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Machine Learning Method of Image Processing and Embedding of Flowers using Pattern Recognition

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Abstract: *This research paper is attempted to identify the pattern of two types of images using machine learning methods of cluster analysis. These two different images were collected from various web domains with different pixels and under the head of flowers. The flowers are basic colours of RGB with size of different Kilo Bytes(KB). The python based data mining software generate image Width, Height and Sizes. The image embedding method of machine learning methods widget generate the database from n_0, n_0,n_1,n_2,…n_2047. The cosine distance indentifies the similar pair of images with help of their coordinates of these two types of images. Subsequently, the distance measure is to identify the similar clusters of images using various clustering algorithms. In addition, the clustered images to visualize using image viewer widget. The images associated with each cluster are displayed separated from other clusters.*

Keywords: *Image Processing, Data Mining, Hierarchical Clustering, Cosine distance and Image Visualization.*

1. Introduction

Image processing is very interest and informative analytical tool for pattern recognition of and data base like bio medical images, inscription and many other fields. An image is nothing more than a two dimensional signal. It is defined by the mathematical function $f(x,y)$ where x and y are the two co-ordinates horizontally and vertically. The value of $f(x,y)$ at any point is gives the pixel value at that point of an image. Image segmentation can be defined as the classification of all the picture elements or pixels in an image into different clusters that exhibit similar features. Segmentation involves partitioning an image into groups of pixels which are homogeneous with respect to some criterion [1]. Different groups must not intersect each other and adjacent groups must be heterogeneous. The groups are called segments. Image segmentation is considered as an important basic operation for meaningful analysis and interpretation of image acquired. It is a critical and essential component of an image analysis and or pattern recognition system, and is one of the most difficult tasks in image processing, which determines the quality of the final segmentation. Researchers have extensively worked over this fundamental problem and proposed various methods for image processing.

2. Review of Literature

Many researchers are used for images to identify the dimensionality reductions, similarities between other images, etc. High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. G. E. Hinton, et.al. [2] used Gradient descent for fine-tuning the weights in such ‘‘auto encoder’’ networks, but this works well only if the initial weights are close to a good solution. The author describe an effective way of initializing the weights that allows deep auto encoder networks to learn low-dimensional codes that work much better than Principal Components Analysis (PCA) as a tool to reduce the dimensionality of data.

Segmentation is one of the most important steps in the analysis of digital images [3, 4]. It consists of dividing an image into non-overlapping regions based on similarity of their spectral and/or spatial characteristics (texture, size, shape, etc.). The most common approach to the segmentation of satellite images is based on data clustering algorithms [5]. Clustering methods can be divided into two major groups: hierarchical and non-hierarchical. Non-hierarchical algorithms provide fixed clustering of data and hierarchical algorithms yield a system of embedded clusters corresponding to different hierarchical levels . Hierarchical representation is convenient in interpreting results in the cases where information on the various levels of the cluster structure is required, as well as in situations where the exact number of desired clusters is unknown.

Traditional methods of hierarchical clustering have some disadvantages. For example, the single linkage procedure is susceptible to the so-called chain effect, and the complete and average linkage methods usually work well only with spherical clusters. Furthermore, these methods do not allow separating overlapping clusters [6]. Another serious drawback of these methods is their high computational complexity, which does not allow them to be used for large data arrays such as multispectral images. The ensemble approach has recently been widely used to improve the stability and performance of clustering [7–11]. However, methods based on hierarchical ensemble clustering have been the subject of only few papers [12]. Furthermore, the algorithms used in them are also computationally time consuming. The main objectives of this research paper to identify the groups of flowers are same group or different group using various cluster analysis with cosine distance measure

3. DATABASE

The database of flowers was collected from various World Wide Web with more than three categories of flowers. The image formats are .jpeg and .png format etc.. Image processing generates the data automatically. The machine learning methods automatically generate the flowers height width and size (KB). These three parameters are used for subsequent analysis like, cluster analysis, image embedding, image viewer, image grid and machine learning methods.

4. METHODOLOGIES

4.1 Hierarchical Clustering Methods

Hierarchical clustering techniques proceeded by either a series of successive mergers or series of successive divisions. The following are the step is the agglomerative hierarchical clustering algorithm for grouping N objects or images or variables. [13]

Step 1: Starts with N clusters, each containing a single entity and $N * N$ symmetric of distances and its is denoted by $D = \{d_{ik}\}$

Step 2: To identify the distance matrix for the nearest pair of clusters. Let the distance between most similar clusters X and Y bed_{xy}.

Step 3: Merge clusters X and , Label the newly formed cluster (XY). Update the entire in the distance matrix by (a) deleting the rows and columns corresponding the cluster X and Y and (b) adding row and column giving the distances between the cluster (XY).and the remaining clusters.

Step 4: Repeats steps 2 and 3 a total of $N - 1$. (Figure 1.)

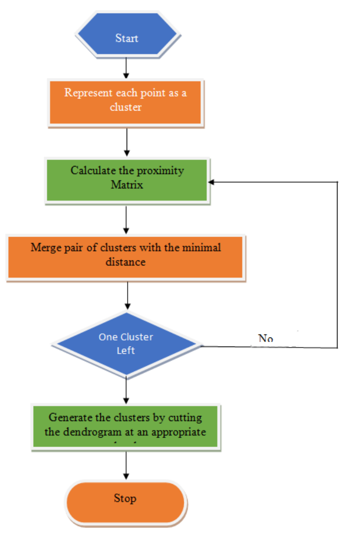


Figure1. *Flow Chart Agglomerative Approach*

4.2 Average Linkage Method

Step 1: Average linkage treats the distance between two clusters as the average distance between all pairs of images where one number of a pair belongs to each other.

Step 2: Again, the input to the average linkage algorithm may be distances or similarities, and the model can be used to group images or objects or variables.

Step 3: Step 3 of general the above general algorithm in the distance between (XY) and any other cluster$W$ are computed by

$$. d_{(xy)w} = \frac{\sum_i \sum_k d_{ik}}{N_{xy N_w}}$$

Where d_{ik} is the distance i in the cluster between (XY) and the object k in the cluster W and N_{xy} and N_w are the number of items in clusters (XY) and W respectively.

4.3 Weighted Average Linkage Method

Step 1: This method is also known as the Weighted Pair Group Method Average (WPCMA).

Step 2 : The distance between two clusters is defined as the average of the distance between all pairs of data points, each of which comes from a different group.

Step 3: The difference is that the distances between the newly formed cluster and the rest are weighted based on the number of data points in each cluster. When two clusters C_i and C_j are merged, the distance to a third cluster C_l can be recomputed as:

$$D(C_l(C_i\,, C_j)) = \frac{n_i}{n_i+n_j} D(C_l + C_i\,) + \frac{n_j}{n_i+n_j} D(C_l, C_j)$$

4.4 Wards Method

Ward's [ ] is considered hierarchical clustering procedures based on minimizing the loss of information from joining two groups.

Step 1: This method is usually implemented with loss of information taken to be an increase in an error sum of squares criterion. ESS, first for a given cluster$k$, let ESS, be the sum the squared deviations of every item in the cluster from the cluster mean (centroid).

Step 2: If there are currently$k$, clusters defines ESSS as the sum the ESS_k or $ESS = ESS_1 + ESS_2 + ESS_3 + \cdots + ESS_k$,.

Step 3: At each step in the analysis, the union of every possible pair of clusters is considered, and the two clusters whose combination results in the smallest increase in ESS are joined.

Step 4: Initially,, each cluster consists of a single item, and, if there are N,items, $ESS_k = 0, k = 1,2, \ldots, N$, so $ESS = 0$.

Step 5: At the other extreme, when all the clusters are combined in a single group of N terms, the value of ESS is given by

$$ESS = \sum_{j=1}^{N} (x_j - \bar{x})'(x_j - \bar{x})$$

Where, x_j is the multivariate measurement associated with the jth item and $\bar{x}$ is the mean of all the items. The results of Ward's method can be displayed as a dendogram.

4.5 Cosine Distance Similarity

Cosine similarity is computed using the following formula:

$$\text{Similarity}(X, Y) = \frac{\mathrm{X} * \mathrm{Y}}{\|\mathrm{X}\| * \|\mathrm{Y}\|} = \frac{\sum_{i=1}^{n} X_i * Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2} * \sqrt{\sum_{i=1}^{n} Y_i^2}}$$

Values range between -1 and 1, where -1 is perfectly dissimilar and 1 is perfectly similar.

The above formula contains both procedures and functions to calculate similarity between sets of data. The function is best used when calculating the similarity between small numbers of sets. The procedures parallelize the computation and are therefore more appropriate for computing similarities on bigger datasets

4.6 Image processing Model developing Algorithm

Step 1: The two types of images (flowers) were collected from various URL and given a input data matrix.

Step 2: selected images are .jpeg, and png format with various sizes in KB (Kilo Bytes).

Step 3: the images are put in a single folder and give as an input data to file widget

Step 4: the file widget connected to data table and image embedding widget. The image embedding calculated the cosine distance table.

Step5; Based on Image embedding widget is to joint with distance widget and data table widget.

Step 6: the distance widget connect to hierarchical cluster analysis.

Step 7: the cluster analysis widget joint with image view widget. (Figure 2)

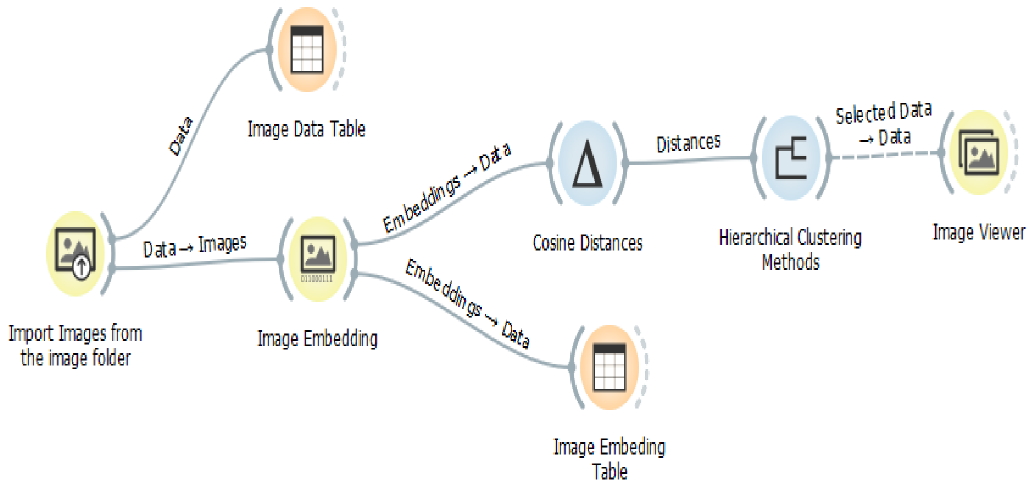


Figure2. *Workflow for Image Processing*

Image embedding widget is the most important for the entire image analytics. A classification and regressions task requires data in the form of numbers and there isn't a good way to perform such tasks with images unless, the researcher represents it in the form of numbers. This is where Embedding widget works by converting it to vectors of numbers. This widget is reads images and uploads them to a remote server or evaluates them locally (folder).

Table1. *Embedding Image Data Table Size, Width and Height*

origi type	image name	image Analysis_final/Lotu image	size	width	height
1	Lotus (1)	Lotus (1).jpg	11113	299	168
2	Lotus (12)	Lotus (12).jpg	9874	275	183
3	Lotus (13)	Lotus (13).jpg	7383	275	183
4	Lotus (14)	Lotus (14).jpg	8368	259	194
5	Lotus (15)	Lotus (15).jpg	344426	3264	1632
6	Lotus (17)	Lotus (17).jpg	45125	700	467
7	Lotus (18)	Lotus (18).jpg	11461	299	168
8	Lotus (2)	Lotus (2).jpg	8033	275	183
9	Lotus (3)	Lotus (3).jpg	7778	280	180
10	Lotus (6)	Lotus (6).jpg	5744	310	163
11	Lotus (9)	Lotus (9).jpg	34294	852	480
12	New Image	New Image.jpg	10494	244	207
13	New_image	New_image.jpg	13196	322	300
14	Rose (12)	Rose (12).jpg	7980	225	225
15	Rose (13)	Rose (13).jpg	7880	195	258
16	Rose (21)	Rose (21).jpg	8186	226	223
17	Rose (22)	Rose (22).jpg	5902	233	216
18	Rose (23)	Rose (23).jpg	6116	262	193
19	Rose (25)	Rose (25).jpg	7668	275	183
20	Rose (30)	Rose (30).jpg	9488	179	281
21	Rose (31)	Rose (31).jpg	9184	275	183
22	Rose (32)	Rose (32).jpg	6625	300	168
23	Rose (34)	Rose (34).jpg	5652	210	210
24	Rose (35)	Rose (35).jpg	5845	276	183

Table2. *Image Data Table Size, Width and Height*

hidden origin type	image name	image Analysis_final/Lotu image	size	width	height	n0 True	n1 True	n2 True	n3 True	n4 True	
1	Lotus (1)	Lotus (1).jpg	11113	299	168	0.126128	0.0834554	1.0676	0.0324196	0.431184	0.93
2	Lotus (12)	Lotus (12).jpg	9874	275	183	0.145857	0.00286179	1.13472	0.0697275	0.217485	1.25
3	Lotus (13)	Lotus (13).jpg	7383	275	183	0.0677118	0.0260406	0.962608	0.00246213	0.0962763	1.06
4	Lotus (14)	Lotus (14).jpg	8368	259	194	0.280852	0.12653	1.15584	0.0717283	0.00702592	1.55
5	Lotus (15)	Lotus (15).jpg	344426	3264	1632	0.124796	0.149431	1.12264	0.0203655	0.112942	0.56
6	Lotus (17)	Lotus (17).jpg	45125	700	467	0.0832772	0.0413975	0.849969	0.254329	0.031259	0.31
7	Lotus (18)	Lotus (18).jpg	11461	299	168	0.517397	0.0862751	1.60606	0.0776988	0.529909	0.97
8	Lotus (2)	Lotus (2).jpg	8033	275	183	0.367563	0.000737024	1.31563	0.0762712	0.230271	1.20
9	Lotus (3)	Lotus (3).jpg	7778	280	180	0.108986	0.100725	1.4912	0.205346	0.55847	0.58
10	Lotus (6)	Lotus (6).jpg	5744	310	163	0.209869	0.0574608	0.636843	0.0409273	0.368745	1.96
11	Lotus (9)	Lotus (9).jpg	34294	852	480	0.146282	0.185763	1.0028	0.296195	0.298177	0.63
12	New Image	New Image.jpg	10494	244	207	0.611523	0.0573273	1.53573	0.0283815	0.217794	0.26
13	New_image	New_image.jpg	13196	322	300	0.29015	0.0132141	1.20321	0.240906	0.145106	0.90
14	Rose (12)	Rose (12).jpg	7980	225	225	0.501188	0.0469499	0.98711	0.182064	0.433293	0.31
15	Rose (13)	Rose (13).jpg	7880	195	258	0.613424	0.127354	0.49535	0.0180623	0.313474	0.85
16	Rose (21)	Rose (21).jpg	8186	226	223	0.121072	0.502059	0.789733	0.234189	0.751644	0.10
17	Rose (22)	Rose (22).jpg	5902	233	216	0.311726	0.0613036	0.882228	0.16445	0.0240209	0.72
18	Rose (23)	Rose (23).jpg	6116	262	193	0.461352	0.00248447	1.4383	0.0499256	0.109974	0.44
19	Rose (25)	Rose (25).jpg	7668	275	183	0.889659	0.0527516	0.784624	0.214263	0.568373	0.88
20	Rose (30)	Rose (30).jpg	9488	179	281	0.335762	0.0426623	0.327426	0.317975	0.277734	0.52
21	Rose (31)	Rose (31).jpg	9184	275	183	0.234392	0.262931	0.80482	0.0855394	0.149253	0.52
22	Rose (32)	Rose (32).jpg	6625	300	168	0.139893	0.10025	1.27548	0.080235	0.440107	0.76
23	Rose (34)	Rose (34).jpg	5652	210	210	0.200276	0.0122115	0.494706	0.0198715	0.206049	0.78
24	Rose (35)	Rose (35).jpg	5845	276	183	0.400119	0.120556	0.206198	0.390877	0.276005	0.37

Table 2. Embedding Image Data Table Size, Width and Height

5. Result and Discussion

5.1 Proposed Image processing algorithm

Step 1: Input images generate data automatically using machine learning methods of Data mining.

Step2: Five parameters are generated like image name, image URL, height width and size in data Table 1.

Step3: Embedding widget is generated the data matrix up to $n_0, n_0, n_1, n_2, \dots n_{2047}$. (Table 2)

Step 3: Embedding widget connected to cosine distance method. The cosine distance method is most familiar and widely used image analysis and it will identify the distance from various pair of images similarity and clustered together.

Step 4; Cluster formed in various statistical methods like Average, Complete, Weighted Average and Ward's method.

Step 5: All the methods generate natural cluster and is represented in dendrogram.

Step 6: Finally, the selected clusters are indentified and labelled as c_1 and . c_2 are visualized their image with the help of image view widget.

The image processing minimum distance results is showed in the following figure 3. The diagonal elements are highlighted in dark blue colours and the values are zero. The cosine distance matrixes of two categories of images are in table 3. The cosines values are closure to ones are in the dark green and dark yellow colours. The lesser values are shaded in light green and yellow colours, In the subsequent results are interpreted separately in the following sections.

Image processing of data mining tools are given interesting results. All the methods are well separated in dendogram and image views. Initially, in this research paper used just 10 +10 images after that to check a images for two categories and they are associated with their own cluster. The cosine distance give a good results between 0 to 1, its indicate the similarity within the images are good. The two type images are separated in two colours in various distance model dendogram. The two types of images are well clustered and are labelled as C1 and C2.

Figure 3. Distance Map of the Images

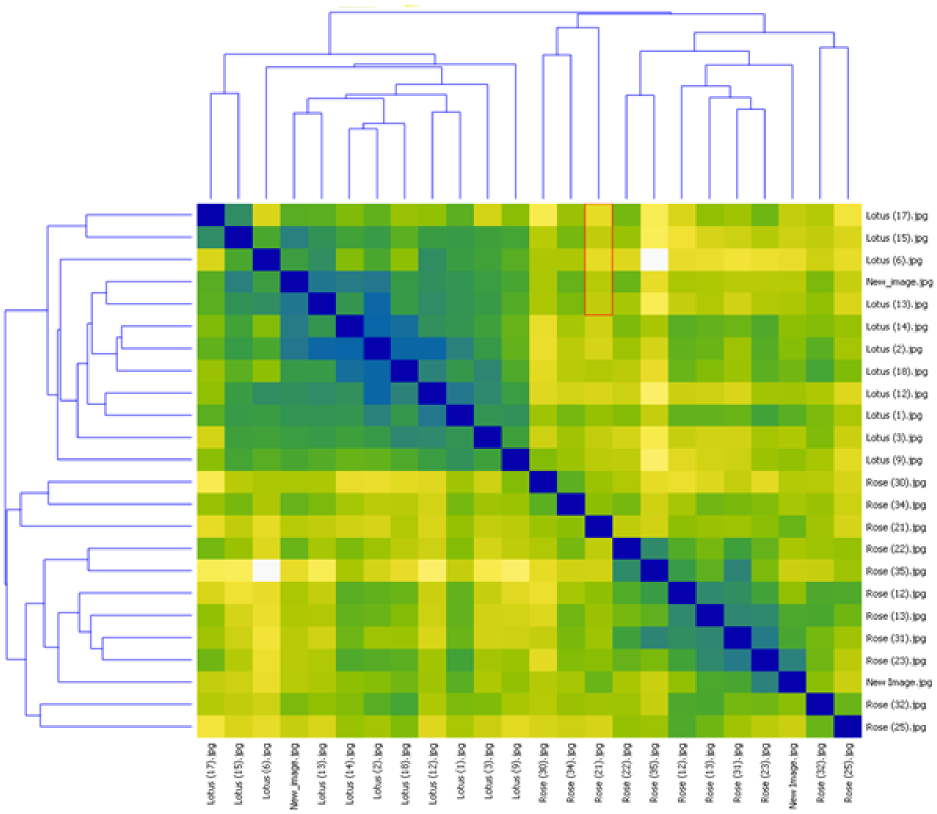


Table 2. Distance Matrix of the Images

Distance Matrix

	0.171	0.225	0.226	0.236	0.285	0.230	0.190	0.224	0.241	0.219	0.283	0.224	0.295	0.293	0.342	0.325	0.253	0.360	0.351	0.300	0.318	0.311	0.386
0.171		0.206	0.216	0.240	0.338	0.191	0.142	0.203	0.211	0.243	0.352	0.216	0.393	0.395	0.409	0.395	0.353	0.417	0.419	0.411	0.365	0.402	0.475
0.225	0.206		0.226	0.220	0.286	0.236	0.144	0.237	0.213	0.278	0.364	0.169	0.387	0.367	0.383	0.357	0.368	0.409	0.362	0.401	0.337	0.318	0.465
0.226	0.216	0.226		0.255	0.321	0.156	0.139	0.249	0.323	0.298	0.335	0.179	0.282	0.293	0.399	0.319	0.272	0.342	0.433	0.304	0.323	0.358	0.359
0.236	0.240	0.220	0.255		0.209	0.286	0.239	0.250	0.266	0.258	0.395	0.188	0.442	0.407	0.383	0.345	0.372	0.410	0.375	0.394	0.383	0.315	0.467
0.285	0.338	0.286	0.321	0.209		0.343	0.293	0.403	0.410	0.332	0.386	0.281	0.408	0.337	0.426	0.312	0.307	0.450	0.465	0.350	0.371	0.345	0.465
0.230	0.191	0.236	0.156	0.286	0.343		0.142	0.199	0.334	0.272	0.307	0.235	0.300	0.323	0.368	0.376	0.286	0.321	0.423	0.347	0.258	0.375	0.431
0.190	0.142	0.144	0.139	0.239	0.293	0.142		0.234	0.267	0.293	0.327	0.172	0.292	0.302	0.407	0.349	0.280	0.354	0.434	0.349	0.285	0.376	0.404
0.224	0.203	0.237	0.249	0.250	0.403	0.199	0.234		0.253	0.251	0.365	0.242	0.389	0.401	0.385	0.405	0.356	0.392	0.397	0.401	0.321	0.351	0.462
0.241	0.211	0.213	0.323	0.266	0.410	0.334	0.267	0.253		0.282	0.433	0.245	0.431	0.435	0.427	0.415	0.437	0.428	0.363	0.446	0.397	0.363	0.504
0.219	0.243	0.278	0.298	0.258	0.332	0.272	0.293	0.251	0.282		0.340	0.264	0.420	0.403	0.378	0.380	0.347	0.422	0.323	0.395	0.359	0.346	0.474
0.283	0.352	0.364	0.335	0.395	0.386	0.307	0.327	0.365	0.433	0.340		0.373	0.337	0.269	0.299	0.359	0.190	0.392	0.372	0.264	0.331	0.357	0.392
0.224	0.216	0.169	0.179	0.188	0.281	0.235	0.172	0.242	0.245	0.264	0.373		0.361	0.366	0.373	0.301	0.375	0.388	0.361	0.374	0.317	0.296	0.427
0.295	0.393	0.387	0.282	0.442	0.408	0.300	0.292	0.389	0.431	0.420	0.337	0.361		0.204	0.335	0.277	0.253	0.273	0.436	0.214	0.271	0.356	0.238
0.293	0.395	0.367	0.293	0.407	0.337	0.323	0.302	0.401	0.435	0.403	0.269	0.366	0.204		0.345	0.313	0.203	0.306	0.415	0.199	0.267	0.307	0.290
0.342	0.409	0.383	0.399	0.383	0.426	0.368	0.407	0.385	0.427	0.378	0.299	0.373	0.335	0.345		0.380	0.330	0.407	0.347	0.349	0.350	0.332	0.400
0.325	0.395	0.357	0.319	0.345	0.312	0.376	0.349	0.405	0.415	0.380	0.359	0.301	0.277	0.313	0.380		0.296	0.341	0.368	0.251	0.349	0.313	0.205
0.253	0.353	0.368	0.272	0.372	0.307	0.286	0.280	0.356	0.437	0.347	0.190	0.375	0.253	0.203	0.330	0.296		0.376	0.424	0.177	0.308	0.324	0.318
0.360	0.417	0.409	0.342	0.410	0.450	0.321	0.354	0.392	0.428	0.422	0.392	0.388	0.273	0.306	0.407	0.341	0.376		0.407	0.351	0.301	0.395	0.349
0.351	0.419	0.362	0.433	0.375	0.465	0.423	0.434	0.397	0.363	0.323	0.372	0.361	0.436	0.415	0.347	0.368	0.424	0.407		0.386	0.372	0.285	0.426
0.300	0.411	0.401	0.304	0.394	0.350	0.347	0.349	0.401	0.446	0.395	0.264	0.374	0.214	0.199	0.349	0.251	0.177	0.351	0.386		0.312	0.315	0.196
0.318	0.365	0.337	0.323	0.383	0.371	0.258	0.285	0.321	0.397	0.359	0.331	0.317	0.271	0.267	0.350	0.349	0.308	0.301	0.372	0.312		0.344	0.389
0.311	0.402	0.318	0.358	0.315	0.345	0.375	0.376	0.351	0.363	0.346	0.357	0.296	0.356	0.307	0.332	0.313	0.324	0.395	0.285	0.315	0.344		0.399
0.386	0.475	0.465	0.359	0.467	0.465	0.431	0.404	0.462	0.504	0.474	0.392	0.427	0.238	0.290	0.400	0.205	0.318	0.349	0.426	0.196	0.389	0.399	

5.2 Average Linkage Method

This method shows that results in the following dendogram (Figure 4) and their images are viewed in figure 5. Average linkage method split into two categories without any overlapping. The test image also clustered in their respective groups.

Figure4. *Dendrogram for Average Linkage Method*

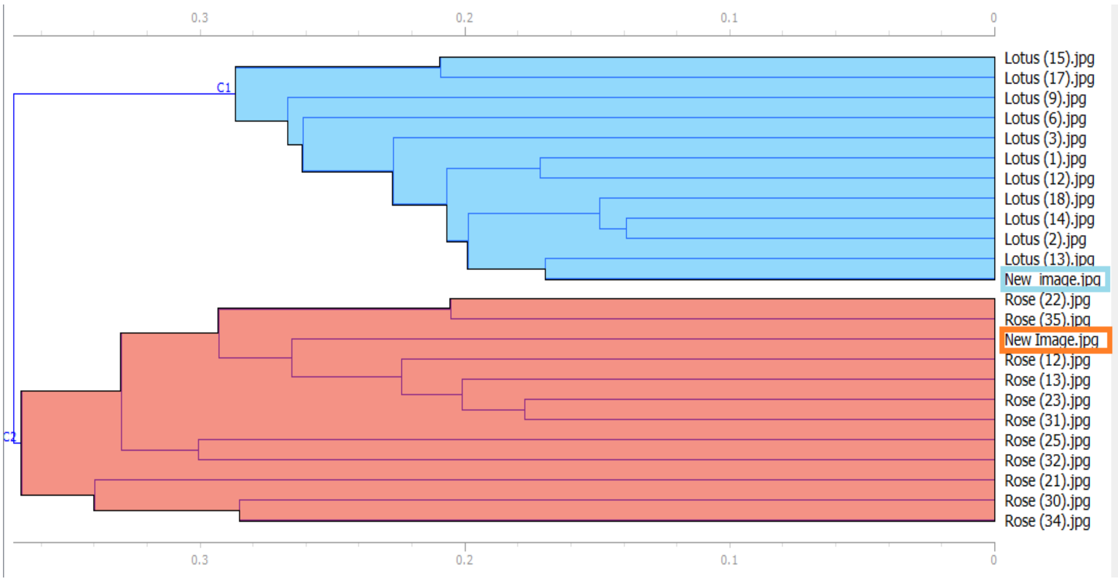
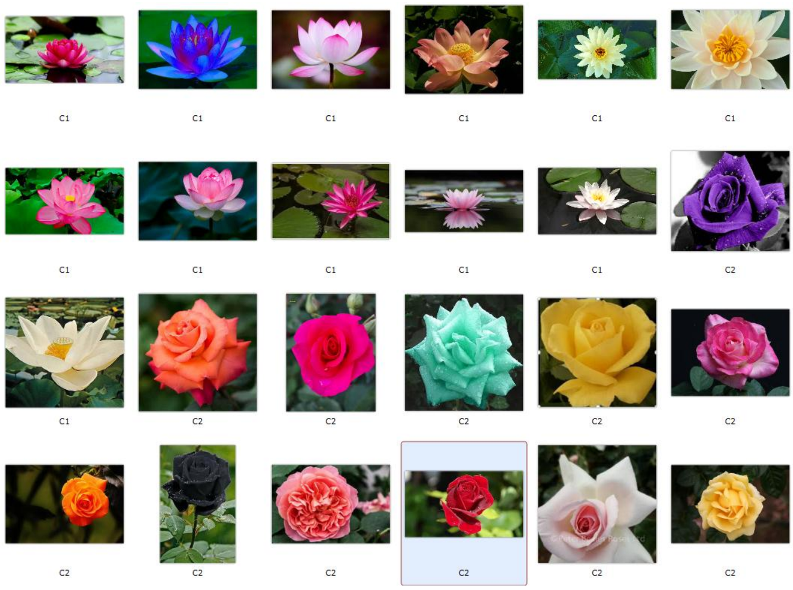


Figure5. *Cluster Image View for Average Linkage Method*



5.3 Weighted Linkage Method

The weighted linkage method shows that results in the following figure 6 and their images are viewed in figure 7. This method split into two categories without any overlapping. The test image also clustered in their respective groups.

Figure6. *Dendrogram for Weighted Linkage Method*

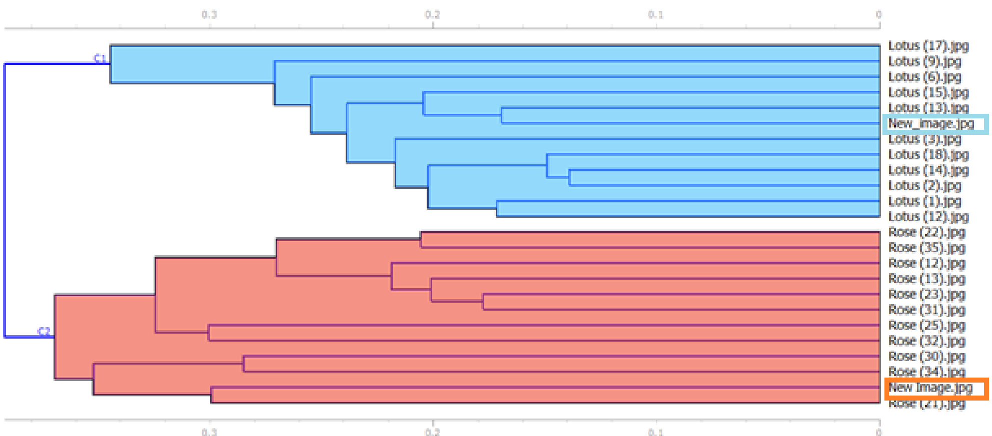
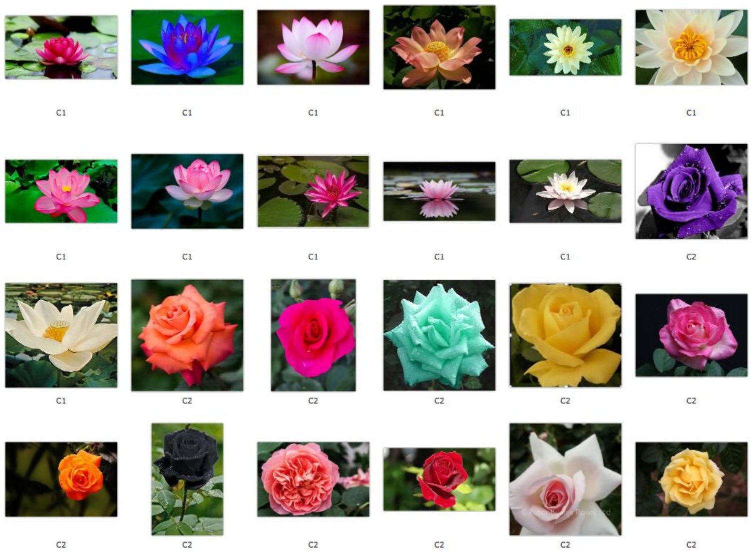


Figure7. *Cluster Image View for Weighted Linkage Method*



5.4 Complete Linkage Method

Complete linkage method shows that results in the following dendogram (Figure. 8) and their images are viewed in figure 9. Complete linkage method split into two categories without any overlapping. The test image also clustered in their respective groups.

Figure8. *Dendrogram for Complete Linkage Method*

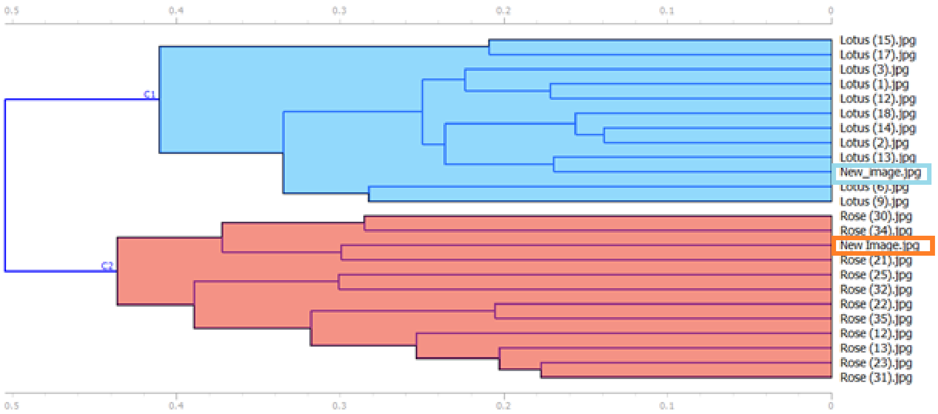
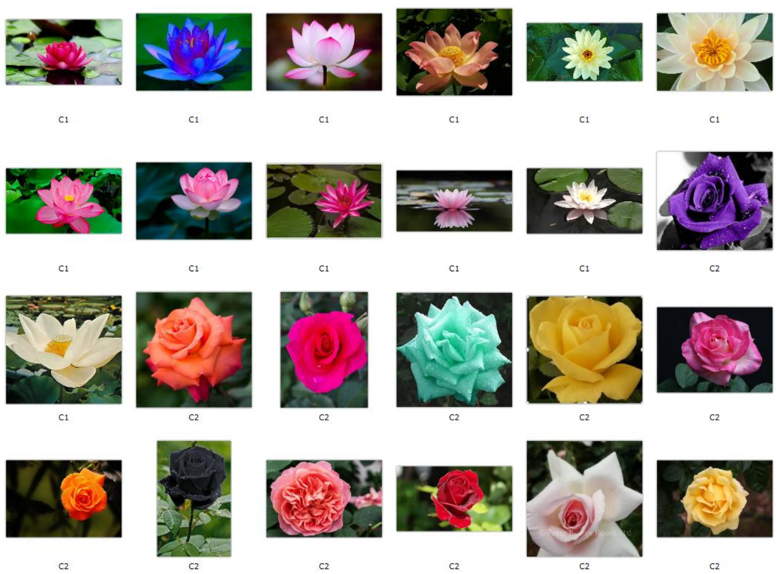


Figure9. *Cluster Image View for Complete Linkage Method*



5.5 Complete Linkage Method

Finally the Ward's method shows that results in the following dendogram (Figure.10) and their images are viewed in figure 11. Wards method split into two categories without any overlapping. The test image also clustered in their respective groups.

Figure9. *Dendrogram for Complete Ward's Method*

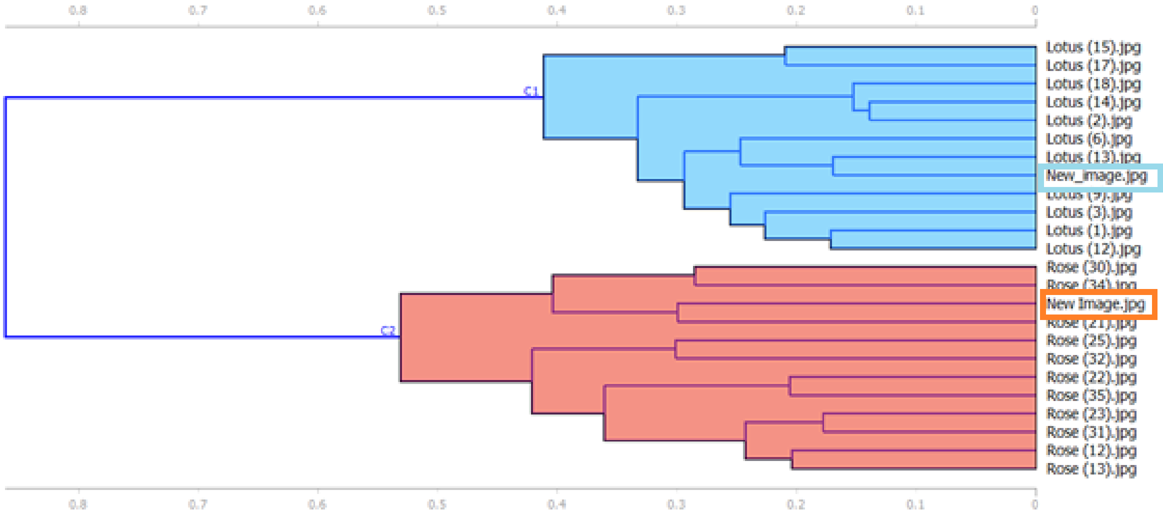
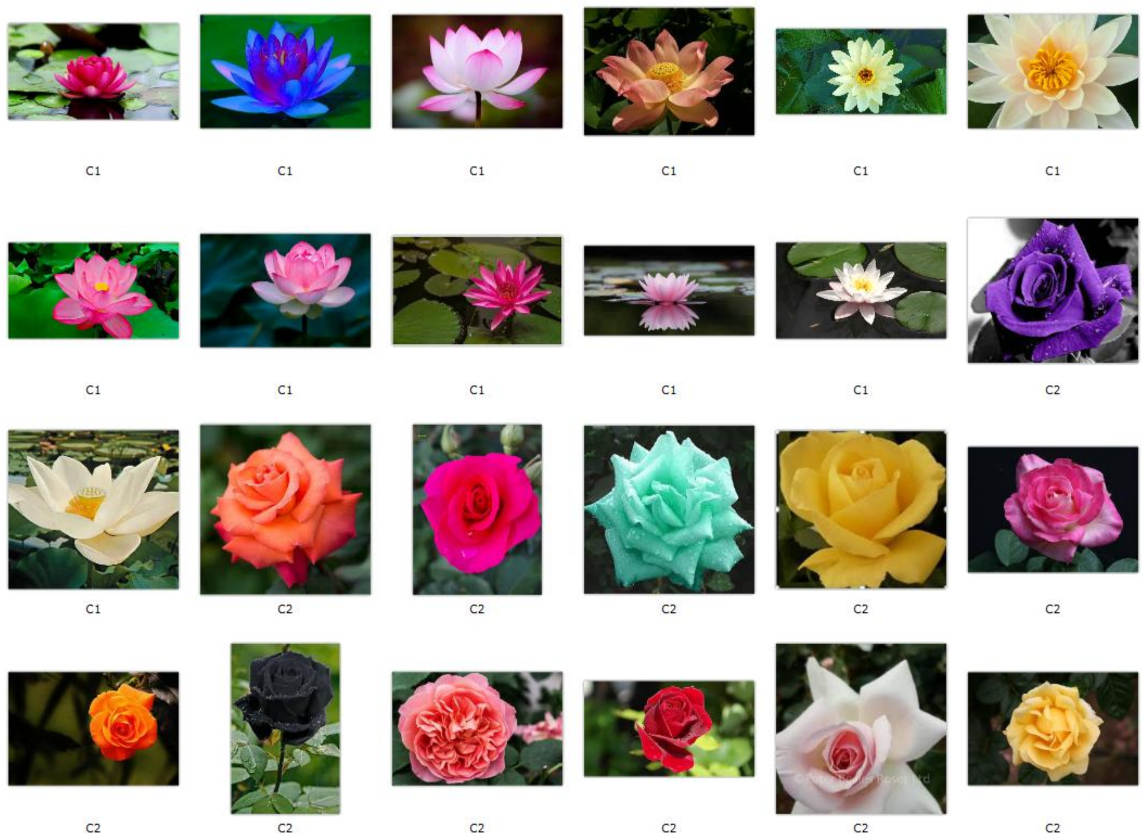


Figure11. *Cluster Image View for Ward's Method*



6. Conclusion

In this research paper is started off with installing image analytics tools which provides us with a few new widgets. Then, the databases of flowers load the images via the Import Images widget. The image embedding widget calculated the vectors. The cosine similarity measure achieved pairs of image distance result using various data mining methods and produced dendogram. The images are to view via the Image Viewer widget. And, also learned to use the Image Embedding widget convert the images to vector of numbers. The Cosine Distances widget to calculate various methods of hierarchical clustering methods and it's showed a dendogram of the cluster. Finally, test it out with a sample flour images. All the methods of clustering techniques achieved natural clusters.

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