteration History of clustering on Area

а Iteration History

Iteration	Change in Cluster Centers									
	1	2	3	4	5	6	7	8		
1	649.813	420.825	1662.792	1128.833	.000	2781.417	.000	2060.188		
2	.000	.000	.000	.000	.000	.000	.000	.000		

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Iteration	His	torv	

Iteration		Charge in Cluster Centers								
	9	10	11	12	13	14				
1	529.025	.000	1237.800	.000	331.438	2533.313				
2	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is 5410.500.

Table 4.5- Iteration History of clustering on Perimeter

а Iteration History

Iteration		Change in Cluster Centers								
	1	2	3	4	5	6	7	8		
1	.000	31.000	9.000	.000	.000	.000	2.889	37.500		
2	.000	.000	.000	.000	.000	.000	8.486	.000		
3	.000	.000	.000	.000	.000	.000	.000	.000		

Iteration History

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Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	24.333	4.667	20.500	10.444	15.000	7.500					
2	14.917	.000	.000	.000	.000	.000					
3	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 73.000.

Table 4.6- Iteration History of clustering on Equivalent-Diameter

Iteration History

ſ	Iteration		Change in Cluster Centers								
		1	2	3	4	5	6	7	8		
	1	.877	.516	2.165	1.309	.000	3.038	.000	2.422		
	2	.000	.000	.000	.000	.000	.000	.000	.000		

Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	.604	.000	1.366	.000	.486	3.078					
2	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is 6.655.

Table 4.7- Iteration History of clustering on Rectangularity

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	a Iteration History									
Iteration		Change in Cluster Centers								
	1	1 2 3 4 5 6 7 8								
1	.003	.016	.014	.013	.022	.002	.017	.000		
2	.000	000. 000. 000. 000. 000. 800. 000.								
3	.000	000. 000. 000. 000. 000. 000.								

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Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	.004	.012	.006	.004	.000	.001					
2	.012	.000	.000	.000	.000	.000					
3	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is .048.

Table 4.8- Iteration History of clustering on Diameter

			I	teration Hist	a ory						
Iteration	Iteration Change in Cluster Centers										
	1	1 2 3 4 5 6 7 8									
1	.000	.000	2.252	2.502	5.000E-007	1.876	3.002	.000			
2	.000	000. 000. 000. 000. 000. 000. 000.									

а Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	.375	.188	.000	3.002	1.501	.000					
2	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is 10.507.

Table 4.9- Iteration History of clustering on Perimeter **Ratio of Branch Length-Branch Width**

0

	lteration History										
Iteration	Change in Cluster Centers										
	1	1 2 3 4 5 6 7 8									
1	.000	.039	.010	.000	.009	.000	.023	.000			
2	000. 000. 000. 000. 000. 000. 000.										
	i a i										

Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	.007	.024	.024	.000	.013	.000					
2	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any

center is .000. The current iteration is 2. The minimum distance between initial centers is .110.

Table 4.10- Iteration History of clustering on Perimeter **Ratio of Diameter**

Iteration Histo

Iteration		Change in Cluster Centers 1 2 3 4 5 6 7 8									
	1										
1	.000	.014	.045	.049	.000	.049	.037	.000			
2	.000	.000	.000	.000	.000	.016	.000	.000			
3	.000	.000	.000	.000	.000	.015	.000	.000			
4	.000	.000	.000	.000	.000	.012	.000	.000			
5	.000	.000	.000	.000	.000	.000	.000	.000			

а Iteration History

			relation matery			
Iteration			Change in Cl	uster Centers		
	9	10	11	12	13	14
1	.016	.014	.015	.000	.009	.000
2	.000	.000	.000	.000	.015	.000
3	.000	.000	.000	.000	.016	.000
4	.000	.000	.000	.000	.021	.000
5	.000	.000	.000	.000	.000	.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 5. The minimum distance between initial centers is .191.

Table 4.11- Iteration History of clustering on Convexity

ð Iteration History

Iteration		Change in Cluster Centers									
	1	2	3	4	5	6	7	8			
1	.529	.029	.505	.370	.426	.000	.096	.270			
2	.000	.000	.000	.000	.000	.000	.199	.000			
3	.000	.000	.000	.000	.000	.000	.000	.000			

а

a Iteration History											
Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	.055	.268	.090	.302	.000	.138					
2	.000	.000	.000	.148	.000	.000					
3	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 3. The minimum distance between initial centers is 1.193.

Table 4.12- Iteration History of clustering on Solidity

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Iteration	History

Iteration		Change in Cluster Centers									
	1	2	3	4	5	6	7	8			
1	.002	.001	.004	.003	.000	.007	.000	.008			
2	.000	.000	.000	.000	.000	.000	.000	.000			

a Iteration History

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	.001	.000	.003	.000	.000	.007					
2	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is .015.

Table 4.13- Iteration History of clustering on On Pixels
8
Iteration History

Iteration		Change in Cluster Centers									
	1	2	3	4	5	6	7	8			
1	649.500	418.800	1671.667	1112.667	.000	2790.687	.000	2075.250			
2	.000	.000	.000	.000	.000	.000	.000	.000			
	a Iteration History										

Iteration		Change in Cluster Centers									
	9	10	11	12	13	14					
1	530.200	.000	1240.000	.000	316.000	2549.500					
2	.000	.000	.000	.000	.000	.000					

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is 5375.000.

Table 4.14- Iteration History of clustering on Narrow-Factor

a Iteration History

			110		' '						
Iteration		Change in Cluster Centers									
	1	2	3	4	5	6	7	8			
1	.000	.005	.000	.001	.000	.000	.001	.005			
2	.000	.000	.000	.000	.000	.000	.000	.000			

Iteration History
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Iteration	Change in Cluster Centers									
	9	10	11	12	13	14				
1	.001	.000	.005	.000	.006	.005				
2	.000	.000	.000	.000	.000	.000				

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is .012.

Information regarding the membership of 15 leaf and 14 fruit clusters build through K-Means Clustering is shown by Table5 and Table 6. The case number field signifies the sample leaf/fruit pattern number. The field called cluster is the cluster number in which a pattern is placed and distance field gives the distance between the pattern and the cluster center, in which the pattern is placed.

Table 5-Cluster membership of leaf clusters build from 12 individual leaf features

Clust	er Memb	ership	Clust	ter Membe	rship
Case Number	Cluster	Distance	Case Number	Case Number	Case Number
1	1	.000	16	10	.375
2	2	.000	17	15	7.339
3	3	2.150	18	13	1.001
4	4	.000	19	15	4.670
5	5	.000	20	12	1.201
6	6	.000	21	10	7.881
7	7	1.148	22	8	1.001
8	15	1.334	23	10	4.128
9	9	.000	24	15	1.668
10	10	1.126	25	15	.167
11	7	.530	26	11	.000
12	12	4.203	27	10	4.878
13	15	1.334	28	8	2.502
14	7	2.031	29	7	.530
15	15	1.668	30	12	4.803

Cluster Membership			
Case	Cluster	Distance	
Number			
31	11	.000	
32	13	4.003	
33	7	2.472	
34	12	4.203	
35	7	.530	
36	10	5.629	
37	10	6.380	
38	15	3.169	
39	14	.000	
40	3	2.150	
41	12	4.803	
42	10	8.631	
43	8	3.502	
44	15	1.334	
45	13	5.004	

Table 5.2-Cluster membership for Minor Axis

Clust	er Members	hip	Clust	ter Memberst	nip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	3	2.637	16	1	5.504
2	3	1.363	17	9	3.502
3	3	.363	18	14	2.842E-014
4	4	4.900	19	6	.375
5	4	7.100	20	6	1.876
6	3	6.363	21	9	2.001
7	7	1.001	22	1	2.001
8	8	.000	23	4	6.465
9	7	.500	24	3	5.294
10	10	.000	25	14	2.842E-014
11	11	.000	26	3	.790
12	12	.000	27	2	.000
13	13	3.002	28	3	6.715
14	15	3.002	29	4	2.542
15	15	4.503	30	1	3.502

Cluster Membership				
Case Number	Cluster	Distance		
31	5	3.333E-007		
32	5	1.501		
33	5	1.501		
34	14	2.842E-014		
35	13	3.002		
36	15	1.501		
37	4	8.546		
38	6	3.377		
39	9	5.504		
40	4	.461		
41	3	.790		
42	4	1.962		
43	7	.500		
44	3	5.294		
45	6	5.629		

Table 5.3-Cluster membership for Aspect Ratio

Cluste	r Membershi	p	Cluste	r Membershi	р
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	15	.062	16	3	.015
2	8	.049	17	7	.013
3	8	.077	18	13	.028
4	11	.022	19	3	.028
5	8	.076	20	5	.016
6	6	.028	21	7	.008
7	6	.001	22	3	.044
8	8	.041	23	2	.000
9	6	.048	24	1	.035
10	8	.104	25	14	.017
11	11	.053	26	14	.012
12	12	.000	27	11	.031
13	6	.013	28	14	.005
14	1	.034	29	9	.000
15	15	.029	30	7	.022

Cluster Membership				
Case Number	Cluster	Distance		
31	6	.050		
32	1	.023		
33	15	.066		
34	1	.001		
35	15	.001		
36	15	.033		
37	13	.023		
38	5	.016		
39	10	.000		
40	6	.044		
41	13	.047		
42	13	.042		
43	8	.039		
44	1	.021		
45	4	.000		

Table 5.4-Cluster membership for Eccentricity

Clust	ter Members	nip	Clus	ter Membersh	ıip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	13	.006	16	3	.000
2	2	.001	17	7	.002
3	8	.002	18	5	.002
4	4	.001	19	3	.001
5	8	.002	20	3	.003
6	6	.000	21	7	.001
7	9	.004	22	3	.002
8	8	.004	23	1	.002
9	9	.002	24	14	.005
10	10	.000	25	14	.003
11	11	.000	26	14	.005
12	12	.000	27	4	.001
13	6	.002	28	14	.004
14	14	2.325E-005	29	3	.005
15	13	.003	30	7	.001

Cluster Membership				
Case Number	Cluster	Distance		
31	6	.002		
32	14	.001		
33	13	.006		
34	14	.003		
35	13	.000		
36	13	.003		
37	5	.000		
38	3	.002		
39	15	.000		
40	9	.002		
41	5	.002		
42	1	.002		
43	2	.001		
44	14	.004		
45	7	.004		

Table 5.5-Cluster membership for Area

Cluste	er Membersh	ip	Cluste	er Membersh	ip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	3	482.281	16	3	1168.906
2	2	2642.500	17	2	194.125
3	3	1969.281	18	15	1167.531
4	4	.000	19	14	1211.875
5	5	.000	20	14	141.375
6	6	914.792	21	3	1260.469
7	7	381.417	22	8	283.021
8	8	605.896	23	3	783.719
9	9	109.938	24	11	948.458
10	10	.000	25	7	565.792
11	9	109.938	26	14	451.125
12	12	.000	27	1	1280.688
13	15	960.406	28	6	846.792
14	14	952.000	29	3	1443.969
15	15	1301.969	30	3	693.844

10 1001.4	00			
Cluster Membership				
Case Number	Cluster	Distance		
31	8	1026.271		
32	7	947.208		
33	15	825.969		
34	1	1280.688		
35	13	.000		
36	11	477.083		
37	8	710.604		
38	2	804.875		
39	2	2031.750		
40	6	1761.583		
41	8	1149.354		
42	11	1425.542		
43	14	49.875		
44	3	561.531		
45	8	55.229		

Table 5.6-Cluster membership for Rectangularity

Cluste	r Membershi	ip	Cluste	r Membershi	ip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	5	.008	16	3	.015
2	2	.002	17	3	.011
3	3	.004	18	13	.014
4	4	.001	19	5	.011
5	4	.001	20	5	.014
6	3	.005	21	3	.012
7	7	.000	22	3	.004
8	1	.005	23	5	.002
9	9	.004	24	8	.006
10	10	.000	25	8	.002
11	11	.000	26	6	.001
12	12	.000	27	9	.004
13	13	.006	28	5	.003
14	14	.006	29	6	.001
15	14	.001	30	3	.013

Cluster Membership				
Case Number	Cluster	Distance		
31	8	.003		
32	1	.007		
33	13	.008		
34	14	.005		
35	1	.002		
36	8	.005		
37	6	.001		
38	5	.011		
39	5	.016		
40	2	.002		
41	15	.007		
42	6	.015		
43	14	.000		
44	15	.007		
45	6	.012		

Table 5.7-Cluster membership for Diameter

Clust	ter Membersh	ıip	Clust	er Membersh	nip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.000	16	7	1.501
2	2	4.500	17	7	3.002
3	3	.000	18	8	3.002
4	2	4.500	19	14	2.001
5	5	.000	20	11	3.002
6	6	.308	21	15	2.627
7	11	1.501	22	7	7.505
8	8	3.002	23	6	1.457
9	9	.000	24	4	4.503
10	7	6.004	25	15	1.876
11	11	6.004	26	6	3.046
12	11	4.503	27	13	4.074
13	13	.429	28	6	7.549
14	14	2.502	29	13	2.573
15	15	2.627	30	6	6.048

Cluster Membership				
Case Number	Cluster	Distance		
31	6	5.960		
32	12	3.002		
33	12	3.002		
34	13	4.074		
35	13	5.575		
36	15	3.377		
37	14	.500		
38	13	7.934		
39	10	.000		
40	4	4.503		
41	7	3.002		
42	6	2.958		
43	6	5.960		
44	13	7.934		
45	11	2.000E-007		

Table 5.8-Cluster membership for Compactness

Clust	ter Membersl	nip	Clus	ter Membersl	nip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.000	16	12	.007
2	2	.009	17	8	.000
3	3	.000	18	9	.004
4	2	.009	19	4	.004
5	5	.000	20	7	.008
6	12	.011	21	4	.016
7	7	.013	22	12	.004
8	9	.020	23	10	.001
9	9	.016	24	14	.000
10	6	.021	25	15	.006
11	9	.008	26	6	8.000E-006
12	9	.009	27	13	.006
13	13	.010	28	10	8.050E-005
14	4	.011	29	15	.016
15	15	.009	30	6	.017

Cluster Membership				
Case Number	Cluster	Distance		
31	6	.016		
32	13	.010		
33	7	.009		
34	13	.001		
35	13	.007		
36	15	.006		
37	4	.001		
38	15	.002		
39	9	.017		
40	11	.000		
41	10	.009		
42	6	.011		
43	10	.011		
44	15	.009		
45	7	.003		

Table 5.9-Cluster membership for Perimeter Ratio of Major Axis-Minor Axis

Cluste	r Membershi	р	Cluste	r Membershi	p
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.034	16	7	.057
2	2	.000	17	14	.014
3	3	.000	18	11	.023
4	5	.020	19	7	.032
5	5	.020	20	9	.044
6	6	.025	21	7	.062
7	7	.048	22	1	.001
8	8	.027	23	14	.043
9	9	.015	24	7	.039
10	9	.059	25	14	.024
11	11	.023	26	13	.050
12	12	.000	27	7	.063
13	1	.033	28	4	.018
14	14	.018	29	13	.065
15	15	.030	30	13	.012

Cluster Membership				
Case Number	Cluster	Distance		
31	14	.041		
32	13	.046		
33	4	.018		
34	8	.008		
35	14	.027		
36	13	.047		
37	15	.028		
38	8	.018		
39	8	.046		
40	6	.025		
41	15	.058		
42	10	.000		
43	14	.029		
44	13	.004		
45	8	.007		

Table 5.10-Cluster membership for Perimeter Ratio of Diameter

Cluste	r Membershi	р	Cluste	r Membershi	p
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	3	.004	16	1	.054
2	2	.000	17	6	.026
3	3	.004	18	15	.022
4	4	.000	19	9	.007
5	5	.000	20	15	.063
6	14	.087	21	7	.072
7	1	.142	22	10	.008
8	8	.013	23	1	.120
9	8	.083	24	13	.001
10	10	.059	25	6	.024
11	11	.009	26	10	.157
12	11	.009	27	6	.078
13	14	.161	28	9	.034
14	14	.007	29	6	.079
15	14	.148	30	6	.074

Cluster Membership					
Case Number	Cluster	Distance			
31	10	.073			
32	14	.039			
33	6	.106			
34	9	.027			
35	10	.145			
36	6	.017			
37	10	.128			
38	7	.072			
39	15	.086			
40	13	.048			
41	12	.000			
42	13	.047			
43	14	.028			
44	1	.076			
45	8	.096			

Table 5.11-Cluster membership for Concavity

Cluste	ar Membershi	p	Cluste	r Membershi	ip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	3	482.281	16	3	1168.906
2	2	2642.500	17	2	194.125
3	3	1969.281	18	15	1167.531
4	4	.000	19	14	1211.875
5	5	.000	20	14	141.375
6	6	914.792	21	3	1260.469
7	7	381.417	22	8	283.021
8	8	605.896	23	3	783.719
9	9	109.938	24	11	948.458
10	10	.000	25	7	565.792
11	9	109.938	26	14	451.125
12	12	.000	27	1	1280.688
13	15	960.406	28	6	846.792
14	14	952.000	29	3	1443.969
15	15	1301.969	30	3	693.844

Cluster Membership				
Case Number	Cluster	Distance		
31	8	1026.271		
32	7	947.208		
33	15	825.969		
34	1	1280.688		
35	13	.000		
36	11	477.083		
37	8	710.604		
38	2	804.875		
39	2	2031.750		
40	6	1761.583		
41	8	1149.354		
42	11	1425.542		
43	14	49.875		
44	3	561.531		
45	8	55.229		

Table 5.12-Cluster membership for R-Factor

Cluste	r Membershi	ip	Cluste	r Membershi	p
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.000	16	10	8.599
2	2	.000	17	7	3.755
3	3	.000	18	9	7.571
4	4	.000	19	14	2.811
5	5	.000	20	11	2.049
6	6	3.420	21	15	3.454
7	11	7.074	22	7	3.755
8	9	1.591	23	6	5.167
9	9	9.163	24	12	8.423
10	10	1.367	25	15	2.458
11	11	12.022	26	6	1.634
12	11	.503	27	13	5.083
13	13	.602	28	6	8.314
14	14	3.522	29	13	3.178
15	15	3.454	30	6	6.101

Cluster Membership				
Case Number	Cluster	Distance		
31	10	8.069		
32	11	17.069		
33	11	9.988		
34	13	5.083		
35	13	6.999		
36	15	4.450		
37	14	.712		
38	13	9.871		
39	8	.000		
40	12	8.423		
41	10	6.173		
42	6	7.462		
43	10	8.069		
44	13	9.871		
45	11	5.408		

Table 6-Cluster membership of fruit clusters build from14 individual fruit features

Table 6.1-Cluster membership for Branch Length

Cluste	r Membershi	р		Cluste	r Membershi	p
Case Number	Cluster	Distance	Case	Number	Cluster	Distance
1	1	.000	15		9	5.066
2	2	1.501	16		11	2.502
3	3	.000	17		8	1.501
4	4	6.380	18		10	.000
5	4	2.627	19		11	5.004
6	6	3.002	20		5	3.753
7	9	.563	21		13	3.002
8	8	1.501	22		9	.938
9	5	2.252	23		14	1.501
10	8	1.501	24		2	4.503
11	11	2.502	25		5	3.753
12	12	3.002	26		8	1.501
13	5	2.252	27		9	.563
14	9	3.565	28		14	4.503

Cluster Membership				
Case Number	Cluster	Distance		
29	6	4.503		
30	6	.000		
31	14	1.501		
32	4	.375		
33	14	4.503		
34	13	3.002		
35	9	3.940		
36	7	.000		
37	2	6.004		
38	4	4.128		
39	6	1.501		
40	9	2.439		
41	9	2.439		
42	12	3.002		

Table 6.2-Cluster membership for Branch Width

Cluste	r Membershi	р	Clust	er Membershi	ip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	8	5.629	15	2	.500
2	2	4.003	16	7	4.803
3	3	3.753	17	7	7.205
4	4	4.503	18	1	5.254
5	5	3.377	19	1	5.254
6	14	4.503	20	12	.375
7	8	2.627	21	5	7.881
8	8	.375	22	3	3.753
9	9	1.501	23	8	7.881
10	7	.300	24	9	.000
11	11	1.201	25	5	5.629
12	9	4.503	26	11	.300
13	2	3.502	27	12	4.128
14	14	1.501	28	12	.375

Cluster Membership				
Case Number	Cluster	Distance		
29	12	3.377		
30	9	3.002		
31	7	1.801		
32	11	4.803		
33	11	.300		
34	11	4.203		
35	5	5.629		
36	7	.300		
37	10	.000		
38	13	.000		
39	6	.000		
40	4	1.501		
41	4	3.002		
42	14	3.002		

Table 6.3-Cluster membership for Length Width Ratio

Cluste	r Membershi	р	Cluste	er Membershi	p
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	3	.023	15	12	.027
2	2	.002	16	7	.034
3	3	.011	17	11	.002
4	4	.002	18	11	.028
5	2	.031	19	8	.009
6	6	.000	20	12	.004
7	7	.032	21	8	.015
8	7	.015	22	7	.011
9	7	.010	23	11	.016
10	11	.021	24	8	.018
11	11	.030	25	5	.015
12	11	.023	26	8	.023
13	13	.008	27	12	.031
14	14	.021	28	14	.021

Cluster Membership				
Case Number	Cluster	Distance		
29	4	.005		
30	5	.010		
31	13	.024		
32	13	.016		
33	13	.017		
34	7	.007		
35	5	.005		
36	3	.013		
37	1	.000		
38	9	.000		
39	10	.000		
40	2	.021		
41	2	.012		
42	4	.004		

Table 6.4-Cluster membership for Area

Cluste	r Membersh	ip	Cluste	er Membersh	ip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	4	2646.583	15	2	420.825
2	8	2053.063	16	14	2533.313
3	2	1081.175	17	14	2533.313
4	9	2388.100	18	4	1128.833
5	8	3303.813	19	9	3817.650
6	6	3369.958	20	11	3268.700
7	4	3775.417	21	11	4254.175
8	8	1675.313	22	12	.000
9	9	899.725	23	10	.000
10	8	3736.813	24	3	909.208
11	11	1237.800	25	8	2060.188
12	8	2110.063	26	13	331.438
13	2	3292.325	27	8	420.313
14	8	2941.813	28	1	649.813

Cluster Membership				
Case Number	Cluster	Distance		
29	1	649.813		
30	2	932.425		
31	3	1662.792		
32	3	753.583		
33	7	.000		
34	13	331.438		
35	2	1699.550		
36	11	4201.575		
37	5	.000		
38	6	588.542		
39	6	2781.417		
40	11	1978.300		
41	9	529.025		
42	9	1058.850		

Table 6.5-Cluster membership for Perimeter

Cluste	r Membershi	р	Cluste	r Membershi	р
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.000	15	7	5.375
2	8	34.500	16	12	34.556
3	3	9.000	17	6	.000
4	9	25.750	18	14	7.500
5	5	.000	19	2	31.000
6	12	49.556	20	13	15.000
7	7	21.625	21	13	15.000
8	12	3.444	22	7	36.375
9	9	39.250	23	11	20.500
10	10	4.667	24	8	37.500
11	9	44.750	25	14	7.500
12	12	34.556	26	7	3.625
13	9	31.250	27	12	40.444
14	3	9.000	28	7	13.625

Cluster Membership					
Case Number	Cluster	Distance			
29	7	20.625			
30	10	21.667			
31	12	2.444			
32	12	39.444			
33	7	11.375			
34	11	20.500			
35	4	.000			
36	12	10.444			
37	7	6.375			
38	10	26.333			
39	12	22.444			
40	8	30.500			
41	8	33.500			
42	2	31.000			

Table 6.6-Cluster membership for Equivalent Diameter

Cluste	r Membershi	p	Cluste	er Membershi	ip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	4	3.052	15	2	.516
2	8	2.413	16	14	3.078
3	2	1.340	17	14	3.078
4	9	2.705	18	4	1.309
5	8	3.882	19	9	4.311
6	6	3.687	20	11	3.633
7	4	4.361	21	11	4.737
8	8	1.967	22	12	.000
9	9	1.015	23	10	.000
10	8	4.387	24	3	1.183
11	11	1.366	25	8	2.422
12	8	2.485	26	13	.466
13	2	4.083	27	8	.487
14	8	3.465	28	1	.877

Cluster Membership				
Case Number	Cluster	Distance		
29	1	.877		
30	2	1.157		
31	3	2.165		
32	3	.981		
33	7	.000		
34	13	.466		
35	2	2.102		
36	11	4.663		
37	5	.000		
38	6	.649		
39	6	3.038		
40	11	2.192		
41	9	.604		
42	9	1.195		

Table 6.7-Cluster membership for Rectangularity

Cluste	r Membershi	D	Cluste	r Membershi	р
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	2	.006	15	2	.024
2	2	.015	16	10	.005
3	10	.007	17	7	.017
4	6	.040	18	6	.024
5	9	.009	19	6	.002
6	5	.043	20	5	.022
7	12	.004	21	5	.008
8	7	.017	22	14	.008
9	9	.016	23	13	.000
10	10	.012	24	1	.003
11	6	.023	25	2	.022
12	12	.004	26	11	.006
13	2	.007	27	6	.004
14	5	.027	28	3	.014

Cluster Membership				
Case Number	Cluster	Distance		
29	3	.014		
30	1	.003		
31	11	.006		
32	8	.000		
33	14	.001		
34	14	.009		
35	9	.007		
36	5	.018		
37	4	.013		
38	4	.013		
39	5	.016		
40	5	.022		
41	5	.002		
42	5	.003		

Table 6.8-Cluster membership for Diameter

Clus	ter Membersk	пip	Clus	ter Memberst	nip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.000	15	10	2.814
2	3	2.252	16	5	4.503
3	13	1.501	17	10	1.313
4	10	10.695	18	13	1.501
5	5	6.004	19	3	2.252
6	6	1.876	20	11	.000
7	9	6.380	21	2	.000
8	7	3.002	22	4	2.502
9	9	.375	23	10	5.817
10	5	4.503	24	8	.000
11	9	2.627	25	4	5.504
12	5	3.002	26	7	3.002
13	5	10.507	27	4	8.006
14	10	6.192	28	6	1.876
Г		uctor Mombo		1	

Cluster Membership				
Case Number	Cluster	Distance		
29	12	3.002		
30	12	3.002		
31	6	4.878		
32	10	.188		
33	10	5.817		
34	9	4.128		
35	5	9.006		
36	14	.000		
37	5	5.000E-007		
38	10	1.313		
39	6	8.631		
40	13	1.501		
41	13	1.501		
42	5	10.507		

Table 6.9-Cluster membership for Perimeter Ratio of Branch Length-Branch Width

Cluste	r Membershi		Cluste	r Membershi	р
Case Number	Cluster	Distance	Case Number	Cluster	Distance
			15	13	.031
1	1	.000	16	13	.005
2	2	.039	17	11	.024
3	3	.010	18	5	.067
4	10	.014	19	7	.029
5	13	.040			
6	13	.031	20	6	.034
7	7	.023	21	6	.000
8	7	.009	22	7	.012
9	7	.008	23	12	.000
10	10	.024	24	4	.000
11	10	.010	25	9	.007
12	6	.020	26	3	.032
13	13	.013	27	9	.083
14	14	.000	28	3	.014

Cluster Membership				
Case Number	Cluster	Distance		
29	6	.033		
30	2	.005		
31	2	.032		
32	7	.002		
33	2	.012		
34	8	.000		
35	5	.009		
36	5	.058		
37	9	.076		
38	11	.024		
39	13	.022		
40	6	.021		
41	3	.017		
42	3	.053		

Table 6.10-Cluster membership for Perimeter Ratio of Diameter

Cluste	r Membershi	р	Cluste	r Membershi	ip
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.000	15	6	.036
2	2	.044	16	4	.049
3	3	.045	17	5	.000
4	6	.011	18	2	.067
5	2	.041	19	2	.014
6	6	.091	20	2	.057
7	11	.015	21	7	.037
8	2	.066	22	2	.010
9	9	.016	23	8	.000
10	9	.065	24	10	.014
11	11	.015	25	5	.000
12	4	.049	26	9	.050
13	6	.081	27	7	.037
14	13	.080	28	13	.095

Cluste	r Membershi	р		
Case Number	Cluster	Distance		
29	13	.080		
30	6	.052		
31	6	.049		
32	6	.119		
33	6	.080		
34	12	.000		
35	2	.117		
36	14	.000		
37	3	.053		
38	3	.098		
39	13	.089		
40	13	.083		
41	13	.060		
42	10	.014		

Table 6.11-Cluster membership for Convexity

Cluste	r Membershi	р	Cluste	r Membershi	р
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	1	.529	15	7	.073
2	2	.029	16	12	.450
3	14	.136	17	6	.000
4	4	.370	18	11	.090
5	5	.426	19	3	.505
6	12	.643	20	8	.270
7	7	.295	21	8	.270
8	12	.045	22	7	.500
9	4	.563	23	13	.000
10	10	.057	24	9	.055
11	4	.639	25	11	.090
12	12	.450	26	7	.050
13	4	.447	27	12	.515
14	14	.136	28	7	.186

Cluster Membership				
Case Number	Cluster	Distance		
29	7	.281		
30	10	.268		
31	12	.032		
32	12	.520		
33	7	.155		
34	1	.529		
35	5	.426		
36	12	.137		
37	7	.086		
38	10	.325		
39	12	.295		
40	9	.055		
41	2	.029		
42	3	.505		

Table 6.12-Cluster membership for Solidity

Cluste	r Membershi	р	Cluste	r Membershi	p
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	4	.007	15	2	.001
2	8	.005	16	14	.007
3	2	.003	17	14	.007
4	9	.006	18	4	.003
5	8	.009	19	9	.010
6	6	.009	20	11	.009
7	4	.010	21	11	.011
8	8	.005	22	12	.000
9	9	.002	23	10	.000
10	8	.010	24	3	.003
11	11	.003	25	8	.006
12	8	.006	26	13	.000
13	2	.009	27	8	.001
14	8	.008	28	1	.002

Cluster Membership					
Case Number	Cluster	Distance			
29	1	.002			
30	2	.002			
31	3	.004			
32	3	.002			
33	7	.000			
34	3	.001			
35	2	.005			
36	11	.011			
37	5	.000			
38	6	.002			
39	6	.007			
40	11	.005			
41	9	.001			
42	9	.003			

Table 6.13-Cluster membership for On Pixels

Cluster Membership		Cluster Membership			
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	4	2664.667	15	2	418.800
2	8	2026.250	16	14	2549.500
3	2	1087.200	17	14	2549.500
4	9	2399.800	18	4	1112.667
5	8	3284.750	19	9	3831.200
6	6	3376.333	20	11	3284.000
7	4	3777.333	21	11	4251.000
8	8	1670.250	22	12	.000
9	9	902.800	23	10	.000
10	8	3740.750	24	3	927.333
11	11	1240.000	25	8	2075.250
12	8	2109.750	26	13	316.000
13	2	3286.800	27	8	433.250
14	8	2930.250	28	1	649.500

Cluste	Cluster Membership				
Case Number	Cluster	Distance			
29	1	649.500			
30	2	931.200			
31	3	1671.667			
32	3	744.333			
33	7	.000			
34	13	316.000			
35	2	1687.200			
36	11	4187.000			
37	5	.000			
38	6	585.667			
39	6	2790.667			
40	11	1980.000			
41	9	530.200			
42	9	1058.800			

Table 6.14-Cluster membership for Narrow-Factor

Cluster Membership		Cluste	r Membershi	p	
Case Number	Cluster	Distance	Case Number	Cluster	Distance
1	2	.005	15	14	.008
2	2	.005	16	8	.005
3	3	.000	17	14	.003
4	7	.003	18	8	.007
5	5	.000	19	4	.001
6	6	.000	20	1	.000
7	7	.001	21	4	.001
8	6	.001	22	12	.000
9	9	.001	23	7	.003
10	10	.000	24	6	.001
11	11	.000	25	7	.001
12	11	.001	26	7	.001
13	8	.002	27	5	.000
14	14	.005	28	7	.001

Cluster Membership				
Case Number	Cluster	Distance		
29	7	.001		
30	9	.001		
31	7	.001		
32	7	.004		
33	7	.001		
34	13	.006		
35	13	.006		
36	7	.001		
37	7	.001		
38	7	.001		
39	7	.001		
40	11	.001		
41	11	.005		
42	11	.003		

After we obtain the clusters, it is to be judged that which feature bears the best cluster formation capability. Feature having the best cluster formation capability is the most important feature for the cluster analysis. K-Means clustering algorithm does not give this feature importance measure. Hence we discuss how this measure is obtained and compare in our experiment -

We have used total 15 different classes of tomato leaves and 14 classes of tomato fruits, with each class consisting of 3 cases (patterns). Now it is to be seen that how many cases of a particular class are included in a same cluster. More is the number of cases of a particular class included in same cluster, better is clustering result. We calculate a measure called "Same Cluster Membership Ratio (SCMR)" for each class from the cluster membership (Table 5 and Table 6) produced from a particular feature and then finding the summation of SCMRs (Total SCMR) of all classes. Higher is the value of Total SCMR of a feature, higher is its importance in cluster formation. SCMR for a particular class can be calculated by finding the ratio of the total number of cases of that class included in same cluster and total number of cases present in that class (in our experiment, this value is 3 for all classes).

Now from the above definition of SCMR, it is obvious that in our problem, we will obtain one of the following three SCMR values for each class under the following conditions-

i) If no case belonging to a particular class is included in same cluster, then SCMR of that class is 0.

ii) If 2 cases of a class are included in same cluster, then SCMR of that class is 2/3=0.67(approx).

iii) If all 3 cases of a class are included in same cluster, then SCMR of that class is 3/3=1.

Thus, the range of values of SCMR in our problem is 0 to 1.

Table 7 and Table 8 show the class number and the corresponding three case numbers (pattern number) that belong to that particular class. Cluster number is the number of the cluster; the case pattern is a member of. And the last field of Table 7 and table 8 is the calculated SCMR value of each class for each feature variables of tomato leaf and fruit. The last row of each table shows the Total SCMR value related to each leaf/fruit feature---

Table 7-SCMR calculation for individual leaf features

SCMR calcula		cluster number	SCMR
ass number	case number	1	3000
	2	2	
1	3	3	0.00
	4	4	0.00
	5	5	
2	6	6	0.00
2	7	7	0.00
	8	15	
3	9	.0	0.00
3	10	10	0.00
	10	7	
4	12	12	0.00
4	12		0.00
	13		
-	14		0.07
5	15	10	0.67
	10	10	
	17		
6	18		0.00
	20	15	
-	20	12	0.00
7	21		0.00
	22		
	23		
8	24		0.00
	25	15	
	20	10	
9			0.0
	28		
	29		
10	30		0.0
	31	11	
	32		
11	33		0.0
	34		
	35		_
12	36		0.0
	37	10	
	38		
13	39		0.0
	40	3	
	41	12	
14	42	10	0.0
	43		
	44	15	
15	45	13	0.00
Total SCMR			0.67

s number	case number	cluster number	SCMR
	1	3	
	2	3	
1	3	3	1.00
	4	4	1.00
	5	4	
2	6	3	0.67
2	7	7	0.07
		8	
3	9	7	0.67
5	10	10	0.07
	11	11	
	12	12	
4	13	12	0.00
	13	13	
-	14	15	
5			0.6
	16	1	
	17	9	
6	18	14	0.0
	19	6	
	20	6	
7	21	9	0.6
	22	1	
	23	4	
8	24	3	0.0
	25	14	
	26	3	
9	27	2	0.0
	28	3	
	29	4	
10	30	1	0.0
	31	5	
	32	5	
11	33	5	1.00
	34	14	
	35	13	
12	36	15	0.0
	37	4	0.01
	38	6	
13	39	9	0.0
10	40	4	0.00
	41	3	
14	42	4	0.6
14	43	7	0.0
	43	3	
45	44	6	0.00
15	40	0	0.00 5.3

ss number	case number	cluster number	SCMR
	1	15	
	2	8	
1	3	8	0.
	4	11	
	5	8	
2	6	6	0.
	7	6	
	8	8	
3	9	6	0.
	10	8	
	11	11	1
4	12	12	O.
	13	6	
	14	1	
5	15	15	0.
	16	3	
	17	7	
6	18	13	0.
	19	3	
	20	5	1
7	21	7	0.
	22	3	
	23	2	1
8	24	1	0.
	25	14	
	26	14	1
9	27	11	0.
	28	14	
	29	9	1
10	30	7	0.
	31	6	
	32	1	
11	33	15	0.
	34	1	
	35	15	
12		15	0.
	37	13	
	38	5	
13	39	10	0.
	40	6	
	41	13	
14		13	0.
	43	8	
	44	1	
15	45	4	0.
tal SCMR			3.

SCMR calcula	tion for Eccei	ntricity	
class number	case number	cluster number	SCMR
	1	13	
	2	2	
1	3	8	0.00
	4	4	
	5	8	
2	6	6	0.00
	7	9	
	8	8	
3	9	9	0.67
	10	10	
	11	11	
4	12	12	0.00
	13	6	
	14	14	
5	15	13	0.00
	16	3	
	17	7	
6	18	5	0.00
	19	3	
	20	3	
7	21	7	0.67
	22	3	
	23	1	
8	24	14	0.00
	25	14	
	26	14	
9	27	4	0.67
	28	14	
	29	3	
10	30	7	0.00
	31	6	
	32	14	
11	33	13	0.00
	34	14	
	35	13	
12	36	13	0.67
	37	5	
	38	3	
13	39	15	0.00
	40	9	
	41	5	
14	42	1	0.00
	43	2	
	44	14	
15	45	7	0.00
Total SCMR			2.68

SCMR calcula			
class number		cluster number	SCMR
	1	3	
	2	2	
1	3	3	0.67
	4	4	
	5	5	
2	6	6	0.00
	7	7	
	8	8	
3	9	-	0.00
	10	10	
	11	9	
4	12	12	0.00
	13	15	
_	14	14	
5		15	0.67
	16	3	
_	17	2	
6	18	15	0.00
_	20	14	
7	21	3	0.67
	22	8	
	23	3	
8	24	7	0.00
	25	14	
	20	14	
9	27	6	0.00
	20	3	
10	30	3	
10	30	8	0.67
	31	° 7	
	32	15	
11	33	15	0.00
	34	13	
40	35	13	0.00
12	30	8	0.00
	37	2	
40	38	2	0.07
13	40	6	0.67
	40	8	
	41	11	0.00
14	42	11	0.00
	43	3	
45	44	3	0.00
15 Tatal SOMD	45	°	0.00
Total SCMR			3.35

SCMR calcula	tion for Recta	ngularity	
		cluster number	SCMR
	1	5	
	2	2	
1	3	3	0.00
	4	4	
	5	4	
2	6	3	0.67
	7	7	
	8	1	
3	9	9	0.00
	10	10	
	11	11	
4	12	12	0.00
	13	13	
	14	14	
5	15	14	0.67
	16	3	
	17	3	
6	18	13	0.67
	20	5	
-	20	3	
7	21	3	0.67
	22	5	
0	23	8	0.00
8	24	8	0.00
	25	6	
0	20	9	0.00
9	28	5	0.00
	20	6	
10	30	3	0.00
10	30	8	0.00
	32	1	
11	32	13	0.00
	34	13	0.00
	35	1	
12	36		0.00
12	37	6	0.00
	38	5	
13	39	5	0.67
15	40	2	0.07
	41	15	
14	42	6	0.00
14	43	14	0.00
	44	15	
15	45	6	0.00
Total SCMR		-	3.35
			0.00

lass number	case number	cluster number	SCMR
	1	1	
	2	2	1
1	3	3	0.0
	4	2	
	5	5	1
2	6	6	0.0
-	7	11	
	8	8	
3	9	9	0.0
	10	7	0.0
	11	11	1
4	12	11	0.6
	13	13	0.0
	14	14	
5	15	15	0.0
5	16	7	0.0
	17	7	1
6		8	0.6
0	19	14	0.0
	20	11	1
7	21	15	0.0
'	22	7	0.0
	23	6	
8	24	4	0.0
0	25	15	0.0
	26	6	1
9	27	13	0.0
5	28	6	0.0
	29	13	1
10	30	6	0.6
10	31	6	0.0
	32	12	1
11	32	12	0.6
	34	12	0.6
	34	13	1
10		15	0.0
12	30	13	0.6
	38	14	1
13	39	10	
13	40	4	0.0
	40	4	1
	41	6	
14	42		0.0
	43	6	-
15	45	11	0.0
Total SCMR			3.3

	tion for Compa case number	cluster number	SCMR
	1	1	
	2	2	
1	3	3	0.0
	4	2	
	5	5	
2	6	12	0.0
_	7	7	
	8	9	
3	9	9	0.6
	10	6	
	11	9	
4	12	9	0.6
	13	13	
	14	4	
5	15	15	0.0
-	16	12	
	17	8	
6	18	9	0.0
	19	4	
	20	7	
7	21	4	0.6
	22	12	
	23	10	
8	24	14	0.0
	25	15	
	26	6	
9	27	13	0.0
-	28	10	
	29	15	
10	30	6	0.0
	31	6	
	32	13	
11	33	7	0.0
	34	13	
	35	13	1
12	36	15	0.6
	37	4	
	38	15	1
13	39	9	0.0
	40	11	
	41	10	1
14	42	6	0.0
	43	10	
	44	15	1
15	45	7	0.0
	•	•	2.68

SCMR calcula	SCMR calculation for Perimeter Ratio of Major Axis-Minor Axis				
class number	case number	cluster number	SCMR		
	1	1			
	2	2			
1	3	3	0.00		
	4	5			
	5	5			
2	6	6	0.67		
	7	7			
	8	8			
3	9	9	0.00		
	10	9			
	11	11			
4	12	12	0.00		
	13	1			
_	14	14			
5	15	15	0.00		
	16	7			
_	17	14			
6	18	11	0.00		
	19	7			
_	20	9			
7	21	7	0.67		
	22	1			
	23	14			
8	24	7	0.00		
	25	14			
	20	7	0.00		
9	27	4	0.00		
	20	4			
10	30	13	0.07		
10	30	13	0.67		
	31	14			
	33	4	0.00		
11	33		0.00		
	34	14			
40	35	14	0.00		
12	30	15	0.00		
	38	8			
13	39	8	0.67		
13	40	6	0.67		
	40	15			
1.4	41	10	0.00		
14	42	14	0.00		
	43	14			
15	44	8	0.00		
Total SCMR	45		2.68		
TOTAL SCIVIR			2.68		

s number		cluster number	SCMR
	1	3	
	2	2	
1	3	3	0.
	4	4	
	5	5	
2	6	14	0.
	7	1	
	8	8	
3	9	8	0.
	10	10	
	11	11	
4	12	11	0.
	13	14	
-	14	14	
5		14	1.
	16	6	
	17	15	
6	18	9	0.
	20	15	
7	20	7	0
/	22	10	0.
	23	1	
8	24	13	0.
0	25	6	υ.
	26	10	
9	27	6	0.
	28	9	0.
	29	6	
10	30	6	0.
	31	10	
	32	14	
11	33	6	0.
	34	9	
	35	10	
12	36	6	0.
	37	10	
	38	7	
13	39	15	0.
	40	13	
	41	12	
14	42	13	0.
	43	14	
	44	1	
15	45	8	0.
al SCMR			5.

class number	case number	cluster number	SCMR
	1	3	
	2	2	
1	3	3	0.6
	4	4	
	5	5	1
2	6	6	0.0
	7	7	
	8	8	
3	9	9	0.0
	10	10	
	11	9	
4	12	12	0.0
	13	15	
	14	14	
5	15	15	0.6
	16	3	
	17	2	
6	18	15	0.0
	19	14	
	20	14	
7	21	3	0.6
	22	8	
	23	3	
8	24	11	0.0
	25	7	
	26	14	
9	27	1	0.0
	28	6	
	29	3	
10	30	3	0.6
	31	8	
	32	7	
11	33	15	0.0
	34	13	
	35	13	
12	30	8	0.0
	37	2	
10	30	2	
13	39	6	0.6
	40	8	
	41	11	
14	42	11	0.0
	43	3	
45	44	3	
15	45	8	0.0

s number	case number	cluster number	SCMR
	1	1	
	2	2	
1	3	3	0.0
	4	4	
	5	5	
2	6	6	0.0
	7	11	
	8	9	
3	9	9	0.6
	10	10	
	11	11	
4	12	11	0.6
	13	13	
	14	14	
5	15	15	0.0
	16	10	
	17	7	
6	18	9	0.0
	19	14	
	20	11	
7	21	15	0.0
	22	7	
	23	6	
8	24	12	0.0
	25	15	
	26	6	
9	27	13	0.0
	28	6	
	29	13	_
10	30	6	0.6
	31	10	
	32	11	
11	33	11	0.0
	34	13	
10	35	13	~
12	30	15	0.0
	37	14	
13	39	8	0.0
13	40	12	0.0
	40	10	
14	41	6	
14	42	10	0.0
	43	13	
15	45	11	0.0
	40		3.3

Table 8-SCMR calculation for individual fruit features

SCMR calcula	SCMR calculation for Branch Length			
		cluster number	SCMR	
	1	1		
	2	2		
1	3	3	0.00	
	4	4		
	5	4		
2	6	6	0.67	
	7	9		
	8	8		
3	9	5	0.00	
	10	11		
4	12	12	0.00	
4	12	5	0.00	
	13	9		
5	15	9	0.67	
	16	11	0.07	
	17	8		
6	18	10	0.00	
	19	11	0.00	
	20	5		
7	21	13	0.00	
	22	9		
	23	14		
8	24	2	0.00	
	25	5		
	26	8		
9	27	9	0.00	
	28	14		
	29	6		
10	30	6	0.67	
	31	14		
	32	4		
11	33	14	0.67	
	34	9		
12	36	7	0.00	
12	37	2	0.00	
	38	4		
13	39	6	0.00	
15	40	9	0.00	
	41	9		
14	42	12	0.67	
Total SCMR			3.35	
			5.55	

s number	case number	h Width cluster number	SCMR
snumber	case number	8	SCIMK
	2	2	
1	3	3	0.0
	4	4	0.0
	5	5	
2	6	14	0.0
	7	8	
	8	8	
3	9	9	0.6
	10	7	
	11	11	
4	12	9	0.0
	13	2	
	14	14	
5	15	2	0.6
	16	7	
	17	7	
6	18	1	0.6
	19	1	
	20	12	
7	21	5	0.0
	22	3	
	23	8	
8	24	5	0.0
	25	5	
0	20	12	
9	28	12	0.0
	20	12	
10	30	9	0.6
10	31	7	0.0
	32	11	
11	33	11	0.6
	34	11	
	35	5	
12	36	7	0.0
	37	10	
	38	13	
13	39	6	0.0
	40	4	
	41	4	
14	42	14	0.6
SCMR			4.02

CMR calculation for Length-Width Ratio				
ss number 1	case number	3	0.6	
	2	2	0.0	
	3	3		
2	4	4	0.0	
2	5	2	0.0	
	6	6		
3		7	1.0	
	8	7		
	9	7		
4	10	11	1.0	
	11	11		
	12	11		
5	13	13	0.0	
	14	14		
	15	12		
6		7	0.6	
	17	11		
	18	11		
7	19	8	0.6	
	20	12		
	21	8		
8	22	7	0.0	
	23	11		
	24	8		
9	25	5	0.0	
	26	8		
10	27	12	0.0	
10	20	4	0.0	
	30	5		
11	31	13	1.0	
	32	13	1.0	
	33	13		
12	34	7	0.0	
	35	5	0.0	
	36	3		
13	37	1	0.0	
	38	9		
	39	10		
14	40	2	0.6	
	41	2		
	42	4		
tal SCMR			5.6	

class number	case number	cluster number	SCMR
	1	1	
	2	8	1
1		3	0.0
	4	9]
	5	5]
2		12	0.0
	7	7	
	8	12	
3		9	0.0
	10	10	
	11	9	
4		12	0.0
	13	9	
	14	3	
5		7	0.0
	16	12	
	17	6	
6		14	0.0
	19	2	
_	20	13	
7	21	13	0.6
	22	11	
		8	
8	24	14	0.0
	20	7	-
g		12	
8	28	7	0.0
	28	7	
10		10	0.6
10	30	10	0.0
	32	12	
11		7	0.6
	34	11	0.0
	35	4	1
12		12	0.0
12	37	7	0.0
	38	10	1
13		12	0.0
10	40	8	
	41	8	1
14	42	2	0.6
Total SCMR		1	2.6

SCMR calculation for Perimeter			
class number	case number	cluster number	SCMR
	1	1	
	2	8	
1	3	3	0.00
	4	9	
	5	5	
2	6	12	0.00
	7	7	
	8	12	
3	9	9	0.00
	10	10	
	11	9	
4	12	12	0.00
	13	9	
-	14	3	
5	15	7	0.00
	16	12	
	17	6	
6	18	2	0.00
	20	13	
-	20	13	0.07
7	21	7	0.67
	22	11	
	23	8	0.00
8	24	14	0.00
	25	7	
9	27	12	0.00
9	28	7	0.00
	20	7	
10	30	10	0.67
10	31	12	0.07
	32	12	
11	33	7	0.67
	34	11	0.07
	35	4	
12	36	12	0.00
12	37	7	0.00
	38	10	
13	39	12	0.00
	40	8	
	41	8	
14	42	2	0.67
Total SCMR			2.68

SCMR calcula	tion for Equiv	/alent Diameter	
class number	case number	cluster number	SCMR
	1	4	
	2	8	
1	3	2	0.00
	4	9	
	5	8	
2	6	6	0.00
	7	4	
	8	8	
3	9	9	0.00
	10	8	
	11	11	
4	12	8	0.67
	13	2	
_	14	8	
5	15		0.67
	16	14	
	17	14	
6	18	4	0.67
	19	9	
-	20	11	0.07
7	21	12	0.67
	22	12	
8	23	3	0.00
8	24	8	0.00
	25	13	
9	20	8	0.67
	28	1	0.07
	20	1	
10	30	2	0.67
	31	3	0.07
	32	3	
11	33	7	0.67
	34	13	0.01
	35	2	
12	36	11	0.00
12	37	5	0.00
	38	6	
13	39	6	0.67
	40	11	
	41	9	
14	42	9	0.67
Total SCMR			6.03

	tion for Rect case number	cluster number	SCMR
	1	2	
	2	2	
1	3	10	0.6
	4	6	
	5	9	
2	6	5	0.0
	7	12	
	8	7	
3	9	9	0.0
	10	10	
	11	6	
4	12	12	0.0
	13	2	
	14	5	
5	15	2	0.6
	16	10	
	17	7	
6	18	6	0.0
	19	6	
_	20	5	
7	21	5	0.6
	22	14	
	23		
8	24	1	0.0
	25		
0	20	6	
9	27	3	0.0
	20	3	
10	30	1	0.6
10	31	11	0.0
	32	8	
11	33	14	0.0
	34	14	0.0
	35	9	
12	36	5	0.0
	37	4	
	38	4	
13	39	5	0.6
	40	5	
	41	5	
14	42	5	1.0
otal SCMR		1	4.3

	ation for Diam		
lass number		cluster number	SCMR
	1	1	
	2	3	
1	3	13	0.00
	4	10	
-	5	5	
2	6	6	0.00
	7	9	
	8	7	0.07
3	10	5	0.67
	10	9	
	12	5	0.07
4	12	5	0.67
	13	10	
-	14	10	0.07
5	15	5	0.67
	10	10	
0	17	13	0.00
6	19	3	0.00
	20	11	
7	20	2	0.00
7	22	4	0.00
	22	10	
8	23	8	0.00
0	25	4	0.00
	25	7	
9	20	4	0.67
5	28	6	0.01
	29	12	
10	30	12	0.67
10	31	6	0.01
	32	10	
11	33	10	0.67
	34	9	0.01
	35	5	
12	36	14	0.0
12	37	5	0.00
	38	10	
13	39	6	0.00
15	40	13	0.00
	41	13	
14	42	5	0.67
otal SCMR		, j	4.69

SCMR calculation for Perimeter Ratio of Branch Length-Branch Width			
class number		clusternumber	SCMR
	1	1	
	2	2	
1		3	0.00
	4	10	
	5	13	
2		13	0.67
	7	7	
	8	7	
3		7	1.00
	10	10	
	11	10	
4		6	0.67
	13	13	
-	14	14	
5	15	13	0.67
	10		
		11 5	0.00
6	18	5	0.00
	20	6	
	20	6	0.07
7	21	7	0.67
	22	12	
8		4	0.00
0	25	9	0.00
	26	3	
9		9	0.67
	28	3	0.01
	29	6	
10		2	0.00
	31	2	0.00
	32	7	
11	33	2	0.67
	34	8	
	35	5	
12	36	5	0.67
	37	9	
	38	11	
13		13	0.00
	40	6	
	41	3	
14	42	3	0.67
Total SCMR			6.36

SCMR calcula	tion for Perim	eter Ratio of Dia	ameter
class number	case number	cluster number	SCMR
	1	1	
	2	2	
1	3	3	0.00
	4	6	
	5	2	
2	6	6	0.67
	7	11	
	8	2	
3	10	9	0.00
	10	9	
	12	4	0.00
4	12	4	0.00
	13	13	
5	14	6	0.67
	16	4	0.67
	17	- 5	
6	18	2	0.00
	19	2	0.00
	20	2	
7	21	7	0.67
	22	2	0.01
	23	8	
8	24	10	0.00
	25	5	
	26	9	
9	27	7	0.00
	28	13	
	29	13	
10	30	6	0.67
	31	6	
	32	6	
11	33	6	1.00
	34	12	
	35	2	
12	36	14	0.00
	37	3	
	38	3	
13	39	13	0.67
	40	13	
	41	13	
14	42	10	0.67
Total SCMR			5.02

	ation for Conv	cluster number	SCMR
	1	1	
	2	2	
1	3	14	0.00
	4	4	
	5	5	
2	6	12	0.00
	7	7	
	8	12	
3	9	4	0.00
	10	10	
	11	4	
4	12	12	0.00
	13	4	
-	14	14	
5	15	12	0.00
	10	6	
0	17	11	0.00
6	19	3	0.00
	20	8	
7	20	8	0.67
	22	7	0.07
	23	13	
8	24	9	0.00
	25	11	0.00
	26	7	
9	27	12	0.00
-	28	7	
	29	7	
10	30	10	0.67
	31	12	
	32	12	
11	33	7	0.67
	34	1	
	35	5	
12	36	12	0.00
	37	7	
	38	10	
13	39	12	0.00
	40	9	
	41	2	0.00
14	42	3	0.00
al SCMR			2.01

SCMR calculat	ion for Solidit	y	
class number	case number	cluster number	SCMR
	1	4	
	2	8	
1	3	2	0.00
	4	9	
	5	8	
2	6	6	0.00
	7	4	
	8	8	
3	9	9	0.00
	10	8	
	11	11	
4	12	8	0.67
	13	2	
	14	8	
5	15	2	0.67
	16	14	
	17	14	
6		4	0.67
	19	9	
_	20	11	
7	21	11	0.67
	22	12	
_	23	10	
8	24	3	0.00
	25	3	
_	26	13	
9	27	8	0.00
	28	1	
	29	1	
10	30 31	3	0.67
	31	3	
	32	7	0.07
11	33	3	0.67
	34	2	
10	35		
12	30	5	0.00
	37	6	-
10	38	6	
13	39	11	0.67
	40	9	-
		9	0.07
14	42	9	0.67
Total SCMR			5.36

SCMR calcula	ation for On P	ixels	
class number	case number	cluster number	SCMR
	1	4	
	2	8	
1	3	2	0.00
	4	9	
	5	8	
2	6	6	0.00
	7	4	
	8	8	
3	9	9	0.00
	10	8	
	11	11	
4	12	8	0.67
	13	2	
	14	8	
5	15	2	0.67
	16	14	
_	17	14	
6	18	4	0.67
	19	9	
_	20	11	
7	21	11	0.67
	22	12	
	23	10	
8	24	3	0.00
	25	8	
	20	13	
9	27	8	0.67
	28	1	
10	30	2	0.07
10	30	3	0.67
	31	3	
11	32	7	0.67
	34	13	0.67
	35	2	
12	36	11	0.00
12	37	5	0.00
	38	6	
13	39	6	0.67
- 10	40	11	0.07
	41	9	
14	42	9	0.67
Total SCMR			6.03

SCMR calculation for Narrow-Factor			
class number	case number	cluster number	SCMR
	1	2	
	2	2	
1	3	3	0.67
	4	7	
	5	5	
2	6	6	0.00
	7	7	
	8	6	
3	9	9	0.00
	10	10	
	11	11	
4	12	11	0.67
	13	8	
	14	14	
5	15	14	0.67
	16	8	
	17	14	
6	18	8	0.67
	19	4	
	20	1	
7	21	4	0.67
	22	12	
	23	7	
8	24	6	0.00
	25	7	
	26	7	
9	27	5	0.67
	28	7	
	29	7	
10	30	9	0.67
	31	7	
	32	7	
11	33	7	1.00
	34	13	
	35	13	
12	36	7	0.67
	37	7	
	38	7	
13	39	7	1.00
	40	11	
	41	11	
14	42	11	1.00
Total SCMR			8.36

Total SCMR value of each of the leaf features (Table 9) and fruit features (Table 10) defines the fact that 'Minor Axis'(Total SCMR value 5.35) ' and 'Major Axis'(Total SCMR value 0.67) are the leaf features with highest and lowest Total SCMR value. Hence 'Minor Axis' and 'Major -Axis' are the most important and least important leaf features in terms of cluster formation respectively. Where as fruit feature having the highest and lowest importance are 'Narrow-Factor'(Total SCMR value 8.36, highest among all fruit features) and 'Convexity' (Total SCMR value 2.01, lowest among all fruit features) respectively.

Table 9- Leaf features with their Total SCMR values

FEATURE NAME	TOTAL SCMR
Major Axis	0.67
Minor Axis	5.35
Aspect Ratio	3.35
E ccentricity	2.68
Area	3.35
Rectangularity	3.35
Diameter	3.35
Compactness	2.68
Perim eter Ratio of Major Axis-Minor Axis	2.68
Perimeter Ratio of Diameter	5.02
Concavity	3.35
R-Factor	3.35

Table 10- Fruit features with their Total SCMR values

FEATURE NAME	TOTAL SCMR
Branch Length	3.35
Branch Width	4.02
Length Width Ratio	5.68
Area	2.68
Perimeter	2.68
Equivalent Diameter	6.03
Rectangularity	4.35
Diameter	4.69
Perimeter Ratio of Branch Length-Branch Width	6.36
Perimeter Ratio of Diameter	5.02
Convexity	2.01
Solidity	5.36
On Pixels	6.03
Narrow-Factor	8.36

4.2 Two-step Clustering Results

Two-step clustering algorithm has used 12 and 14 number of feature variables of tomato leaf and fruit as input and 15 & 14 final clusters of leaf and fruit are produced (Figure 1).

Model Summary

Algorithm	TwoStep
Inputs	12
Clusters	15

Model Summary

Algorithm	TwoStep
Inputs	14
Clusters	14

Figure 1: Summary of Two-step clustering

Figure 2 shows the quality of the cluster formation of tomato leaf and fruit based on Silhouette measure of cohesion and separation. Silhouette measure is obtained with in the range of -1.0 to 1.0. Silhouette measure of greater than 0.5 signifies that the cluster formation is of a good quality. So from Figure 2, it is obvious that Two-step clustering has formed good quality clusters from sample patterns of tomato leaf and fruit.

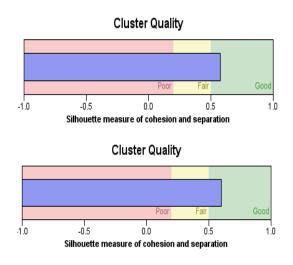


Figure 2: Cluster formation quality for leaf and fruit.

Number of patterns placed in a cluster defines the size of that cluster. Figure 3 depicts the pie chart representation of the leaf and fruit clusters according to their sizes expressed in terms of percentage of the total number of leaf and patterns.

Cluster Sizes

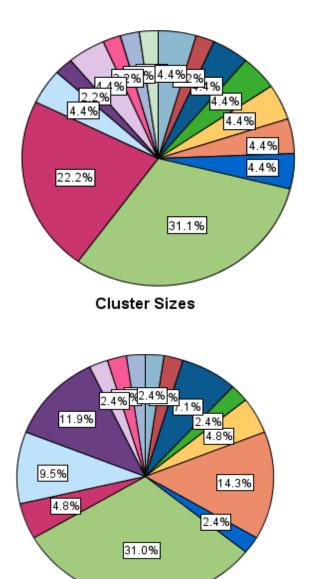
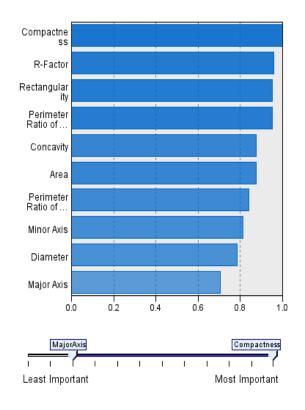


Figure 3: Pie chart of leaf and fruit clusters (size wise)

All features don't contribute in the same manner in the cluster formation process. Some features contribute highly where contribution of some features may be low. Features with higher level of contribution have higher importance in the formation of clusters. Figure 4 shows the top-down arrangement of leaf and fruit features in descending order of their importance in cluster formation. According to Figure 4, Compactness and Major Axis are the most important and least important leaf features. Where as Rectangularity and Branch Length are the fruit features with highest and lowest importance.

Predictor Importance



Rectangular ty Perimeter Ratio of ... Equivalent Diameter Perimeter Area On Pixels Convexity Diameter

Diameter Solidity Branch Length 0.2 0.4 0.0 0.6 0.8 1.0 BranchLength Rectangularity I I Least Important Most Important

Figure 4: Order of Importance of leaf and fruit features

5. CONCLUSION

The scheme for K-Means and Two-step clustering algorithm to discriminate the tomato leaf, fruiting habit image samples along with morphological feature importance has been introduced. Formation of valid clusters assures the successful execution of the clustering techniques on the feature set and there by reflecting the categorical distribution of tomato species. Feature importance calculation through SCMR measure declares Minor Axis and Narrow-Factor as the respective leaf and fruit features upon which best cluster formation is observed. Where as according to Two-step clustering, Compactness and Rectangularity are the most important leaf and fruit feature as per as cluster formation capability is concerned. Considering this phenomena, one of the aspects of future work is to use these features to validate a large volume image dataset of tomato leaves and fruits. Another important futuristic aspect is to build up a leaf / fruit categorization system with relevant feedback mechanisms to help the persons related to cultivation process and collection of feedback from them for the enhancement of the system. Also applying the other renowned clustering methods like fuzzy clustering, neural network based clustering on the sample data set and hence analyzing the result is a future work.

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Predictor Importance

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