Supervised Deep Machine Learning Methods of Floral Data Image Processing

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ABSTRACT
This research paper attempts to identify the pattern of three types of images using deep machine learning methods for cluster analysis. These three different images were collected on different web domains with different pixels and under the floral head. The flowers have a basic RGB colour and Black and white colour with different Kilo Byte (KB) sizes. Python data-based software creates image Width, Height and Size. The machine-readable image embedding widget image generates a vector base database from $n_0, n_1, n_2, \dots n_{2047}$ using inception v3 embedded. It generates the vectors from deep learning server or individual system. The cosine distance matrix proves the same images with the help of their links for these three types of images. These measures of the distance vector identify the image distance of three types of images using a variety of clustering techniques. In addition, clustered images are visualized using the image viewer widget. The images associated with each collection are displayed separately from other categories.

Keywords
Image Processing, Image Embedded, Data Mining, Hierarchical Clustering, Cosine Distance and Image Visualization.

1. INTRODUCTION
Image processing is very interesting and is an informative analytical tool for pattern recognition and data such as medical bio images, text and many other fields. The image is nothing more than a two-dimensional signal. The mathematical function $f(x, y)$ is defined when x and y are two co-coordinates horizontally and vertically. The value of $f(x, y)$ at any time gives the pixel value at that point of image. The separation of an image can be defined as separation of all the elements of the image or pixels in the image into different categories that reflects same features. Separation involves dividing an image into groups of identical pixels according to a specific procedure [1]. Different groups should not be united and adjacent groups should be different. Groups are called segments. Image classification is considered the most important function of meaningful analysis and interpretation of an acquired image. It is a critical and important part of image analysis system or pattern recognition system and is one of the most difficult tasks in application of images, determining the quality of final separation. Researchers have worked extensively on this basic issue and have come up with incredible options.

2. REVIEW OF LITERATURE
Many researchers used images to identify weight loss, similarities between other images, etc. High-level data can be converted into low-level codes by training a multilayer neural network with a small medium layer to reconstruct high input vectors. G. E. Hinton, et.al. [2] used Gradient dropper to fine-tune the instruments in such networks as ‘‘ auto encoder ’’, but this only works best when the first instruments are close to a good solution. The author describes an effective tool for implementing tools that allow deep auto encoder networks to read low-dimensional codes that work much better than Principal Components Analysis (PCA) as a data reduction tool.

Separation is one of the most important steps in the analysis of digital images [3, 4]. It consists of separating an image into unbroken regions according to the similarity of their visual and / or space features (texture, size, shape, etc.). The most common method of classifying satellite imagery is based on data clustering algorithms [5]. Methods of integration can be divided into two main groups: consecutive and non-sequential. Non-sequential algorithms provide consistent data integration and hierarchical algorithms produce a system of embedded clusters corresponding to different sequence levels. Hierarchical representation makes it easy to interpret results in cases where details are needed at various levels of the structure of collection, as well as in cases where maximum number of desirable collections is unknown.

Traditional methods of collecting positions have some drawbacks. For example, a single connecting process is triggered by a so-called chain effect, and complete and standard coupling methods usually work best only with round clusters. Moreover, these methods do not allow for the separation of scattered clusters [6]. Another serious drawback of these methods is their high complexity of calculation, which does not allow it to be used for data processing as many images. The recent integration approach has been widely used to improve stability and performance of integration [7-11]. However, methods based on collection of congregational congregations have been the subject of only a few papers [12]. In addition, the algorithms used in it also take time to calculate. The main objective of this research paper is to identify a flower group that belongs to same group or different group using different group analysis by cosine range scale.

3. DATABASE
The database of floral data were collected on a variety of World Wide Web with three categories of flowers like RGB and BW (Black and White), images are in .jpeg formats. Image processing deep learning methods automatically generates vector database using Inception V3 embedded. The machine learning methods automatically generates the flowers height, width and size (KB). The embedded vectors of

$n_0, n_1, n_2, \dots n_{2047}$ are used for subsequent analysis of deep machine learning methods of supervised cluster analysis.

4. METHODOLOGIES

4.1 Hierarchical Clustering Methods

The hierarchical collection techniques are carried out by a series of consecutive encounters or a series of subsequent phases. The next step is the hierarchical clustering algorithm for collecting N objects or images or variables. [13]

Step 1: It starts with groups of$N$, each containing one business and $N * N$ symmetric grades and defined by $D = \{d_{ik}\}$.

Step 2: Identify the matrix range of adjacent clusters. Allow distance between identical X and Y bed_{xy}sets.

Step 3: Combine X collections with the newly created collection label(XY). Update everything in distance matrix (a) by removing rows and columns corresponding to group X and Y and (b) by adding a row and column to give the distances between group (XY) and remaining groups.

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

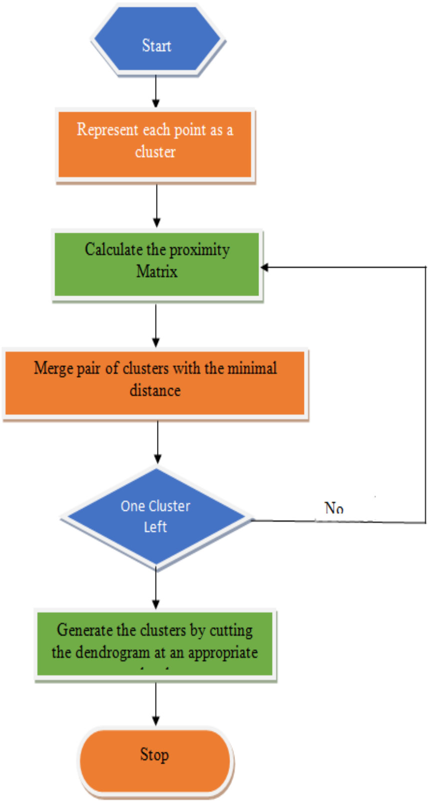


Fig. 1. Flow Chart of Supervised Algorithm

4.2 Average Linkage Method

Step 1: Intermediate communication treats the distance between two sets as a normal distance between all pairs of images where one number of pairs is another.

Step 2: Also, the input in average link algorithm can be distances or similarities, and the model can be used to collect images or objects or variables.

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

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

Where d_{ik} is the distance i in the cluster between (XY) and the object k in 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 Weighted Pair of Group Method Average (WPCMA).

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

Step 3: The difference is that the distances between the newly formed and others are weighed according to the number of data points in each collection. 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 Complete Linkage

Complete linkage clustering proceeds in the much same manner as single linkage clustering's, with one important exception.

Step 1: At each stage the distance between clusters is determined by the two elements, one from each cluster, that are most distant.

Step 2: This method ensure that all items in a cluster are with in some maximum distance of each other.
Step 3: The general agglomerative algorithm repeat by finding the minimum entry in D_{ik} and merging the corresponding objects, such as U and V, to get cluster (UV).
Step 4: The distances between $(UV$ and any other cluster W are computed by

$$d_{(uv)w} = \max\{d_{uw}, d_{vw,}\}$$

Where, d_{uw} and $, d_{vw,}$ are the distances between the most distant members of clusters U and W and clusters V and W respectively.

4.4 The Ward Method

Ward's [14] is considered as a process of clustering positions based on minimizing the loss of information in 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 of tsquared deviations of every item in 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 analysis, union of every possible pair of clusters is considered, and the two clusters whose combination results in a 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 dendrogram.

4.6 Cosine Distance Similarity

Cosine similarity is computed using the following formula:

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

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 similarity between small numbers of sets. The procedures parallelize the computation and are therefore more appropriate for computing similarities on bigger datasets

4.7 Image Processing and Model Developing Algorithm

Step 1: Three types of images (floral) were collected from a different URL and assigned to the input data matrix.

Step 2: Selected images in .jpeg format, with various sizes of images in KB (Kilo Bytes).

Step 3: Images are placed in a single folder and are provided as input data to insert the widget.

Step 4: A file widget connected to data table with image embedding widget. Image embedding calculates their vectors using Inception V3 embedded. Subsequently the distances are identified using Cosine Distance and identifies the similarities of images using image embedding widget.

Step 5: The distance widget connects to the hierarchical cluster analysis and it is visualized in dendrogram.

Step 6: The image view widget shows the clustered image, image name and cluster numbers. (Figure 2)

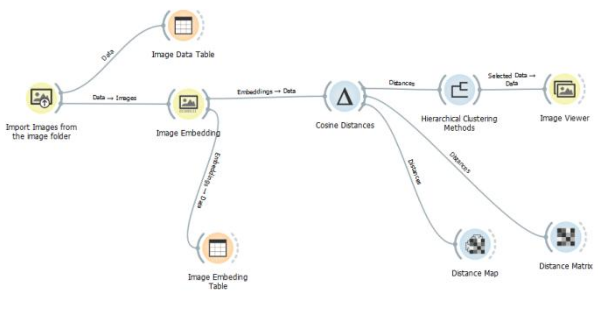


Fig. 2. Workflow for Image Processing

Image embedding widget is very important for all 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 reads images and uploads them to a remote server or evaluates them locally (folder).

5. RESULT AND DISCUSSION

5.1 Proposed Image Processing Algorithm

Step 1: Input images generate data automatically using deep machine learning methods for data mining.

Step 2: Initially, it generate five parameters such as image name, image URL, height, width and size in Table 1 data.

Step 3: The image embedding widget generates the vectors from $n_0, n_1, n_2, \ldots n_{2047}$.(Table 2). These vectors are used for supervised clustering methods.

Table 1. Sample Image Data and their image, image name, Size, Width and Height

Image Data Table

Variables
☑ Show variable labels (if present)
☐ Visualize numeric values
☑ Color by instance classes

Selection
☑ Select full rows

origi type	image name	image IJCA/Lotus_Rose_ 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 (17)	Lotus (17).jpg	45125	700	467
6	Lotus (2)	Lotus (2).jpg	8033	275	183
7	Lotus (3)	Lotus (3).jpg	7778	280	180
8	Lotus (6)	Lotus (6).jpg	5744	310	163
9	Lotus (9)	Lotus (9).jpg	34294	852	480
10	Lotus B_W (10)	Lotus B_W ...	78646	299	299
11	Lotus B_W (2)	Lotus B_W ...	60188	299	299
12	Lotus B_W (3)	Lotus B_W ...	76040	299	299
13	Lotus B_W (4)	Lotus B_W ...	87277	299	299
14	Lotus B_W (5)	Lotus B_W ...	58938	299	299
15	Lotus B_W (6)	Lotus B_W ...	58717	299	299
16	Lotus B_W (7)	Lotus B_W ...	67544	299	299
17	Lotus B_W (8)	Lotus B_W ...	71404	299	299
18	Lotus B_W (9)	Lotus B_W ...	93134	299	299
19	New Image	New Image.jpg	10494	244	207
20	New_image	New_image.jpg	13196	322	300
21	Rose (13)	Rose (13).jpg	7880	195	258
22	Rose (16)	Rose (16).jpg	9184	275	183
23	Rose (21)	Rose (21).jpg	8186	226	223
24	Rose (22)	Rose (22).jpg	5902	233	216
25	Rose (23)	Rose (23).jpg	6116	262	193
26	Rose (25)	Rose (25).jpg	7668	275	183
27	Rose (30)	Rose (30).jpg	9488	179	281
28	Rose (31)	Rose (31).jpg	9184	275	183
29	Rose (34)	Rose (34).jpg	5652	210	210
30	Rose B_W (1)	Rose B_W (1).png	65321	299	299
31	Rose B_W (10)	Rose B_W ...	64347	299	299
32	Rose B_W (2)	Rose B_W (2).png	65005	299	299
33	Rose B_W (3)	Rose B_W (3).png	84247	299	299
34	Rose B_W (4)	Rose B_W (4).png	66320	299	299
35	Rose B_W (5)	Rose B_W (5).png	60268	299	299
36	Rose B_W (7)	Rose B_W (7).png	57263	299	299
37	Rose B_W (8)	Rose B_W (8).png	82588	299	299
38	Rose B_W (9)	Rose B_W (9).png	76503	299	299

Table 2. Sample Image embedded (Inception V2) Data and their image, image name, Size, Width, Height and $n_0, n_1, n_2, \ldots n_{2047}$.

Image Embeding Table

Variables
☑ Show variable labels (if present)
☑ Visualize numeric values
☑ Color by instance classes

Selection
☑ Select full rows

hidde origin type	image name	image IJCA/Lotus_Rose_ image	size	width	height	n0 True	n1 True	n2 True	n3 True	n4 True	
1	Lotus (1)	Lotus (1).jpg	11113	299	168	6.09338	11.562	-0.821214	4.11414	6.04248	6.33
2	Lotus (12)	Lotus (12).jpg	9874	275	183	10.799	23.7101	6.35208	8.34697	6.28634	12.2
3	Lotus (13)	Lotus (13).jpg	7383	275	183	5.15625	16.7504	7.829	13.8734	12.7625	17.2
4	Lotus (14)	Lotus (14).jpg	8368	259	194	10.4111	15.6161	9.55054	9.0188	11.1655	14.3
5	Lotus (17)	Lotus (17).jpg	45125	700	467	2.24732	7.28581	2.84468	1.7281	7.43921	7.09
6	Lotus (2)	Lotus (2).jpg	8033	275	183	6.99254	11.1159	3.65452	5.62752	6.53686	10.7
7	Lotus (3)	Lotus (3).jpg	7778	280	180	10.6065	14.4531	10.543	13.7703	8.54455	14.4
8	Lotus (6)	Lotus (6).jpg	5744	310	163	7.35653	12.3745	12.7728	10.1833	8.34458	12.2
9	Lotus (9)	Lotus (9).jpg	34294	852	480	12.8672	16.7756	13.1715	15.6418	17.9274	15.0
10	Lotus B_W (10)	Lotus B_W (10)....	78646	299	299	3.9932	4.30293	4.85223	7.40589	9.61251	6.25
11	Lotus B_W (2)	Lotus B_W (2).p...	60188	299	299	6.00814	9.88006	9.54373	11.0676	10.8818	10.4
12	Lotus B_W (3)	Lotus B_W (3).p...	76040	299	299	9.07328	8.65137	10.7015	14.2487	10.9396	9.70
13	Lotus B_W (4)	Lotus B_W (4).p...	87277	299	299	4.05135	2.44841	6.21544	6.59474	14.6612	12.0
14	Lotus B_W (5)	Lotus B_W (5).p...	58938	299	299	9.30993	13.6888	12.0683	11.5911	14.5129	12.3
15	Lotus B_W (6)	Lotus B_W (6).p...	58717	299	299	5.67257	10.0378	12.6694	12.2688	9.04266	8.69
16	Lotus B_W (7)	Lotus B_W (7).p...	67544	299	299	7.56508	15.089	15.7282	15.5703	16.6708	14.4
17	Lotus B_W (8)	Lotus B_W (8).p...	71404	299	299	10.1258	11.8648	14.1282	14.6858	14.105	10.4
18	Lotus B_W (9)	Lotus B_W (9).p...	93134	299	299	3.88601	5.14616	10.071	8.50878	9.83247	3.61
19	New Image	New Image.jpg	10494	244	207	12.1137	4.09083	5.64018	5.09025	6.57274	3.22
20	New_image	New_image.jpg	13196	322	300	8.03819	7.76973	11.1192	11.5722	17.2069	15.6
21	Rose (13)	Rose (13).jpg	7880	195	258	9.78115	14.1259	-0.381006	7.33502	9.93087	15.6
22	Rose (16)	Rose (16).jpg	9184	275	183	8.9881	4.97096	-1.17764	1.98804	4.77715	9.10
23	Rose (21)	Rose (21).jpg	8186	226	223	5.78381	7.62396	6.88442	12.8322	13.6524	18.0
24	Rose (22)	Rose (22).jpg	5902	233	216	8.07717	11.9794	12.3414	15.411	14.5801	16.8
25	Rose (23)	Rose (23).jpg	6116	262	193	12.1816	7.40826	2.51827	4.89137	3.46357	10.5
26	Rose (25)	Rose (25).jpg	7668	275	183	9.03415	10.9643	5.84905	8.63871	12.9072	12.5
27	Rose (30)	Rose (30).jpg	9488	179	281	11.7646	5.39137	7.50143	12.6735	5.7421	11.6
28	Rose (31)	Rose (31).jpg	9184	275	183	8.9881	4.97096	-1.17764	1.98804	4.77715	9.10
29	Rose (34)	Rose (34).jpg	5652	210	210	6.95773	11.3259	11.0139	10.7842	17.2777	16.4
30	Rose B_W (1)	Rose B_W (1).png	65321	299	299	5.68475	3.86277	5.52236	6.41982	12.2565	7.15
31	Rose B_W (10)	Rose B_W (10)....	64347	299	299	11.185	5.61977	6.08104	5.08087	8.35642	9.40
32	Rose B_W (2)	Rose B_W (2).png	65005	299	299	6.03288	4.82661	6.75026	6.23243	8.39052	12.1
33	Rose B_W (3)	Rose B_W (3).png	84247	299	299	2.8144	3.31547	8.62905	11.1649	16.1972	11.7
34	Rose B_W (4)	Rose B_W (4).png	66320	299	299	5.23073	5.63428	5.24559	6.92214	11.6512	9.33
35	Rose B_W (5)	Rose B_W (5).png	60268	299	299	10.7343	5.76296	6.37342	8.00246	9.56191	12.8
36	Rose B_W (7)	Rose B_W (7).png	57263	299	299	5.82056	7.51545	4.65799	5.72805	9.72129	6.20
37	Rose B_W (8)	Rose B_W (8).png	82588	299	299	11.878	4.03729	6.29862	5.9452	6.15718	4.99
38	Rose B_W (9)	Rose B_W (9).png	76503	299	299	11.1048	3.00671	3.04815	4.49602	8.39093	9.84

Step 4: Embedding a widget connected to cosine distance method. The cosine distance method is the most common and

widely used in image analysis and will determine distance from the similarity of various images and is cluster together.

Step 5; Cluster is made up of a variety of statistical methods such as Average, Complete, Weighted Average and Ward's method.

Step 6: All methods form a natural cluster and are represented in dendrogram program.

Step 7: Finally, selected clusters are displayed and labelled as $c_1, c_2, c_3, c_{4,} c_5$ and c_6 and are shown in picture with the help of image view widget.

The results of image minimization are shown in Figure 3. The separated elements are highlighted in blue and the values are zero. The cosine distance matrixes of the three categories of pictures are in table 3. The concentrations of the cosines are closed in those of blue and dark yellow. Small numbers are inserted in bright pink and blue colours, the diagonal matrix are highlighted in blue colour, the following results are interpreted separately in the following sections.

Image processing of data mining tools has given exciting results. All methods are well separated in dendrogram view and image view. Initially, in this research paper only (19, 19) images were used. when looking at pictures of three categories and corresponding to their collection, the cosine distance gives good result between the ranges 0 to 1; the similarities within the images are well. These three images are divided into three colours with different types of distance model in dendrogram. These three types of images are well integrated and labelled as C1, C2, C3, C4, C5 and C6.

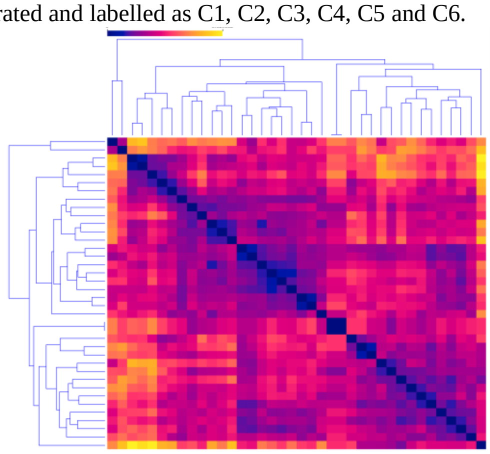
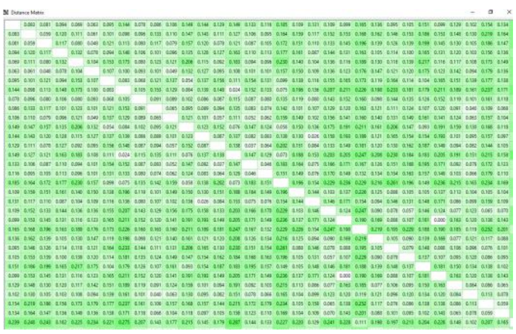


Fig. 3. Distance Map of the Images

Table 3. Distance Matrix of the Images



5.2 Average Linkage Method

This method shows the result in the following dendrogram (Figure 4 and 5) and C3 cluster shows the results of RGB and BW images are visualized in Figure 5. The middle link method is divided into three sections with few overlap. The test image was re-integrated into their groups.

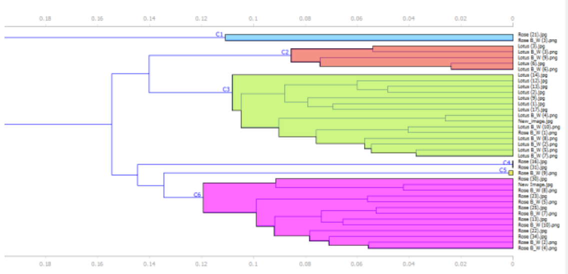


Fig. 4. Dendrogram for Average Linkage Method

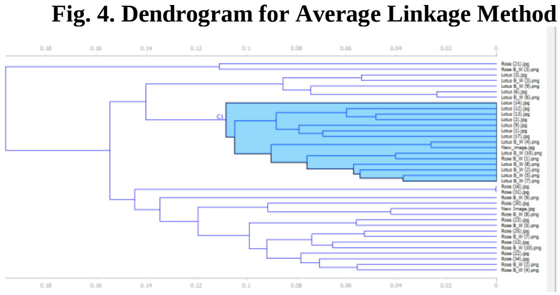


Fig. 4. Sample View of Dendrogram for Average Linkage Method

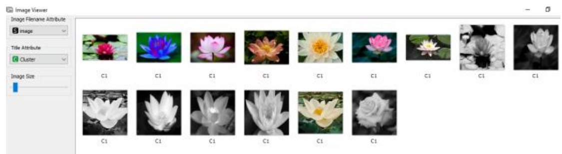


Fig. 5. Cluster Image View for Average Linkage Method

5.3 Weighted Linkage Method

The weighted linkage method shows the results in figure 6 and their images are shown in figure 7. This method is divided into two phases without overlap. The test image was re-integrated into their groups.

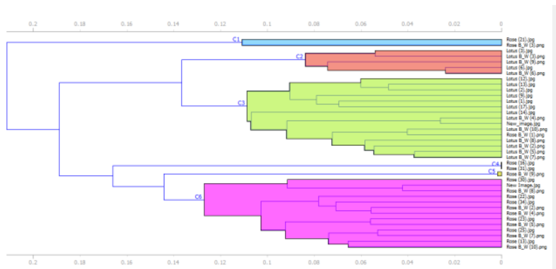


Fig. 6. Dendrogram for Weighted Linkage Method

Fig. 7. Cluster Image View for Weighted Linkage Method

5.4 Complete Linkage Method

The complete connection method shows the results in the following dendogram (Figure 8) and their images are shown in figure 9. The complete communication method is divided into two phases without overlap. The test image was re-integrated into their groups.

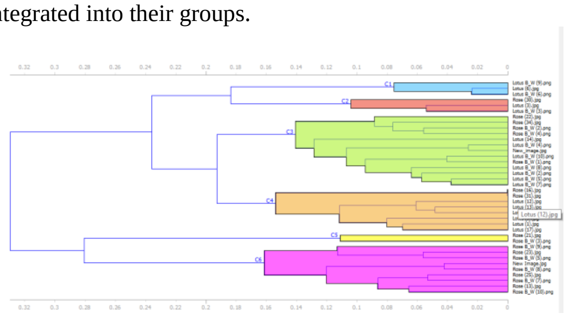


Fig. 8. Dendrogram for Complete Linkage Method

Fig. 9. Cluster Image View for Complete Linkage Method

5.5 Wards Method

Initially the Ward method shows the results in the following dendograms (Figure.10) and their images are shown in Figure 11. The Ward Road is divided into two sections without overlap. The test image was re-integrated into their groups.

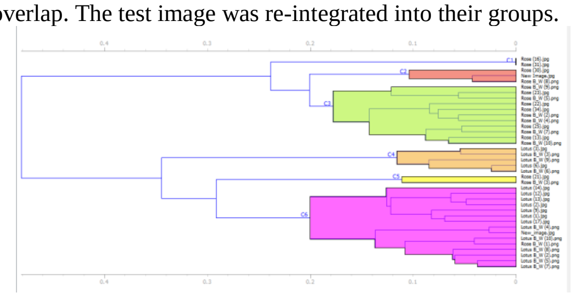


Fig. 10. Dendrogram for Complete Ward's Method

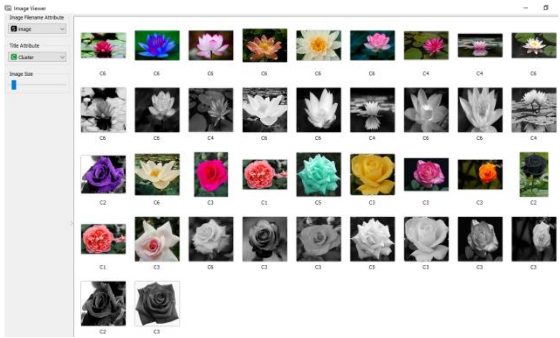


Fig. 11. Cluster Image View for Ward's Method

6. CONCLUSION

This research paper begins with the introduction of image analysis tools that give a few new results. Then the, floral details upload images via import images widget. Image embedding widget calculates image vectors matrix. The cosine distance calculates the similarity measurement and achieved in pairs of the image range effect using a variety of data mining methods and visualized the results in dendogram. Clustered images are viewed via the image viewer widget. Also, the researchers learned to use image embedding widget to convert images into a vector of numbers. The Cosine Distances widget calculates the various methods of positioning methods and is displayed in collection dendrogram. Finally, test it with a sample of flora images of RGB and BW colours. All methods of integration techniques have achieved C1, C2, C3, C4, C5 and C6 natural collections except few images.

Data does not always come in a nice tabular form. It can also be a collection of text, audio recordings, video materials or even images. However, computers can only work with numbers, so for any data mining, we need to transform such unstructured data into a vector representation.

For retrieving numbers from unstructured data, Orange can use deep network embedders. Currently, they are available for text and images.

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