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Color Reduction and Quantization using Kohonan Self Organizing Neural Networks and K-means algorithms

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الملخص:

يهدف هذا البحث على استخدام نظام يستخدم تميز الألوان لغرض تقليل عدد الألوان الفريدة في الصور الفوتوغرافية مع الحفاظ على مستوى عالٍ من دقة الألوان مقارنة بالصور الأصلية. تتأثر جودة الصورة بنظام الألوان الذي تختاره، لذا يعد الحصول على نظام يقلل او يزيل عدد الالوان الغير مهمة في الصور مع الحفاض على جودة الصورة أمرًا ضروريًا. إن تحديد نطاق كل لون في الصورة بشكل أفضل هو الهدف الذي يمكن من تقليل حجم الصورة، وهي التي يمكن أيضًا ان تكون مشكلة عندما يكون الاوان مدمجة. في هذه الدراسة، تم استخدام خوارزميتين شبكات كوهونين العصبية ذاتية التنظيم SOM و k-means لتحديد تقليل اللون لبعض الصور ومن ثم مقارنة النتائج التقنيتين k-means و SOM. أظهرت النتائج أن تقنية k-means أكثر فعالية من SOM في تصنيف قيم k في تقليل اللون.

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Abstract

Color quantization aims to decrease the number of unique colors in photographs while maintaining a high level of color fidelity in comparison to the original images. The quality of the final image is strongly influenced by the color scheme you choose, so getting it right is essential. Identifying the clusters that best capture the colors in an image is the goal of the color quantization issue, which may also be thought of as a clustering problem. In this study, Kohonen Self-Organizing Neural Networks (SOM) and k-means algorithms were implemented to determine the color reduction and quantization of some images and then compare the results against k-means clustering. The findings indicate that when it comes to identifying k values in color reduction and quantization, the k-means method performs better than SOM.

Keywords: Color Reduction and Quantization, Kohonan Self Organizing Neural Networks and K-means

1. Introduction and Background

artificial intelligence (AI) is subfield of computer science which focuses on automating intelligent behavior. It also attempts to mimic humans' intelligence. AI aims to create intelligent computer systems, i.e., machines that exhibit intelligence-like traits found in human behavior, such as the capacity to learn and reason as well as solve problems. While some people believe that the goal of AI is to create intelligence without taking any human qualities into account and the purpose of AI is to mimic human cognition. In another word, AI should not be judged by an abstract idea of intelligence but rather should be used to develop useful artifacts for human comfort and needs [Taulli,2019]. A branch of artificial intelligence and computer science called "machine learning" is concerned with replicating human learning processes and improving accuracy over time through the use of data and algorithms. The development of novel products based on machine learning, including Netflix's recommendation engine and self-driving cars, has been made possible by technical advancements in storage and processing capacity over the past couple of decades [Technology and business newsletters, 1/8/2023].

One of the areas of computer science that is expanding the fastest is machine learning. It is a group of statistical methods for creating mathematical models that may draw conclusions from subsets of data (referred to as a training set). Artificial intelligence includes machine learning, which has to adjust to its environment. How to select amongst the main types of machine learning is basically shown in Figure 1. Three main categories of learning exist: There are three types of learning: supervised learning (the training set is labeled and contains the attribute the model is attempting to estimate), unsupervised learning (the training set is unlabeled), and reinforcement learning (the learned results prompt actions that alter the environment).

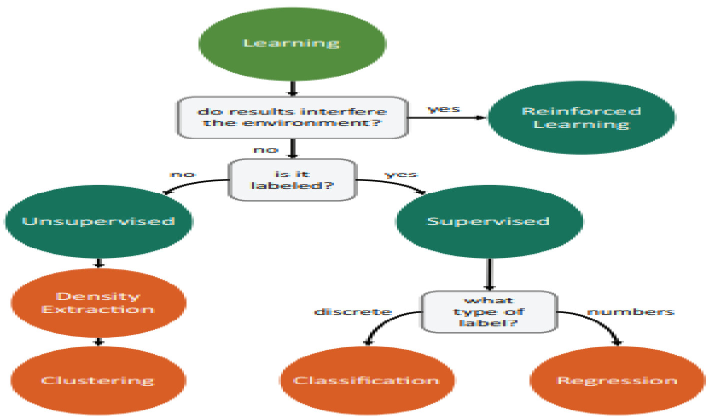


Fig. 1: Machine learning methods categorization

The labels in supervised learning can be discrete or continuous, which are handled by classification and regression algorithms respectively. Classification is used mostly for prediction, pattern recognition and outlier detection, whereas regression is used for prediction and ranking. Unsupervised learning is known as density estimation in statistics and is represented mainly by clustering algorithms. Classification, regression and clustering are widely used in data mining (applications of machine learning to large databases), whereas reinforced learning is mostly used in decision-making problems (e.g., a computer playing chess). Machine learning approaches operate similarly regardless of the applications previously mentioned: the model learns from a training set and then develops the ability to draw conclusions for a new data set. The development of a universal infrastructure to support all machine learning algorithms is motivated by this notion [Ribeiro,2015]. The topic of this paper focuses on color reduction and quantization using machine learning techniques such as self-organizing neural network clustering and K-means.

2.Used techniques

2.1Kohonen Self-Organizing Neural Networks (SOM)

An intriguing aspect of the human brain is how the way it is physically organized appears to correspond to how external stimuli are given to it. Early in the 1980s, Teuvo Kohonen created an algorithm to imitate the brain's capacity to organize itself in response to environmental cues. His method was referred to as a self-organizing feature map. The Kohonen algorithm is an example of an ANN that can learn on its own without being guided. Because the output neurons of the network compete with one another to be activated or fired, only one output neuron or one neuron per group is ever "on" at any given time in this sort of unsupervised learning. 'Winner-takes-all' neurons are the output neurons that triumph in the competition. Kohonen network, as shown in Fig.2, typically consists of an input layer and a two-dimensional Kohonen layer that nonlinearly maps a distribution of m-dimensional vectors into two dimensions while maintaining the order of the high dimension input data. Each Kohonen neuron is fully coupled to the input vectors, which are supplied sequentially in time without indicating the desired output. After presenting sufficient input vectors, the Kohonen network maps input data with related properties into contiguous clusters. The Euclidean distance between two m-dimensional vectors can be used to gauge how similar input vectors are to one another [Aggarwa,1998].

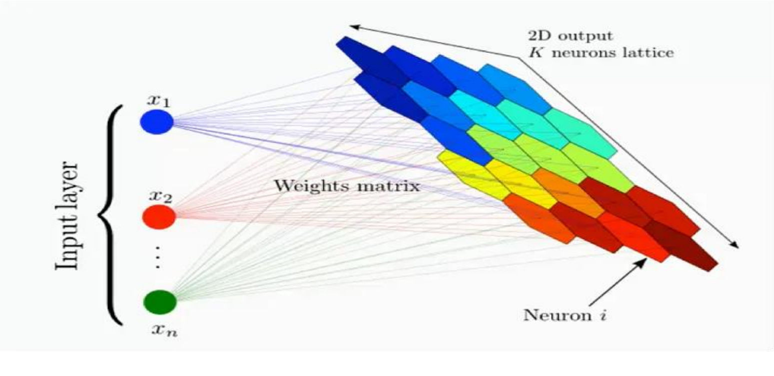


Fig2: Structure of a Kohonen neural network.

SOM is a type of neural network that is trained to produce a two-dimensional discretized representation of the input space of the training samples, called a map. Precisely, it is a nonlinear, ordered, smooth mapping of high dimensional input data onto the elements of a regular, low-dimensional array. Because of theirs ability to convert the nonlinear statistical relationships between high-dimensional data into simple geometric relationship of their image points on a regular two-dimensional grid of nodes, the SOM maps can be used for classification and visualizing of high-dimensional data [Dragomir,2014].

The key benefits of employing SOM for data mining include its numerical nature, non-parametric nature, lack of need for previous assumptions on the distribution of the data, and ability to recognize unexpected structures or patterns through unsupervised learning [Deboeck,1998].

2.1.1 Principles of Self-Organization in SOMs

Competitive Process

The values of a discriminant function are calculated by all neurons for each input pattern vector that is provided to the map. The neuron that most closely mimics the input pattern vector is the winner (best matching unit, or BMU).

Cooperative Process

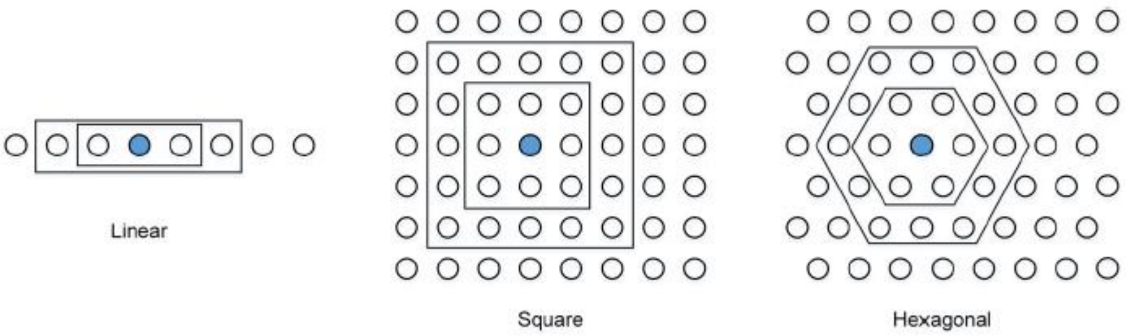
Finding a topological neighborhood of active neurons in space is the task of the winning neuron (BMU). The neurons in this region might then cooperate.

Synaptic Adaptation

Describes how the values of the discriminant function can be altered in relation to the input pattern vector that is being presented by activated neurons via weight changes. [Miljković,2017]

Common Topologies

SOM topologies can be in one, two, or even three dimensions. The two two-dimensional grid types most frequently employed in SOMs are rectangular and hexagonal. Three-



dimensional topologies might resemble cylinders or toroids. The 1-D (linear) and 2-D grids are shown in Figure 3, and the matching SOMs are shown in Figures 4 and 5.

Fig3. Most common grids and neuron neighborhoods

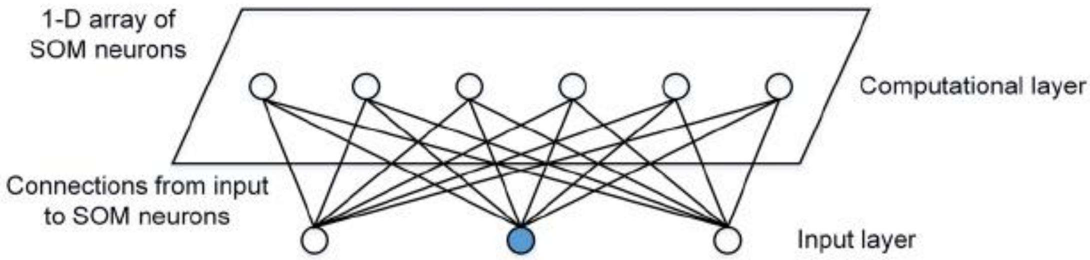


Fig4. 1-D SOM network.

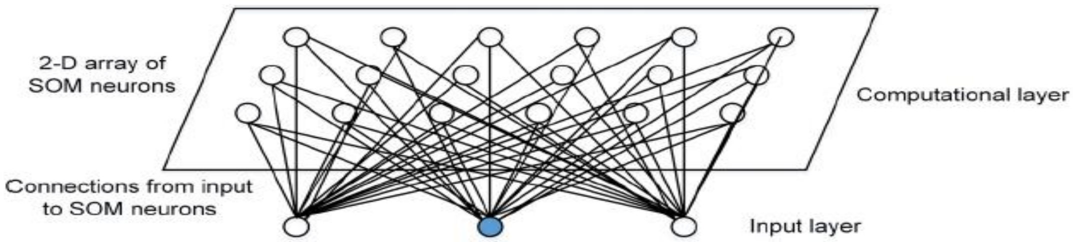


Fig5.2-D SOM network.

- Learning Algorithm

Professor Kohonen first introduced his SOM method in 1982. With the field advanced further with the release of the Second Edition of his book "Self-Organization and Associative Memory" in 1988.

-Measures of Distance and Similarity

Distance measurements are used to find commonalities between the neurons and the input vector. Among input pattern and SOM units, some common distances are:

- Euclidian
- Correlation
- Direction cosine
- Block distance

In practical applications, the squared Euclidean distance is most frequently used.

$$dj = \sum_{i} \left(x_i - w_{ij}\right)^2 \qquad (1)$$

-Neighborhood Functions

The neighbor function helps neurons in a grid communicate with one another. While there are other possible functions (such as the Gaussian, cone, and cylinder), neighborhood functions typically resemble the Mexican hat seen in Figure 6. There is a scientific explanation for this function, which involves rejecting those neurons that are close to the winning neuron.

The ordering procedure is independent of the function type selection if both the neighbor radius and learning rate reach 0. The most popular choice is the exponential decline.

$$h_g\left(w_{ij}, w_{mn}, r\right) = e^{-\frac{1}{2}\left(\frac{\sqrt{(i-n)^2+(j-m)^2}}{r}\right)^2} \qquad (2)$$

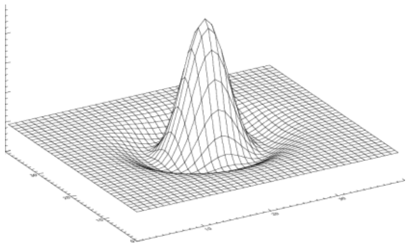


Fig6. Mexican hat function

-Initialization of Self-Organizing Maps

Prior to training, units, or the weights of the SOM, should be initialized. Typical techniques consist of:

1. using of random values unrelated to the training set.
2. Making use of arbitrary samples from the input training data
3. An initialization that attempts to reproduce the distribution of the data (Principal Components)

- Training

The most well-liked algorithm in the unsupervised learning category is used by self-organizing maps. The total of distances between all input vectors xn and their corresponding winning neuron weights wi, which are determined at the conclusion of each epoch, is the criteria D that is minimized.

$$D = \sum_{i=1}^{k} \sum_{n \in c_i} \left(\boldsymbol{x}_n - \boldsymbol{w}_i\right)^2 \qquad (3)$$

Self-organizing map training could be completed sequentially or in batches, as described in:

-Sequential training

- A single vector is supplied to the map at a time
- When each vector is delivered, the neuron weights are adjusted
- Suited for online learning

- Batch training

- Previously any adjustments are made to the neuron weights, the entire dataset is used.
- suitable for offline learning

Now are the current steps for the training in sequence:

1. Initialization: (iteration step n=0) Initialize the weights of the neurons.

2. Sampling: Choose a vector x(n) at random from the dataset.

3. Similarity Matching: Using weights wbmu=wc, identify the best matching unit (BMU),

$$c = \arg\min_i \left(\left\| x(n) - w_i(n) \right\| \right) \qquad (4)$$

4. Updating: Update each unit i with the following rule:

$$w_i(n+1) = w_i(n) + \alpha(n) h\left(w_{bmu}(n), w_i(n), r(n)\right) \left\| x(n) - w_i(n) \right\| \qquad (5)$$

5. Continuation: Increase n. Continue doing steps 2-4 until a stopping condition is satisfied (such as the predetermined number of iterations or the map has stabilized).

The neighborhood radius r and learning rate α(n) must both be decreasing with each iteration towards zero in order to ensure convergence and stability.

The number of input vectors that each SOM classification unit classifies is depicted in SOM Sample Hits as shown in Fig. 7 [Miljković,2017].

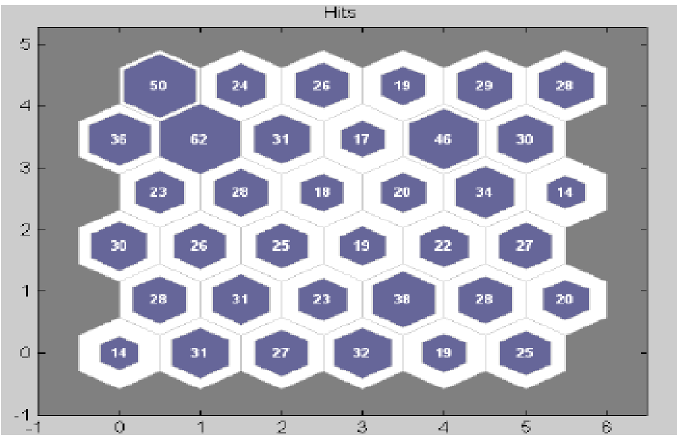


Fig 7. SOM Sample Hits.

Two steps of the training process may be identified:

•The initial step of self-organization is topological ordering, which occurs in the map (approximately the first 1000 repetitions). Both the neighborhood radius r and the learning rate n are declining.

•

•Convergence (fine-tuning) phase: In this stage, the input space is accurately statistically represented. At least (500 × number of neurons) iterations are usually required. The neighborhood radius r and the slower learning rate n may be left constant (for example, the most recent values from the previous phase) [Kohonen,2014].

-Classification

search for the best matching unit (BMU), c, Test pattern x belongs to the class represented by the best matching unit c. [Miljković,2017]

$$c = \arg\min_{i} \left(\left\| x - w_i \right\| \right) \qquad (6)$$

The process of implementing the SOM algorithm is shown in Figure 8:

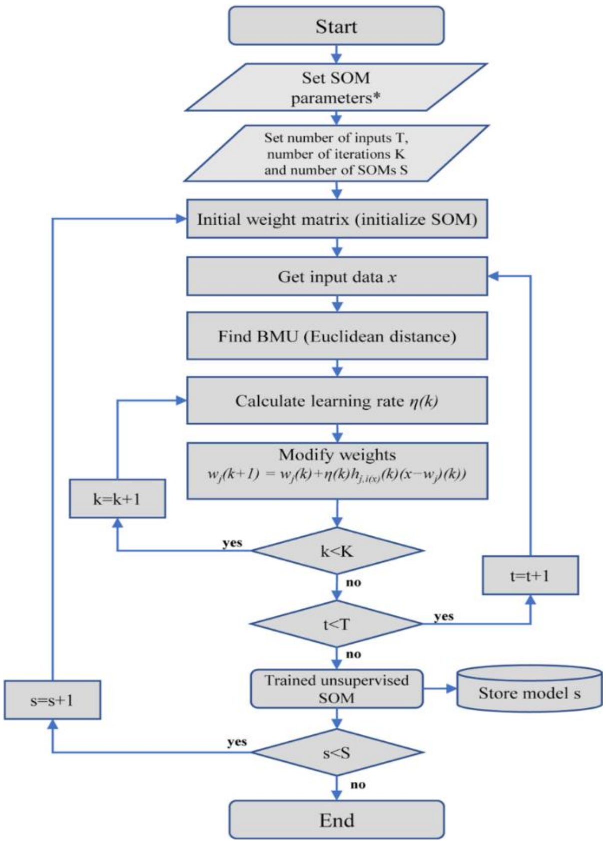


Fig8. Flowchart SOM algorithm

2.2 Uses of self-organizing maps

SOMs may be employed for a variety of application classes despite their simplicity. This broadly speaking comprises visualizations, feature map creation, categorization and pattern recognition. The following categories of applications were presented by Kohonen: Image analysis and machine vision are used for optical character recognition and script reading, speech analysis and recognition, musicals and acoustic studies, signal processing and radar measurements, telecommunications, industrial and other real-world measurements, process control, robotics, chemistry, physics, electronic circuit design, medical applications without image processing, and data processing logic (among others). We can only include a handful of them from the extensive and lengthy list that is provided here, due to space constraints.

2.2.1 Speech Recognition

Kohonen created the neural phonetic typewriter for Finnish and Japanese speech in 1988.

2.2.2 Text Clustering

The method of analyzing a lot of texts and determining their division is called text clustering. [Miljković,2017]

2.2.3 Chemistry application

SOMs have uses in the field of chemistry. Using a hexagonal grid, Fig9. illustrates the output layer of the SOM model for the combinatorial design of cannabis molecules.

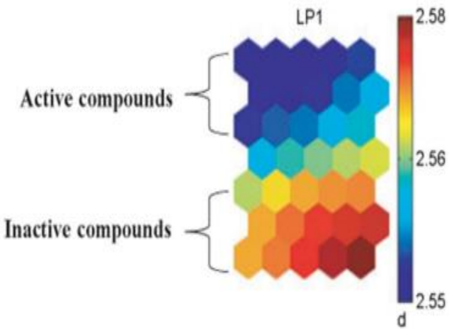


Fig9.Application of SOM in chemistry [Maltarollo,2013]

2.2.4 Medical Imaging and Analysis

SOMs may identify illnesses based on medical pictures (ECG, CAT scans, ultrasonic scans, etc.). Image segmentation, seen in Fig.10, is part of this process and is used to identify areas of interest and aid in diagnosis.

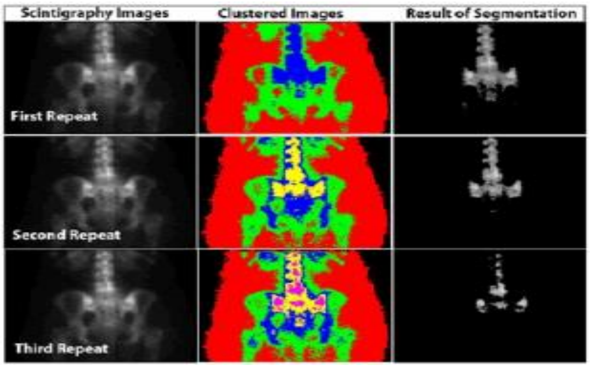


Fig10. Segmentation of hip image using SOM. [Aslantas et al.,2017]

2.2.5 Maritime Application

SOMs are widely utilized for maritime applications. Passive sonar record analysis is one example. Additionally, ship trajectories have been planned using SOMs [Lobo, 2009].

2.2.6 Robotics

Controlling a robot arm, learning a motion map, and resolving the traveling salesman issue (multi-goal route planning problem), are some examples of applications for SOMs.

2.2.7. Classification of Satellite Images

SOMs may be used to classify land cover in satellite photography, for example. The SOM may also be used to identify dust sources in photos, as demonstrated in Fig.11. [Miljković,2017]

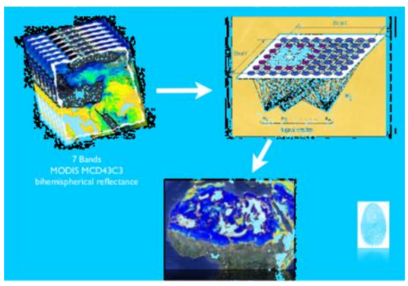


Figure 11. Detecting dust sources using SOMs

2.2.8. Exploring Music Collections

Analyzing the lyrics, instruments, melody, rhythm, artists, or feelings elicited by a piece of music can help assess how similar two or more pieces of music are. [Pampalk,2004].

2.2.9 Business Applications

Fig. 12(a) depicts the customer segmentation of the international tourism sector. Using the welfare map to categorize global poverty is another example, Fig. 12.b depicts the ranking of the items in relation to the 39 attributes describing different aspects of quality of life, like diet, health, and educational services. Countries with similar quality of life indices were placed together on a map.

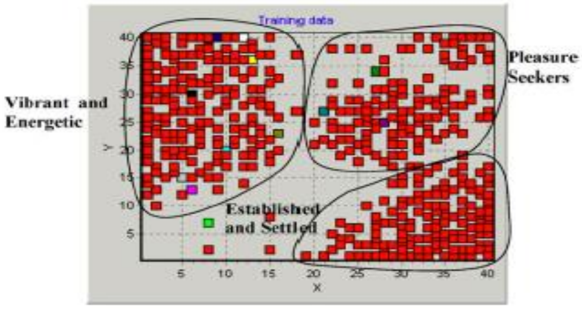


Fig12.(a) Customer segmentation of the international tourist market. [Bloom,2005]

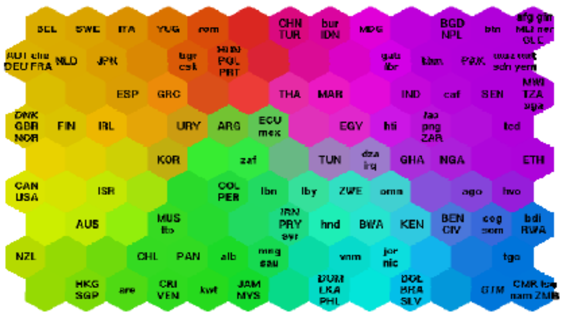


Fig12. (b) Poverty map based on 39 indicators from World Bank statistics (1992). [Bastos,2021]

2.2.10 color reduction

True color images can be represented using the common image processing approach known as "color quantization." employing only a small number of colors and is beneficial for picture compression, image retrieval, and displaying images on hardware with limitations, such as mobile devices. True color photographs frequently employ 24 bits per pixel, giving them a total gamut of 224, or more than 16 million distinct colors. Color quantization employs a color palette with a limited number of colors (often 8 to 256), and pixel information is then saved as indices to this palette. It is obvious that the palette's selection of colors has a significant impact on the quantized image's image quality.

The best color scheme selection is recognized to be a np-hard task, nevertheless. Many alternative techniques have been proposed in the literature on image processing with the goal of finding a palette that allows for high image quality in the quantized image. To find a suitable palette, soft computing techniques like genetic algorithms have also been used.

The job of finding the clusters that most accurately capture the colors in an image is what is known as the "best representation" problem in the context of color quantization [Schaefer,2009].

2.3 Advantages of SOM

Self-organizing maps are useful for reducing data complexity and illuminating underlying patterns and linkages. SOMs have a number of advantages:

1. A straight forward algorithm.
2. Topological grouping.
3. An algorithm that uses nonlinear data sets and is unsupervised.
4. It is exceptional for dimensionality reduction because of its capacity to display high-dimensional data onto 1 or 2 dimensional spaces.

2.4 Disadvantages of SOM

1. A lot of high-quality training data is needed for SOMs.
2. Self-organizing maps have very high computational expenses.
3. In the face of slowly developing data, SOMs require a considerable amount of training time.
4. They don't work well with mixed-type and categorical data.
5. Clustering patterns are influenced by the initial weight vector.
6. Determining the ideal map size is challenging [Patole et al.,2010].

4. Methodology

4.1 Applied Self-organizing maps method

The new color reduction technique that is suggested in this paper takes advantage of both the local spatial image properties and the colors of the pixel. There is no color palette used throughout the color reduction procedure. A color grouping method based on neural networks chooses the final colors automatically. Each pixel's color is influenced by its neighbors' colors and textures. The novel method can be viewed as a feature grouping strategy. The first three attributes are specifically thought of as the RGB or HSV parts of each pixel. Additional features that are drawn from nearby pixels complete the entire feature set. These qualities, including entropy, contrast, and mean values, can be connected to spatial picture attributes. A Kohonen is fed by the feature set [Aggarwa,1998].

A color picture may be thought of as a collection of n*m pixels, where each pixel corresponds to a single RGB color point. Each pixel (i, j) in RGB space is defined by an ordered triple of red, green, and blue coordinates, or (r (i, j), g (i, j), and (b(i, j)). The relationship may thus be used to create a generic image function:

$$I(i,j,k) = \begin{cases} r(i,j), & \text{if } k = 1, \\ g(i,j), & \text{if } k = 2, \\ b(i,j), & \text{if } k = 3 \end{cases} \quad (7)$$

The intensity of each main color component—red, green, or blue—varies linearly from zero to the highest value, C max. The definition of color allocation spans an RGB space cube with opposing vertices at (0, 0, 0) and (Cr_max, Cg_max, Cb_max). Examine the situation when Cr_max = Cg_max = Cb_max = 255.

Let's also call the area around pixel (i, j) N (i, j). The majority of the time, it is safe to presume that pixel (i, j) belongs to N (i, j). In this method, the pixel (i, j) serves as the center of the 3*3 mask called N (i, j). The majority of the time, the local texture of the picture and the colors of the nearby pixels are used to determine the color of each pixel. For these reasons, local picture attributes that are collected from the adjacent area N (i, j) can be linked to the color of pixel (i, j). Local characteristics can be defined using the color values of N (i, j), fk, k = 1,2,..., K. These are regarded as picture spatial features. This allows for the relationship between each pixel (i, j), its components (r(i, j), g(i, j), and b(i, j)), as well as the K extra features (fk). Regarding the kind of features, there are no suggested limitations. Nonetheless, the features need to depict basic spatial properties like entropy of the surrounding masks, contrast, and median RGB values. By using local masks, it is simple to extract such features, which can be linked to either linear or nonlinear operators. According to the study above, the optimum way to convert the original color image into a new one with just J colors and about the same local features is the color reduction issue.

Viewing it as a clustering problem and solving it with a proper SOFM neural network is a useful strategy. It is commonly known that a SOFM neural network's primary objective is to represent a sizable collection of input vectors with a smaller collection of "prototype" vectors, allowing for the "good" approximation of the original input space. In other words, a SOFM neural network effectively shrinks the input feature space. The final feature space meets the primary statistical features of the input space since it is a representation of the original feature space.

The Kohonen SOFM neural network's structure is shown in Figure 2 of the SOFM neural network. It has J output neurons and K 1 3 input neurons set up in a 1-D grid. The RGB values of pixel (i, j) are sent into the first three input neurons. The values of the remaining K neurons are sent to those that correspond to the local features fk, k = 1, 2,..., K. In the competition layer, each neuron stands for a certain class, which is related to both the spatial information employed and the RGB values.

The amount of colors in the final image may be controlled by varying the number of output neurons. The wi,j, i =1,..., K 1 3 and j = 1,..., J coefficients connect the input neurons and the output J neurons. The following weight update function determines how the SOFM is competitively trained:

$$\Delta w_{ji} = \begin{cases} a(y_i - w_{ji}), & if \quad |c - j| \leq d, \\ 0, & otherwise \end{cases} \qquad (8)$$

$$i = 1, \ldots, K+3 \; and \; j = 1, \ldots, J$$

where an is the learning parameter, d is the nearby parameter (an initial value of less than 0.25 is common), c is the winner neuron, and y and j are the input values. In the process of learning, the values of parameters a and d are lowered to zero. Kohonen's learning is the name given to this learning algorithm. Following training, the neural network's ideal RGB values are equal to

$$\left.\begin{aligned} r(j) &= w_{1j}, \quad j = 1, \ldots, J \\ g(j) &= w_{2j}, \quad j = 1, \ldots, J \\ b(j) &= w_{3j}, \quad j = 1, \ldots, J \end{aligned}\right\} \qquad (9)$$

The first image is then rescanned. The neural network creates a new image with just J colors that closely mimics the spatial properties of the original image using the spatial information that was used. If spatial features are not needed, RGB colors can be used to feed and train the neural network instead. It is evident that this technique yields a reduced range of RGB colors that are ideally similar to the original image's color distribution (as per Kohonen's learning rule) [Papamarkos, 1999]..

In this project a self-organizing map algorithm was applied as shown in Figure 13 for color reduction and quantization. It first loads the image and converts it to an RGB or HSV color space. Then the user is asked to select the number of colors needed. Finally, it performs compilation with SOM and generates a thumbnail.

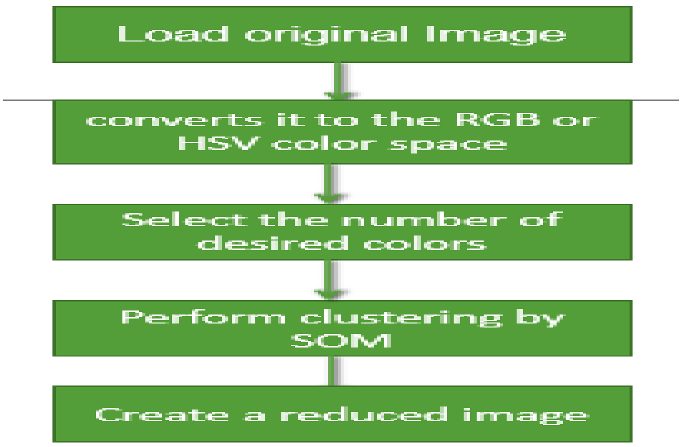


Fig13. Flowchart of color reduction and quantization using SOM

4.2 K-means Clustering Method

It is clear from the literature that one of the most often used clustering methods for data clustering is K-means clustering. Starting with k random clusters, the K-means technique. When using k-means clustering, all input data is assigned to the cluster with the fewest repetitions of data intervals. The mean of specific data is used to calculate the centroid of the cluster, and this process is repeated until the centroid of the cluster remains constant. As a result, the palette's colors are chosen from the centroid of the final clusters' centroids. The k-means algorithm was introduced by the authors, and we use the same technique in our study [Hu et al.,2007].

The following summarizes a typical k-means clustering algorithm:

- Step1: Select k centroids vectors in space
- Step2: Assign every input to the cluster which consists of the nearest centroid
- Step3: Re-calculate the entirecentroid vectors that display the average of the vectors that allocated to this cluster
- Step4: Repeat stages 2 and 3 until the method attain the stopping criterion. The K-means clustering aims is to minimize an objective function (sum of squared error (SSE)):

$$\arg\min \sum_{i=1}^{k} \sum_{x \epsilon S_i} \|X - \mu_i\|^2 \qquad (10)$$

(x1,x2,….xn) is a set of observation where μi is the average of points in Si .The target of k-means clustering is divided inton observation into k (≤ n) sets S={S1,S2,…,SK} for minimizing of the within-cluster sum of squares.

4.3 Performance evaluation

In our study, the performance indicators employed to evaluate the efficacy of color quantization are mean square error (MSE). This is how the MSE assessment measure is explained: Mean Square Error, or MSE Mean square error evaluates the quantized image by drawing a comparison between it and the original. Since MSE is normally a non-negative number, higher performance is indicated by lower MSE values. The mean-square error can be calculated using the formula below:

$$MSE(X, \hat{X}) = \frac{1}{HW} \sum_{h=1}^{H} \sum_{w=1}^{W} \|X(h,w) - \hat{X}(h,w)\|_2^2 \qquad (11)$$

Where X and X illustrate original and quantization image respectively. In addition, H and W present image height and width respectively [SAMIRA et al.,2019].

5. Results and Discussion

The entire method has been implemented using MATLAB. In this section, we discuss the experimental findings and performance evaluation of the self-organizing map color quantization method. Fig.14a, Fig.14b, Fig.14c, Fig.14d and Fig.14e presents the quantized of tested images .

a) b) c) d)

e) f) g) h)

Fig14a. The original images used to test the self-organization map

This section contains the experimental findings that we used to evaluate the efficacy of color quantization methods, k-means clustering, and self-organizing maps. In this experimental setting, we have taken two pictures(g and h) into account two true-color(24-bit) test images, namely (g) Lena picture and (h) Pepper image with varied k (k=16,32,64, and 128) that are widely utilized in the literature. The RGB lab space is where the color quantization is put into practice. For the various k values (k=16, 32, 64, 128), we have shown the quantized pictures for the Lena image and the pepper image in the figures from 1 to 8. Along with the quantized pictures, we have also included the mean square error to assess the quantized image using the four-color quantization tables for various k values, i.e. for (k=16, 32, 64, and 128) in the quantization tables.

Fig.14b The results of Lena image by self-organizing maps with different k (16 32,64and 128).

Fig.14c The results of Lena image by k-means algorithm with different k (16 32,64and 128).

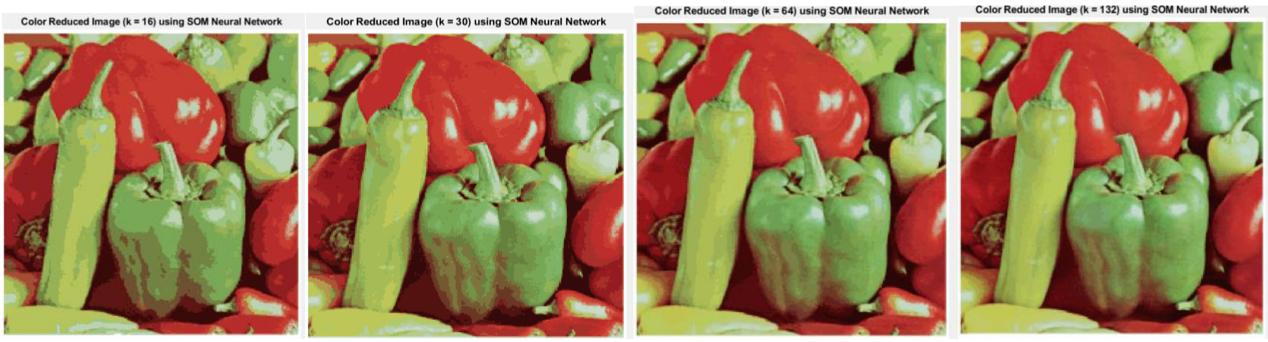


Fig.14.d The results of Peppers image by self-organizing maps with different k (16 32,64and 128).

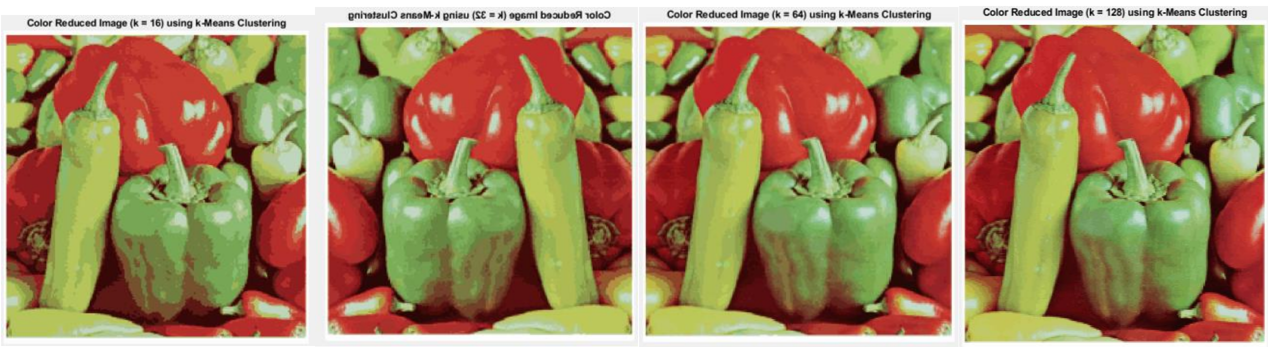


Fig14e The results of Peppers image by k-means algorithm with different k (16 32,64and 128).

- Table 1 shows that for all possible k values, the MSE for the K-means approach is lowest for both the Lena and Pepper pictures. When compared to the SOM approach, the K means' strong resilience is indicated by the smallest MSE value. Additionally, Table 1 demonstrates that SOM is ranked second for the best value.

- In some situations, SOM's performance is on par with K-means. The effect of the winner is diminished when SOM utilizes a big enough size of map for learning, which is the primary cause of the performance decline of SOM.
- The experimental findings also show that the k-means clustering is a straightforward but effective approach for color quantization. The temporal complexity of k-means is the sole issue it faces.

Table1. The results of MSE comparison values of the color quantization methods.

image	k	K_means	SOM
Lena	16	71.27(1.50)	72.72(1.88)
	32	37.02(0.23)	39.92(0.29)
	64	22.00(0.15)	22.82(0.22)
	128	13.77(0.04)	14.40(0.22)
Peppers	16	121.30(1.32)	123.52(1.48)
	32	70.30(0.64)	76.01(0.66)
	64	41.17(0.16)	43.20(0.43)
	128	25.29(0.11)	26.99(0.33)

6. Conclusion

It is seen in Table 1 that for all possible k values, the MSE for the K-means method is lowest for both the Lena and Pepper images. When compared to the SOM approach, the K means' strong resilience is shown by the smallest MSE value compared to SOM. As a result, the structure, ideas, benefits, drawbacks, and applications of the self-organizing map algorithm are covered in great detail in this paper. Self-organizing maps, the K-means color quantization approach, and, in order to assess the effectiveness of color quantization approaches, the mean square error was also used as a performance measure. The K-means algorithm is the more efficient method, according to the experimental data k values, since it performs better.

7. Reference

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