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Case Report

Artificial Intelligence Perspectives on Mexican Art: A Case Study

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Abstract: In this article a set of images corresponding to paintings of eight painters considered an Artistic Heritage of Mexico was clustered to identify clusters of images with similar characteristics between themselves. The images were acquired from a public source available on the Internet, a Pre-processing phase was applied in order to standardize the images in size and number of pixels, an extraction phase of features was applied for each image using Principal Components Analysis (PCA) and Histograms of Oriented Gradients (HOG), a segmentation phase of the features that were derived in the extraction phase was applied using the K-Means technique and the quality of the clusters that were obtained was evaluated using the Silhouette measure. As a result, seven clusters were attained with interesting characteristics: two of the most renowned Mexican painters worldwide whose artistic work is known for using a rich variety of shapes and colors (Diego Rivera and Frida Kahlo) clearly predominated in two clusters; an artist who is recognized for capturing Mexican landscapes in his paintings (José María Velasco) predominated in another cluster; in other three clusters a mixture of various Mexican artists predominated and in the last cluster Diego Rivera clearly predominated. According to the results, it seems that the paintings of Diego Rivera stand out due to a greater number of shapes used compared to the rest of the paintings analyzed. This article is a sample of the potential of Artificial Intelligence applied to Mexican art (and to art in general).

Keywords: Principal Components Analysis (PCA), Histograms of Oriented Gradients (HOG), Clustering, K-Means

1. Introduction

Computer Vision is one of fastest growing branches of Artificial Intelligence. It is divided into several sub-areas, one of which is Image Recognition which has two approaches: supervised approach (its main goal is to classify an image by training models from scratch or by using a technique called Transfer Learning through which pre-trained models are used for a specific problem) and unsupervised approach (its main goal is to divide a set of instances in clusters where the instances of each cluster are the most similar between themselves and the clusters are the most different between themselves) [1].

In this article the unsupervised approach has been used for clustering a set of images which belong to the pictures of eight Mexican painters (Diego Rivera, Frida Kahlo, José Clemente Orozco, David Alfaro Siqueiros, Gerardo Murillo, José María Velasco, Remedios Varo and Saturnino Herrán) whose pictures were declared as an Artistic Heritage of Mexico in 2022. The goal of the research was to identify clusters of images with similar characteristics between themselves regardless of their authors. This kind of clustering would be useful for artistic analysis and shows how some techniques pertaining to the Artificial Intelligence field can be used for that kind of analysis considering that nowadays most of it is done by human experts whose work could be complemented in such a way.

The research background of Artificial Intelligence techniques applied to an artistic analysis is extensive, for example: the use of Machine Learning algorithms to classify a set of pictures which belong to painters of different nationalities and periods by genre [2], the use of Kohonen maps for classifying the style of pictures of European painters from XIX century [3] and the use of Machine Learning techniques for analyzing pictures by Vincent Van Gogh [4].

The methodology proposed for clustering the images has four phases: in the first phase the images are collected from WikiArt Web site [5]; in the second phase the images are preprocessed in order to standardize them; in the third phase the main features of each image are extracted using Principal Components (PCA) and Histogram of Oriented Gradients (HOG) and in the last phase the K-Means clustering technique is applied over the extracted features and the clusters are evaluated by Silhouette measure.

As a result, we got seven clusters. In the first cluster 90% of the images belong to four painters (Diego Rivera, Frida Kahlo, David Alfaro Siqueiros and José Clemente Orozco); in the second cluster 49% of the images belong to Diego Rivera; in the third cluster 71% of the images belong to three painters (Diego Rivera, José María Velasco and Remedios Varo); in the fourth cluster 55% of the images belong to Diego Rivera and Frida Kahlo; in the fifth cluster 54% of the images belong to José María Velasco; in the sixth cluster 85% of the images belong to four painters (José Clemente Orozco, Diego Rivera, Frida Kahlo and Remedios Varo) and in the last cluster 52% of the images belong to Diego Rivera and Frida Kahlo.

The nearest images of the centroids of the clusters were: “The Dream the Bed” of Frida Kahlo (first cluster), “The Huastec Civilization” of Diego Rivera (second cluster), “Visit to the Plastic Surgeon” of Remedios Varo (third cluster), “Breaking Off” of Remedios Varo (fourth cluster), “Valley of Mexico from Tacubaya” of José María Velasco (fifth cluster), “Winter” of José Clemente Orozco (sixth cluster) and “Woman Grinding Maize” of Diego Rivera (last cluster).

2. Theoretical Background

2.1. K-Means

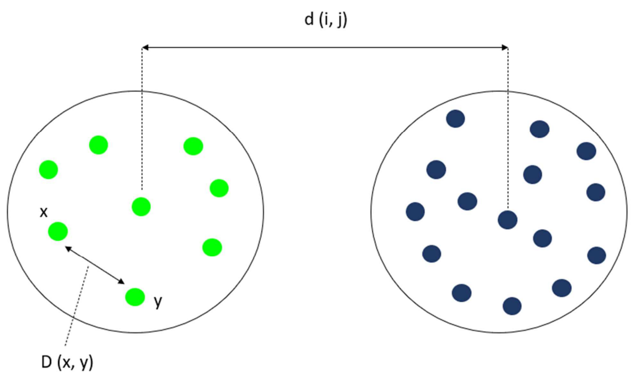


Figure 1. *K-Means clustering algorithm.*

The standard version of this algorithm was proposed by Stuart Lloyd [6] and E. W. Forgie [7] and it is one of the most popular clustering algorithms. The clusters obtained through this algorithm must fulfill the following according to the Figure 1: the distance between the instances of a same cluster D (x, y) should be the smallest and the distance between the centroids d (i, j) (i.e. the distance between the geometric centers) of the clusters should be the largest.

There are several ways for measuring the distance between instances D (x, y) [8], one of the simplest is the Euclidean distance (1) while the distance between centroids d (i, j) can be measured with a metric called similitude S according to (2).

$$D\ (x, y) = \sqrt{(x-y)^2} \tag{1}$$

$$S = 1\,/\,(1 + \sqrt{1 + (i-j)^2}) \tag{2}$$

The quality of the clusters can be evaluated by several measures, one of the most popular is the Silhouette Index which measures the similarity of an instance regarding of its own cluster (cohesion) and regarding the rest of clusters (separation). The Silhouette Index value is in the range [-1, 1] and the higher is the value the greater is the separation between the clusters [9]. The Silhouette Index can be used with any distance measure (for example, the Euclidean distance).

2.2. Principal Component Analysis (PCA)

This popular technique was proposed by Karl Pearson [10] and it is used for analyzing a large dataset containing a high number of dimensions or features per instance, allowing the reduction of dimensionality by linearly transforming the data where most of the variance can be described with fewer dimensions than the original set of data. PCA allows the visualization of multidimensional data using the first two principal components [11].

PCA extracts the dimensions or features by getting a covariance matrix C [12] where ϕ is the matrix of dimensions or features and ϕ_t is the transposed matrix of ϕ (3).

$$C = \phi_t\ x\ \phi \tag{3}$$

The highest Eigenvectors (also called latent vectors that are those vectors different from zero that remain proportional to the original vectors after a multiplication of matrices) are gotten from the covariance matrix C and they will correspond to the principal components of the original set of data.

2.3. Histogram of Oriented Gradients (HOG)

This technique was introduced as part of a patent by Robert K. McConnell [13, 14] and was popularized by Navneet Dalal and Bill Triggs [15]. It is based on the concept that edges within an image can be described by the distribution of gradients. The image is divided into small regions and a histogram of gradient directions is gotten for the pixels inside each region.

In general, the magnitude of a gradient would be calculated as indicated in Equation (4) [15]:

$$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \tag{4}$$

On the other hand, the orientation of a gradient would be calculated as indicated in Equation (5) [15]:

$$\theta = \tan^{-1}\left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}}\right) \quad (5)$$

3. Methodology and Results

3.1. Methodology

Figure 2 shows the methodology that was applied for clustering the images associated with the pictures of the eight Mexican painters considered as an Artistic Heritage of Mexico.

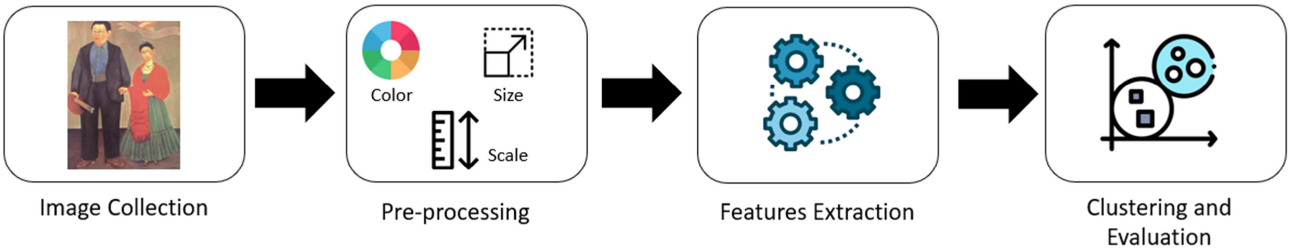


Figure 2. *The methodology applied for this research.*

3.2. Image Collection

Table 1 shows the total of images gathered by painter from WikiArt Web (which contains just the most representative paintings of each painter. WikiArt does not have any images from María Izquierdo who is another painter whose work is also considered as an Artistic Heritage of Mexico). In total there were gathered 520 color images in jpg or png format and all of them have an acceptable resolution to the naked eye. Regarding the painters they belong to different artistic schools and lived between the XIX and XX centuries.

Table 1. *Total of images by painter.*

Painter	Year of birth	Year of death	Total of images
Diego Rivera	1886	1957	128
José María Velasco	1840	1912	103
Frida Kahlo	1910	1954	100
José Clemente Orozco	1883	1949	64
David Alfaro Siqueiros	1896	1974	55
Remedios Varo	1908	1963	50
Saturnino Herrán	1887	1918	11
Gerardo Murillo	1875	1964	9

3.3. Preprocessing

This phase prepares the images in order that they can be comparable between themselves in color, scale and size. Regarding the color we decided to set all the images in grayscale for simplicity; regarding the scale the pixels of all the images were set within the range [0, 255] and regarding the size all the images were set to 128 x 128 pixels. The preprocessing phase was developed using Python language and Google Collaboratory environment. Figure 3 shows an example of an image (“Portrait of The Young Girl Elenita Carrillo Flores” painted by Diego Rivera in 1952) before and after the preprocessing phase.

Figure 3. *An example of an image before and after preprocessing phase.*

3.4. Features Extraction

In this phase we mixed the HOG and PCA techniques to extract the features of each image to take advantage of the goodness of each of them: the first technique allows us to extract the borders of the shapes into each image (see an example in Figure 4 belonging to “The Hands of Dr. Moore”, painted by Diego Rivera in 1940) while the second technique allows us to reduce the dimensional space of features to 319 principal components that explain 95% of the variance as it is shown in Figure 5.

Figure 4. *An example of an image before and after applying HOG.*

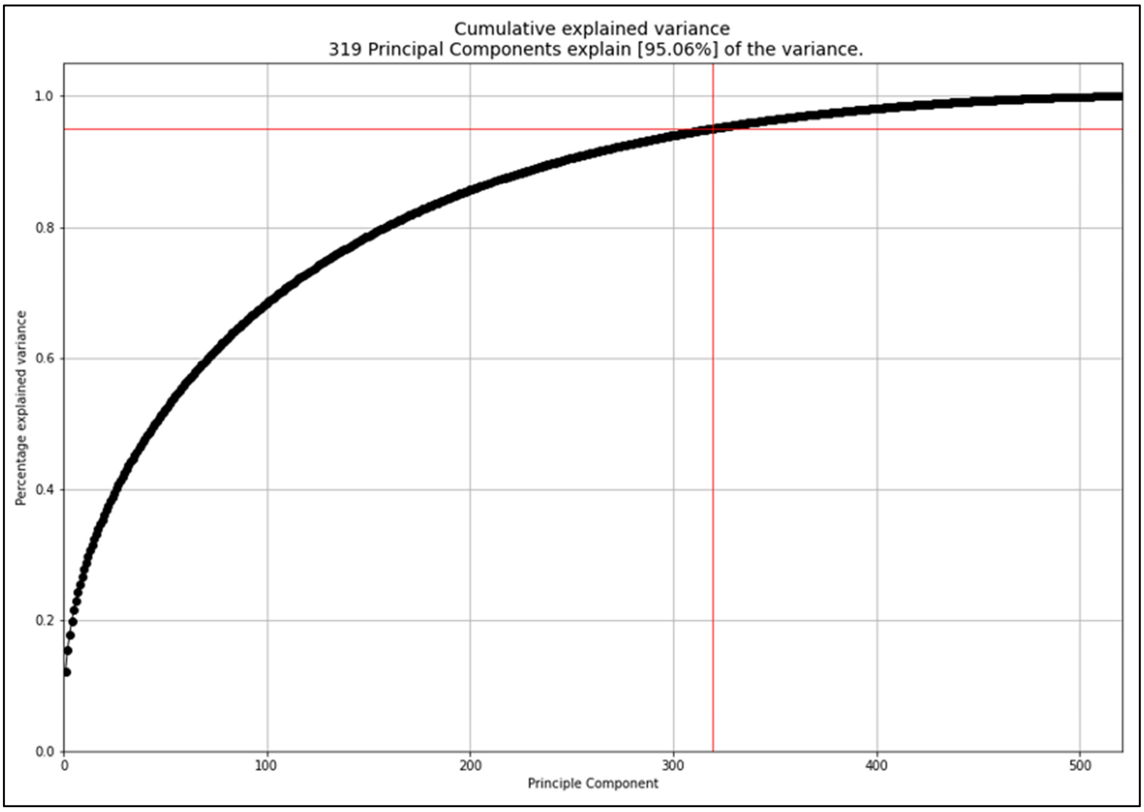


Figure 5. *PCA graphic for cumulative explained variance.*

3.5. Clustering and Evaluation

In this phase we applied the K-Means technique for clustering the features that were extracted in the previous phase. It was found that the optimal number of clusters were seven according to the Silhouette coefficient (Figure 6). According to the Silhouette graphic (Figure 7) the clusters are balanced (cluster 3 is a little thinner than the rest) and they have a Silhouette coefficient above the average (dotted red line in Figure 7). The scatterplot for the first two principal components of the clusters shows that they are separated between themselves as shown in Figure 7.

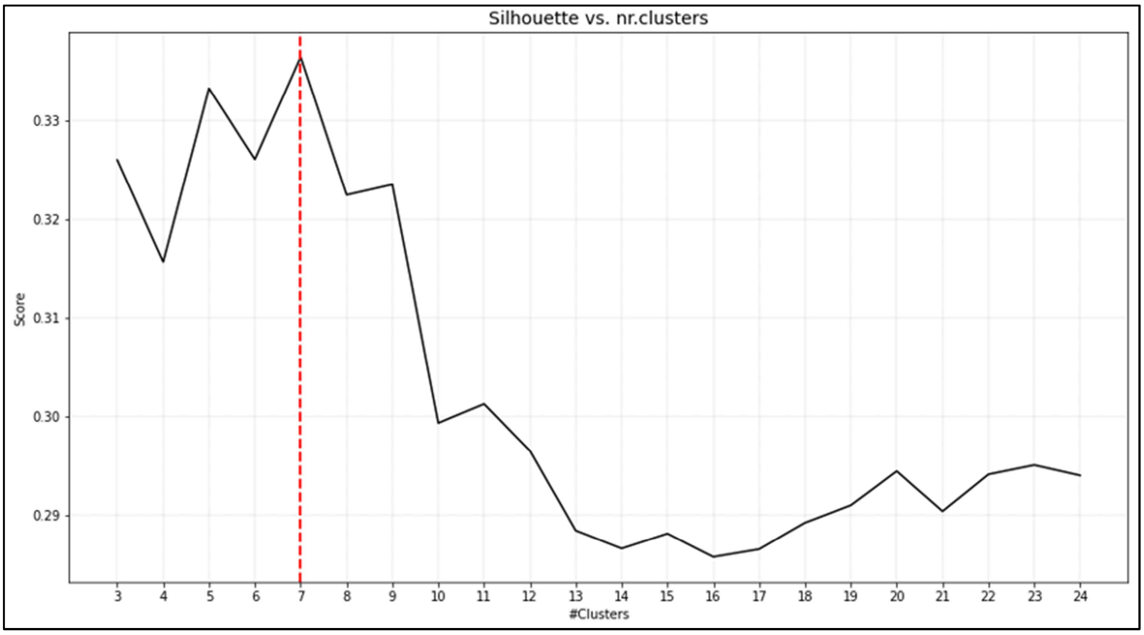


Figure 6. *Number optimal of clusters.*

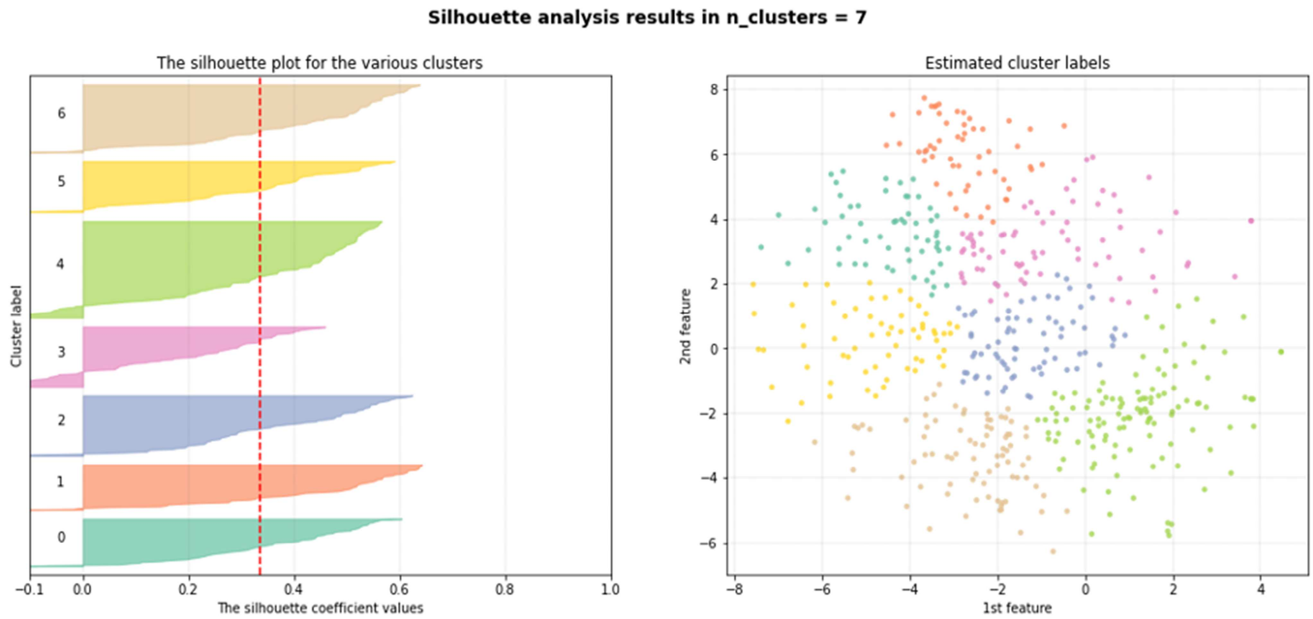


Figure 7. *Silhouette and Scatterplot graphics for seven clusters.*

Figure 8 and Table 2 show the nearest images of the centroids per cluster: pictures of Diego Rivera and Remedios Varo are the most centroid images in two clusters while pictures of Frida Kahlo, José Clemente Orozco and José María Velasco are the most centroid images in the others four clusters. According to Table 2, pictures from the XIX century are the most centroid images in just one cluster (Cluster 4) while pictures of the XX century are the most centroid images for the others six clusters.

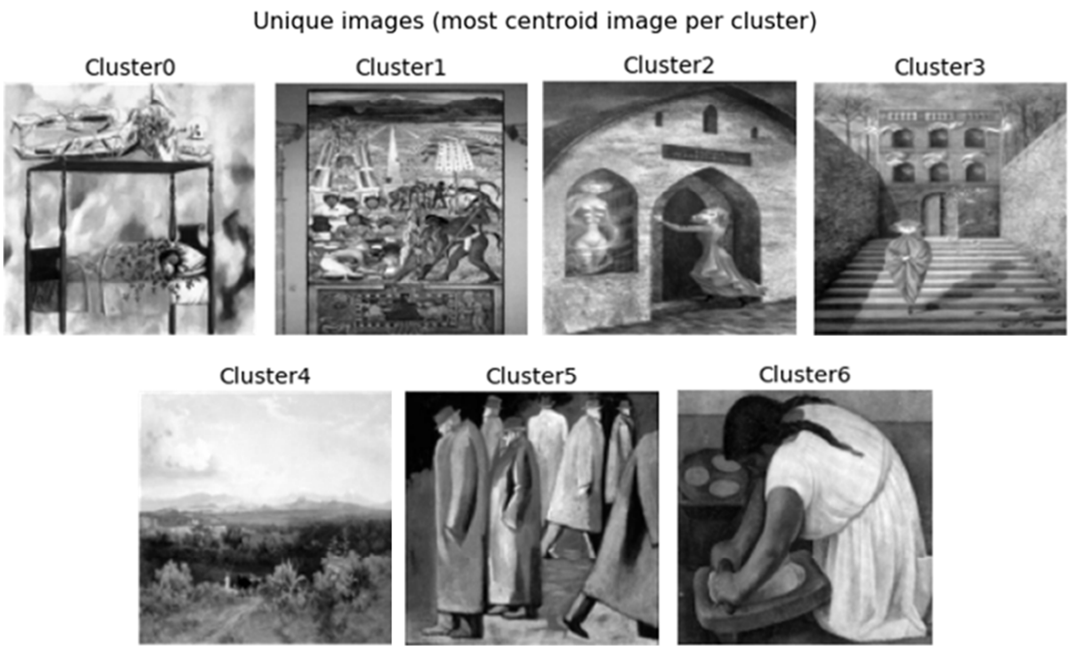


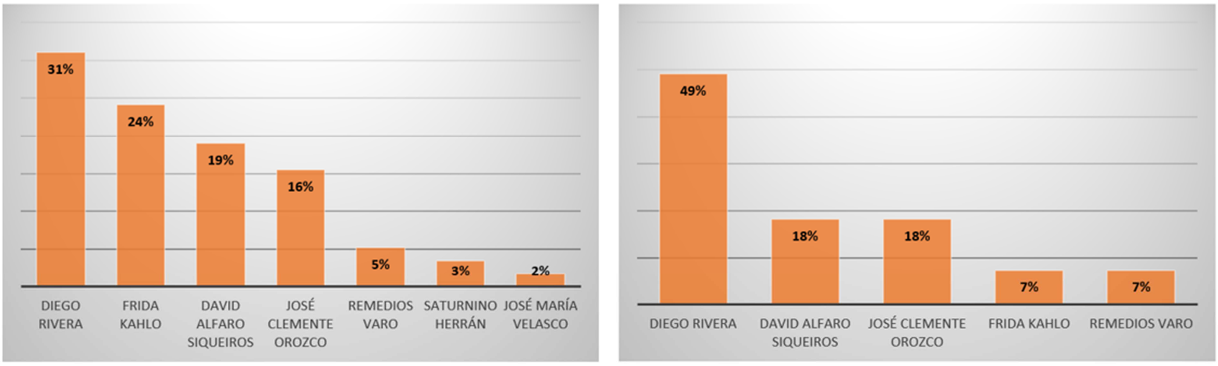
Figure 8. *The most centroid images per cluster.*

Table 2. *The most centroid image per cluster.*

Cluster	Image	Painter	Year
Cluster 0	The Dream the Bed	Frida Kahlo	1940
Cluster 1	The Huastec Civilization	Diego Rivera	1950
Cluster 2	Visit to the Plastic Surgeon	Remedios Varo	1960
Cluster 3	Breaking Off	Remedios Varo	1955
Cluster 4	Valley of Mexico from Tacubaya	José María Velasco	1873
Cluster 5	Winter	José Clemente Orozco	1932
Cluster 6	Woman Grinding Maize	Diego Rivera	1924

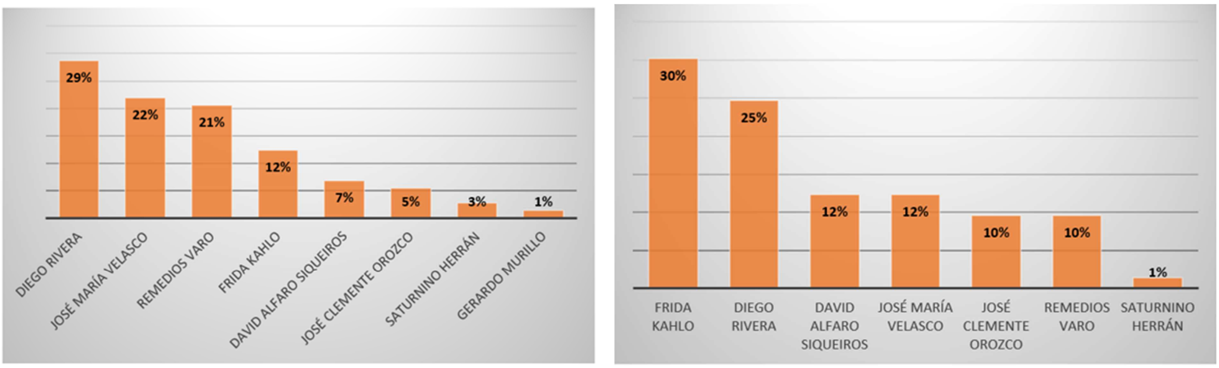
Figures 9-12 show the distribution of images per painter for each cluster. The 90% of the images belong to four painters (Diego Rivera, Frida Kahlo, Remedios Varo and José Clemente Orozco) and non-image of Gerardo Murillo appears in Cluster 0 (Figure 9). The 49% of the pictures belong to Diego Rivera and non-image of Gerardo Murillo, José María Velasco or Saturnino Herrán appear in Cluster 1 (Figure 9). The 71% of the images belong to three painters (Diego Rivera, José María Velasco and Remedios Varo) in Cluster 2 (Figure 10). The 55% of the images belong to two painters (Frida Kahlo and Diego Rivera) and non-image of Gerardo Murillo appears in Cluster 3 (Figure 10). The 54% of the images belong to José María Velasco in Cluster 4 (Figure 11). The 85% of the images belong to four painters (José Clemente Orozco, Diego Rivera, Frida Kahlo and Remedios Varo) in Cluster 5 (Figure 11). The 52% of the images belong to Frida Kahlo and Diego Rivera in Cluster 6 (Figure 12). Clusters 2, 4, 5 and 6 contain images of the eight painters.

Diego Rivera predominates in six of the seven clusters. One of the reasons for this is that his images are the largest group in the set of images collected and the second reason would be that there was more variety of shapes used by the painter compared to the rest of the painters analyzed.



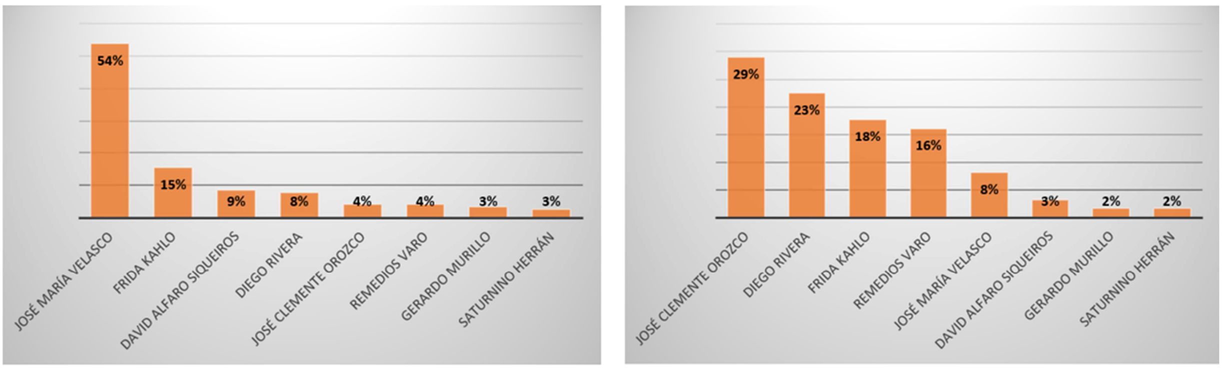
Cluster 0 Cluster 1

Figure 9. *Distribution of images per painter for Cluster 0 and Cluster 1.*



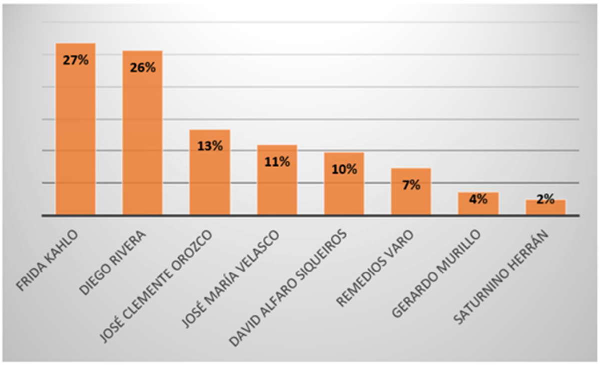
Cluster 2 Cluster 3

Figure 10. *Distribution of images per painter for Cluster 2 and Cluster 3.*



Cluster 4 Cluster 5

Figure 11. *Distribution of images per painter for Cluster 4 and Cluster 5.*



Cluster 6

Figure 12. *Distribution of images per painter for Cluster 6.*

4. Discussion

In previous studies the features of artistic paints had been extracted using techniques such as EdgeHistogramFilter and SimpleColorHistogramFilter [2]. Those techniques are like HOG and are proper for analyzing not just only the shapes but also the colors of the paints, nevertheless they are more complex, and they would demand more computational resources.

Other techniques have been applied for getting the brushstrokes of the paints [3] and although they allow to get a more precise analysis of a set of paints, they also have the limitation of being more complex than HOG and PCA.

The results in this research were obtained using simple and well-known techniques such as HOG and PCA and they offer a starting point for later research applying more complex techniques in the specific case of Mexican art, a field in which research about Artificial Intelligence applications is barely arising.

5. Conclusion

The clustering images obtained in this research would be useful for artistic analysis purposes since it is based on the shapes of each picture regardless of the style and epoch of each painter and thus it offers a new perspective for analyzing the work of eight of the painters considered as an Artistic Heritage of Mexico.

This research would also be useful by showing the perspectives of Artificial Intelligence techniques applied to an artistic analysis: although the authors opinion is that Artificial Intelligence will not replace to the art experts in the very short term it can be a powerful tool for them to obtain a better analysis of artistic works.

The authors propose as future research to get subclusters of each one of the seven clusters to get a more specific analysis of the features of each of them, to try a clustering image based on color instead of grayscale, to try other clustering techniques and other techniques for getting the features of the images, to replicate the methodology with pictures of other painters (whether Mexican or from other countries) and to complement the analysis with the feedback of art specialists.

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