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Original Article

The novel self-organizing map combined with fuzzy C-means and K-means convolution for a soft and hard natural digital image segmentation

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ABSTRACT: Digital image segmentation plays an important role in noise reduction and pixel clustering for pre-processing of deep learning or feature extraction. The classic Self-Organizing Map (SOM) algorithm is a well-known unsupervised clustering neural network model. This classic method works on continuous data instead of discrete data sets with a widely scattered distribution. The novel SOM(SOM2) modelling solved this problem for the classic, simple tabular discrete data set but not for the digital image data. As the essence of digital image pixels data are different from tabular datasets, we have to look at them differently. This paper proposes exploiting the novel SOM method with a hybrid combination of the fuzzy C-Means and K-means convolution filter as image segmentation and noise reduction with soft and hard segmentation as entropy reduction for natural digital images. The main approach of this paper is the segmentation of image contents for the reduction of noises and saturation pixels by entropy criteria. Based on the resulting paper, the combination of SOM2 with FCM for soft segmentation 47%-and the combination of SOM2 with k-means convolution for hard segmentation 33% can reduce the entropy of the original image on average.

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1. Introduction

The importance of data in the age of artificial intelligence has been becoming more and more bright day by day. in forecasting and modelling, we need the previous pattern information. In this case, extracting and cleaning data can be noticeable. We can look at digital images such as rich data mines; they are accessible and replete with broad information. By this means, feature extraction is a significant concept in image processing. The successful feature extraction needs a successful segmentation. By this cause, segmentation and noise reduction play a considerable role in middle and high-image processing.

Image segmentation generally encompasses the practical types of colour and texture. Segmentation in digital images means separating the components in terms of colour or texture with hard or soft boundaries to detect objects and concepts. Colour segmentation is used when colour is an important attribute of the object, such as paint analysing or cancer detection. Recent articles are still introducing new algorithm methods for better performance and more precision for traditional bi-level color segmentation [29, 18] and multi-level color segmentation [13, 1].

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Moreover, another segmentation type is based on texture clustering, which separates objects using the light intensity value; the recent searches still work on their accuracy [32, 34, 17] the trending subject in texture segmentation is based on Gray Level Co-occurrence Matrix [3, 31].

The segmentation methods are divided into; edge detection, region-based, cluster model, fuzzy and training model; the recent articles improved them for various applications [14, 21], and each of which is divided into hard [7, 33, 15] and soft segmentation [10, 8].

Our proposed model relates to texture segmentation with a training model for soft and hard boundaries. Our proposed model is related to texture segmentation with a training model for soft and hard boundaries. Image segmentation has various intents, such as pre-processing for deep learning, feature extraction, and noise reduction of external or internal objects, such as hard or soft segmentation. In such a case, we should define the degree of density for segmentation due to our input image. We should decide which algorithms could be helpful based on the input image and our intention.

For example, suppose the interior detail of the image's object is significant. In that case, we shall use segmentation with a low-density segmentation, such as when we want to detect a tumour in a medical image. By contrast, we shall use a high-density degree of segmentation or hard segmentation if we consider the whole object and contents in a photo when the object's exterior is meaningful, such as animal detection in the forest or galaxy recognition. Some technics of segmentation let us modify the degree of segmentation density, such as K-means. Moreover, another one is the SOM model, in which we can set the size of the map to opt for which density degree of segmentation we consider. Furthermore, each type of segmentation generally has its application and properties; for example, segmentation with a convolution network or K-means algorithm is used for the exterior surface detection of the objects; on the other hand, fuzzy algorithms are used for soft segmentation. The Self-Organised map is used for internal and external contents depending on the map size; in such a case, combined with a soft clustering like the fuzzy model, it causes more noise reduction with a low density of segmentation(or soft segmentation). Furthermore, with the map's small size combined with the hard cluster algorithm such as the K-means Convolution network, we can utilise it for the exterior surface detection of the objects with a high density of segmentation or hard image segmentation. Depending on the project, we should decide which algorithms to use.

The artificial neural network is a well-known training algorithm in supervised, and unsupervised data modelling. The Self-Organizing Map is an eminent neural network data unsupervised clustering presented by Kohonen [16]. Experimentally this method could not be effective for discrete clustering data, mainly when our dataset is so scattered [11] because this model considers just the first winner neuron during learning weights and is not oriented by other candidates. In this model, the result is based just on the first winners; thereby, the local and premature result is possible. The novel Self-Organizing Map(SOM2) was improved for discrete groups of data clustering by Ghaseminezhad and Karami [11]; It solved the main problem of classic SOM. According to the article's conclusion, this modelling has been tested on the traditional simple data set but not for image pixels and interwoven data. By this intent, as we want to utilise this algorithm for image processing, we should first recognise the main difference between the classic data set(tabulate data) and image pixels. In successful deep learning or modelling and analysis, we need successful pre-processing before any data training. Insufficient and noisy data corrupts modelling; our data-based should be cleaned from anomalies and noises in such a case. Reducing entropy reduces noise and outlier data as long as it does not damage the original and essential data, thus cleaning the data and preparing it for modelling and learning. In our proposed model, we are intended to use the blended algorithm for entropy reduction as noise reduction and lightening from outliers; in this way, the benchmark of our proposed model is entropy. In explaining the hybrid model, as we want to use SOM2, which has been tested just for classic data sets, we shall first express the differences between classic data sets and digital images. And then describe the classic SOM and the SOM2; after that, we introduce the proposed improved algorithm for showing image segmentation combined with the K-means convolution network and FCM.

combined with a k-means convolution kernel as a noise reduction and more discrimination between external objects in the photo. When we want a soft segmentation with a low-level segmentation density, we utilise the fuzzy clustering model by C-means for recognising details and smoothing more noises for the image in which the object's interior is significant.

In summary, we use SOM2 with a K-means convolution network for hard segmentation. For soft segmentation, we utilise SOM2 with fuzzy C-means.

2. The differences between the classic data set and digital images.

Let's take a look at C. Gonzalez's definition of digital image processing [12]. We conclude that a digital image is a matrix function comprising a finite number of attributes, each having its spatial location and light intensity value. We can conclude that each value depends on other matters to make a meaningful picture due to the continuous information with discreet pixels. In comparison, our data is interwoven and connected. In contrast to the classic data set, we should consider the total of pixels that every component is not independent. However, each input does not relate to another input in the classic data set. Because of these interwoven pixels, segmentation and feature extraction are fundamental subjects in image processing.

Another main difference is that pre-processing for images is not similar to common classic data sets preparation. As the types of noises in the image are different, and their behaviour is not like the classic data set. For better comprehension, let us take an example; Imagine that there is a bear in the forest predating the fish in the river in one photo. Suppose we want to recognise the bear visually by a segmentation algorithm. In that case, we should consider all of the objects, and details in the photo, like leaves, drops of water, and fish in the bear's mouth, which in terms of biology is not related to the bear. Before image segmentation, we could not eliminate unrelated objects to facilitate object detection. But in a classic data set, we can add or eliminate columns and indexes, detect the outlier and noises and fix them, whereas, in an image, we cannot eliminate or add the column and improving the noises is not similar to classic data sets. Behaviour with image data differs from a classic data set because the only information in the image is just intensity and spatial. Eventually, the behaviour for image segmentation is different from a classic data set.

In this section, we briefly introduce and compare classic SOM and SOM 2.

3. The brief of the classic self-organising map(SOM) and the novel SOM2

3.1. Classic SOM

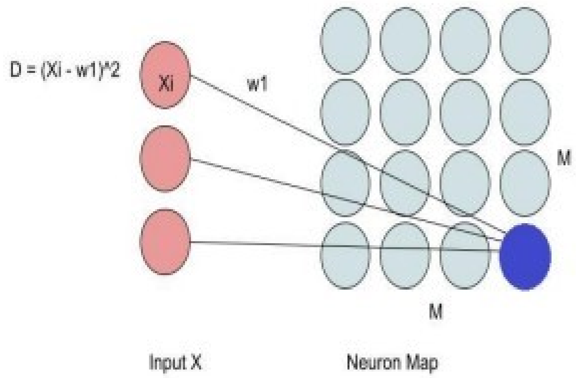

Figure 1: Basic structure of the SOM. Finding the minimum distance between each neuron with input by euclidean distance.

This algorithm is one of the eminent unsupervised methods for data clustering. Moreover, it has frequently been used in new articles [19, 22]. The application of this method is more for the continuous classic data set, not suitable for discrete data. As an image is discontinued data, the main problem of the classic SOM in the image segmentation is that; as the image has got many saturated and noisy data, this algorithm could not make a satisfactory noise reduction; for this reason, it causes poor segmentation.

3.2. Novel SOM2

After the classic SOM in 1990, many articles introduced modified and optimised traditional SOM [25]. The improved SOM2 of Ghaseminezhad and Karami [11] is a novel method based on the classic SOM for discrete data groups.

This algorithm involves two main parts, one of them is: the second winner and the other is batch learning phases, which avoid being trapped in a local solution for discrete data. Moreover, it solves the main problem of the last versions in such a case. This method has been presented for classic data sets instead of image segmentation.

Let us briefly look at the SOM2 and then compare it with the classic model. In the first phase of SOM2, the map gets the neuron weights with random numbers. The next part is the distance of the input with the neuron's map calculated by Euclidean distance; the minimum distance is the first winner. This algorithm considers the second and the first winners near neighbourhoods in addition to the first. The weights (τ: learning rate function) and ρ (neighbourhood order function) update so:

$$weight(t+1) = weight(t) + \tau \exp^{-\varepsilon(\|D\|)D} \tag{1}$$
$$D = xi - weight(t) \tag{2}$$
$$\tau(next) = \tau(0) \times \exp^{-t/T} \tag{3}$$
$$\rho(next) = ceil.\rho(0) \times \exp^{-t/T} \tag{4}$$
$$t = t+1$$

ceil function rounds the number towards up integer and ε is a small value. In contrast to classic SOM, $\tau(0)$ is defined in the range of 2 to 6. This part repeats t time until $t = T$(total iteration)
In the second phase of SOM2, at first, we define the $\tau(0), \rho(0)$ and the Batch learning function.

$$\Gamma(last) = \Gamma(0) \times (1 - \exp^{-t/3T}) \tag{5}$$

Γ is Batch learning function
And, we set a parameter $\varepsilon = 0$. Each time we calculate the weight change of the first winner and its neighbourhood, but not the second winner.

This iteration continues until that $b >= \Gamma$. In this case, the loop stop and goes to the next part the map neurons from the first phase are updated again:

$$weight(next) = weight(last) + \sum(\Delta weight(i)) \tag{6}$$
$$\Delta weight(i) = \tau \times \exp^{-\varepsilon(\|D\|)^2)} \times D \tag{7}$$
$$D = xi - weight(last)$$

When the *weights* are updated we set $\Delta weight = 0$, and it goes to the first loop of the second phase(3).

The total iteration with $t = T$ is finished. Check the article for more information and a total understanding of the SOM2 step by step [16]. The main difference between classic SOM and SOM2 is that the SOM2 in the first phase considers the second winner and the first winner near neighbourhoods (7) instead of just the first winner. Another difference is the definition of new updates of weight and alpha (1)(6), and the amount of $\tau(0)$ in the classic SOM and SOM2 is different. The next difference is Batch learning which does not exist in the traditional SOM. The next difference is Batch learning which does not exist in the classic SOM. Moreover, in terms of time complexity, the classic SOM with $O(n^2)$ works better than SOM2 with $O(n^3)$. In a sense, when the time signs of progress would not be necessary, the SOM2 accuracy is dominant

4. The proposed model as image segmentation

4.1. Pre-processing

As explained, the difference between the image and classic data set, we should behave with the image differently. When we observe the image aspect of signals reciprocally, we must consider the noises. Before denoising, the pixels should be normalised in float32 numbers between -1 to 1 and translated the image to the greyscale mod. As gaussian denoising, it should be defined that one kernel with m*m size should be typically 3*3; with the Gaussian convolution kernel with a lowpass filter, the image would be prepared and relaxed for segmentation.

4.2. Segmentation with SOM2

As it talked, the SOM2 has got two phases. The next part of our proposed image processing is the first phase of SOM2, in which, this time, our xi inputs are the pixel value. The size of the map depends on our target; with a large map, we would have got more class of segmentation, which cause a low level of segmentation intensity; by contrast, with a small map, the number of segmentation classes are reduced; in such cases, the segmentation would be more intense.

Because segmentation with self-organising map segments through pixel by pixel and the first value of the map with random number arranged, it causes some pixels oriented to the wrong class segmentation, in such case after segmentation of map learning we will be confronted with noises and saturation pixels, by this means we need obviously to noise reduction. As our proposed method is for soft and hard segmentation for each type of segmentation, we consider special noise reduction as a supplementary segmentation. This part combines the fuzzy clustering model with neural network clustering. Because of segmentation with probability, it would be called the soft cluster model instead hard cluster. One of the most eminent fuzzy algorithms is C-Means. According to recent articles, this algorithm is still combined with various algorithms for optimisation in hyper and meta-heuristic, supervised and unsupervised [22]. Because the neural network algorithm works on continuous data rather than discrete, it would need a combination with another type of segmentation because of pure clustering and better noise reduction.

As an example, SOM(KM) [4, 27], that classic SOM combined with the K-means model for segmentation, which model is applicable Identification of different manifestations of nonlinear. The hybrid of traditional SOM and FCM has been tested in recent articles [22]. But this time wants to utilise SOM2 with FCM and kmeans+convolution. The C-means algorithm is a powerful clustering model used in the new articles [6, 9] and the review [23]. According to the new research; because of bad and noisy segmentation, pure information is oriented to poor segmentation [28, 20, 26]. This issue is also caused when the amount of clusters is large; it causes incorrect shaping segmentation. This means we need a fuzzy model to improve this problem to have better noise reduction and classification during the procedure. And in this paper, we use C-means after the neural network clustering algorithm. The brief of the process is shown in fig. 2. The blended SOM2FCM for soft texture segmentation was introduced, and the proposed model results were demonstrated in the next part.

4.3. Noise reduction and hybrid supplementary with k-means convolution and FCM

4.3.1. Combining with K-means convolution

If we consider segmentation with high density and hard boundaries, we utilise k-means and a convolution network system. After processing with SOM2, this time, we use this sequential system. K-means is a hard cluster model used for the intensity of light clustering with a defined degree of k. It Lets us define the number of classifications and the degree of segmentation intensity in such a case. This simple classic algorithm is beneficial and, in combination with another algorithm, gives us great results; the hot articles combined it with other models [26]. The first step is noise reduction by a Gaussian lowpass level convolution filter. The convolution Gaussian filter should be in the size of 3*3 and 2D because we need just the intensity of colour and we ignore the RGB attributes. We need a lowpass level of filter because with the Gaussian filter, we want to do a pre-noise reduction for preparing k-means (the main noise reduction). Then light intensity clustering by k-means, we set the first $k = 10$ and again the convolution filter. The next k means continuous with 9 cluster class numbers. This sequential continues until $k = 5$. In Fig. 2, the whole idea is shown in the following figure.

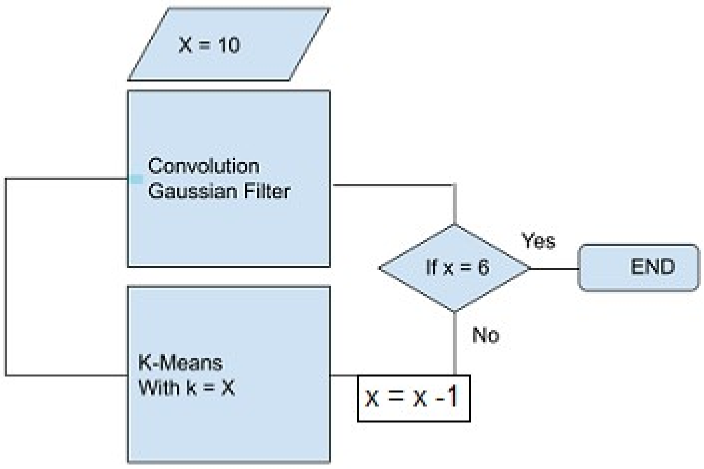

Figure 2: K-means Convolution schema

According to the flowchart each time image is denoised by convolution and k-means, each time the size of k reduces because we want to do noise reduction step by step, the algorithm stops when k gets the 5 value. We do not need k less than 5 values because if the image cluster with less number ($k < 5$) the image content is damaged and would be saturated, moreover with $k > 5$ we cannot expect satisfied noise reduction. Note that, there is no exact restriction thresholding, we consider it by experiment and trial and error in our datasets.

With SOM2 and K-means convolution series, the contents of the image would be segmented with hard boundaries instead SOM2 and FCM; in such a case, the noise would be reduced more than SOM2 FCM

4.3.2. Combining with FCM

When the interior of the objects is necessary, we shall use SOM2 with FCM; FCM is used as combination algorithm in recent articles [21, 2]. We use this combination when we consider soft segmentation. on the other hand, when we want to utilise hard segmentation without interior information, we use SOM2 with a K-means convolution network. The total idea and main flowchart have been shown in the following image:

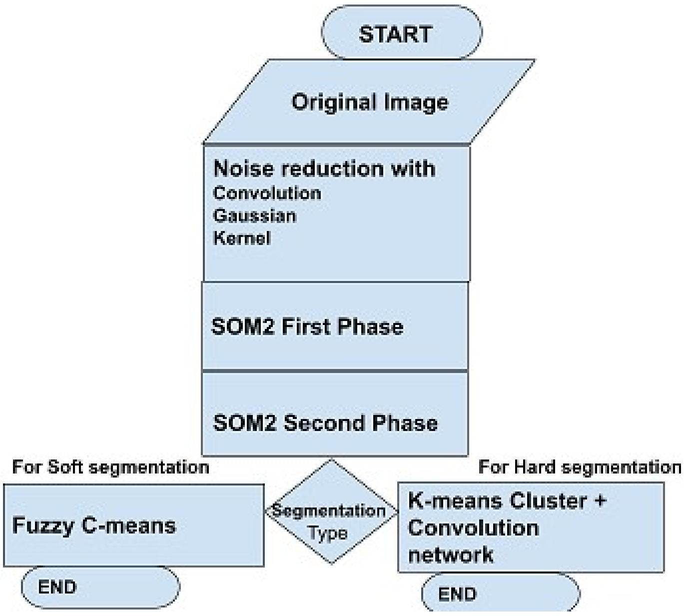

Figure 3: The Scheme of the proposed combined method, SOM2 with FCM and K-means a convolution.

The next part, as a result, shows the segmentation visually with some examples of entropy criteria.

5. Result

In the result, we consider showing practical examples of our proposed noise reduction and segmentation model. As discussed, the proposed model encompasses two main parts; SOM2 + FCM as soft segmentation and SOM2 + K-means convolution as hard separation and noise reduction.

There is no particular function error to success segmentation criteria because each type of segmentation has its application; some segmentation success criteria are observation of the eyes expert, such as tumour detection. We cannot define one global benchmark of success segmentation. During the duration of segmentation, our goal is to reduce noise for better object detection, which depends on our photos and project. Some photos' content is sensitive, and the noise reduction is limited because the object's content would be eliminated, such as handwriting detection or fingerprint feature extraction; in such cases, we should utilise a particular benchmark for each segmentation.

In practice, we should consider which algorithm and filter with which segmentation density degree(Map size) is property depending on the project. The profit of the SOM is that we can define the degree of segmentation density; based on the project, we determine the size map photo.

As expressed in the introduction, the paper's goal is entropy reduction without damaging the original and vital data as one way to lighten data outliers and noises; for this reason, our criteria are based on entropy by comparing the classic model. Entropy has been used as a benchmark of noise reduction in current research as hard segmentation benchmark [30] and soft segmentation noise reduction criteria [24] and as color segmentation criteria [5].

In the result, we have used the classic SOM of Kohonen (1990) [16] and the classic SOM+FCM of Dehghanian(2019) [9] and utilized Prezelj(2022) [27] article for the classic SOM+Kmeans. In this article, all images were used from free and open-source sites of pixabay.com.

5.1. SOM2 + FCM result.

When we desire soft segmentation and the interior contents of the image are necessary, we shall use SOM2 with a vast map + FCM.

According to the proposed model, we should first segment the image by SOM2 and then use the Fuzzy model as soft segmentation. In fig. 5, the left image shows segmentation by SOM2 with a 20*20 size map, and on the right.

With SOM2 + FCM, the girl and leaves are more denoised than SOM2. Noise reduction without damaging the necessary details of the original input is the most important target of success segmentation. To better realise the difference between segmentation, the entropy of the original image and the two-segmented model in fig. 5, let us concentrate more on the difference between the original photo SOM2 and SOM2 + FCM.

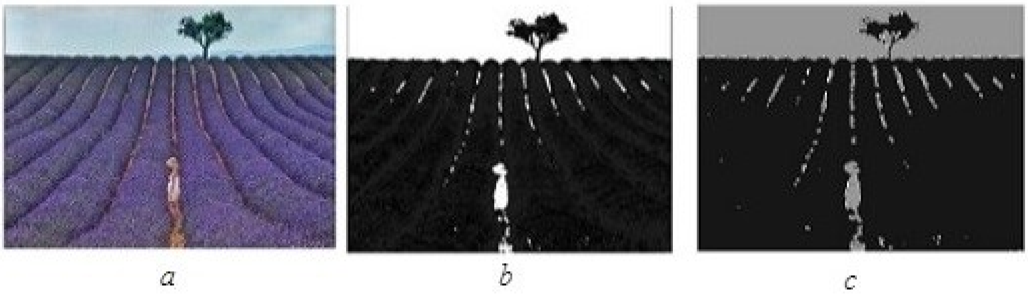

Figure 4: From left to right, (a)Original photo (b) SOM2 with a 20*20 map size from left to right, and (c) SOM2 + FCM segmentation.

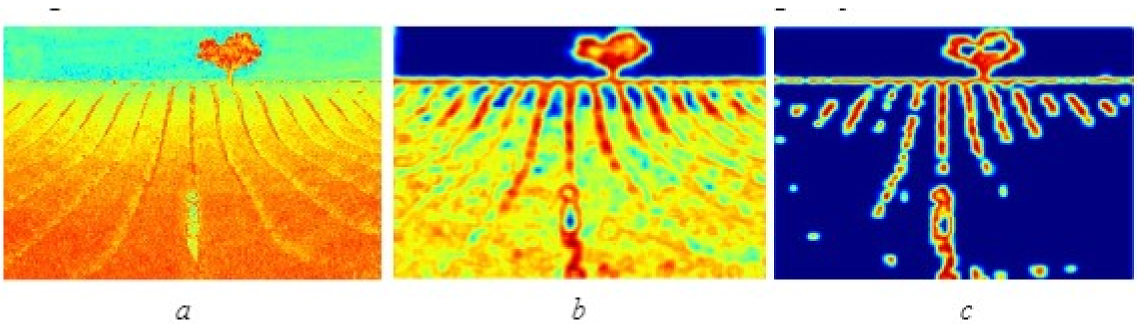

Figure 5: From left to right, (a)Entropy of original image, (b) SOM2 and (c) SOM2 + FCM

Based on fig. 5, visually, the entropy of the SOM2+FCM is less than SOM2 and the original photo. The mean entropy and variance of each photo have been described in the table. 1.

Table 1: Entropy and Variance of the original SOM2 and SOM2 + FCM of the first example with map size = 20*20.

Mean-Entropy	
Original photo	6.81
SOM2	5.02
SOM2+FCM	3.04

According to the table. 1 The variance and mean entropy of the proposed model are more minor than SOM2 and the original image. It means, Without damaging the essential details of the photo, the scattering and confusion of the original photo are reduced by SOM2 + FCM; this result leads to successful noise reduction.

5.2. SOM2 + K-means convolution result.

Another part of the proposed model is hard segmentation with a combination of SOM2 with 15*15 map size and K-means convolution. This model is used when the exterior of the image components is essential, as a matter of fact, with map size and k degree, we can modify the degree of the segmentation density.

Based on the introduced model, we shall segment the image by SOM2 and then use K-means convolution.

As we discussed, the combination of SOM2 and K-means convolution is helpful for hard segmentation when the interior of the contents is not useful. In our example, we consider the sunset image; as we want to segment the light range of the sun in the sky.

When just the boundaries of the contents are essential, not the interior of the objects, we use this type of blended proposed algorithm. In such a case, the image of the tree and hills in the photo is unnecessary and should be denoised.

According to the proposed model, we segment with SOM2 with a 15*15 map size and then denoise with k-means and convolution. The left image in Fig. 8 is segmented with SOM2 and the right image with K-means convolution. The noises in the trees and hills are reduced than absolute SOM2, and also, the light ratios are more separated in SOM2 K-means. To supplement SOM2 segmentation, we have combined K-means convolution. For a better understanding, let analysis with the entropy scheme.

Figure 6: From left to right, (a) Original photo (b) SOM2 with a 15*15 map size, and (c)SOM2 + K-means convolution sunset light segmentation

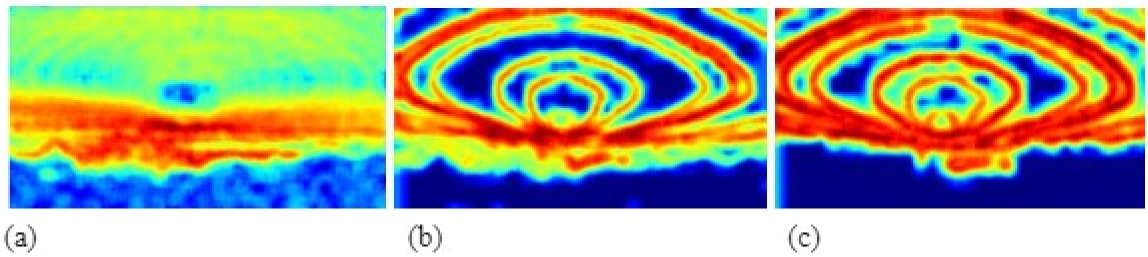

Figure 7: From left to right, (a) Entropy of original image, (b) SOM2 and (c) SOM2 +kmeans convolution

Based on fig. 7, visually, the entropy of the SOM2+Kernel convolution is less than SOM2 and the original photo. The mean entropy and each photo have been described in the table.2.

Table 2: The entropy of the original SOM2 and SOM2 + k-means convolution of the second example with map size = 15*15.

Mean-Entropy	
Original photo	7.11
SOM2	5.39
SOM2+K-means convolution	5.22

According to the table. 2, The mean entropy of the proposed model is less than SOM2; furthermore, the entropy is less than the original image, with little difference being bigger than the original photo. It means, Without damaging the essential details of the photo, the scattering and confusion of the light sunset in the original photo are clustered by SOM2 + FCM; this result leads to successful noise reduction. The reduced noise and entropy in the SOM2 + kernel convolution are observable in the entropy schema. The proposed model results have been shown in this part, but as better discrimination with the classic model of SOM, it's worth comparing the two models.

Other output tests for foreground image segmentation;

By so far we have tested the proposed image for scenery images, moreover we display the proposed output for the foreground image.

In the next figure, we display a hand X-ray original image(a) which is segmented by SOM2+FCM(c). The entropy of the original image has been reduced from 5.93 to 4.37.

In the following example, we test a cat foreground by SOM2+Kmeans_ convolution According to fig.9 the original image with 6.89 entropy and the image is hard segmented by SOM2+k-means_ convolution with 4.54. Based on the output the original photo has been segmented without damaging the main information of the image and the entropy 54% has been reduced.

5.3. Comparision proposed model with classic SOM

Our introduced paper proposed SOM2 (a new version of classic SOM) as image segmentation with a blended algorithm encompassing SOM2 with C-means as soft segmentation and K-means convolution as hard segmentation. We shall compare it with classic SOM to better realise the difference in such a case. This means the classic SOM

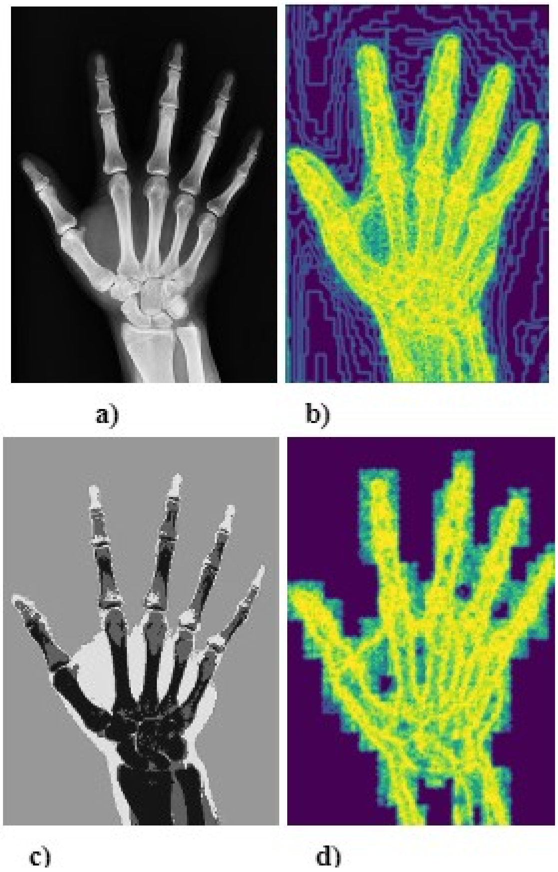

Figure 8: a)original image hand X-ray b)entropy of original image. c) SOM2+FCM segmentation d)entropy of output.

should be blended with C-means as soft and K-means convolution as hard segmentation for a fair comparison. In this part, we compared the classic model SOM + FCM of Dehghanian (2019) [9] with SOM2 + FCM(proposed model) and SOM + k-means of Prezelj(2022) [27] with SOM2 + K-means Convolution(proposed model)

In the next comparison example in Fig. 10, we tested the medical knee X-ray image with the proposed and classic models.

Experimentally, in the proposed model(SOM2+ FCM), the noise in the bone and muscles and cartilage is less than in the classic model, and the scattered pixels in the classic model are more than in the proposed model. Furthermore, according to table 3 and the schema, the entropy of the proposed model is less than classic. It shows that without damaging the significant details of the original image experimentally and in terms of entropy, we have got less noise.

Table 3: The entropy of the original photo and SOM + FCM and SOM2 + FCM of the first comparison example with map size = 20*20.

Mean-Entropy	
Original photo	6.17
Classic SOM + FCM	5.98
SOM2+FCM	5.77

The next comparison is between Classic SOM + K-means convolution and SOM2 + K-means convolution. In the following example, the original image has been segmented by classic SOM with K-means convolution and SOM2 + K-means convolution in fig 14. Based on the pictures experimentally, the noise in the ears and head of the dog in the classic model is observable, but we have got less noise in the proposed model. According to table 4 and fig. 13, the proposed model has got less entropy than the classic model and original photo in terms of entropy.

We verified the proposed models' two types with visual examples and entropy criteria. And practical samples were compared with the classic model showing better entropy and noise reduction. We have prepared another instance in the following table and chart showing us the difference between the proposed model and the classic statistical in terms of entropy.

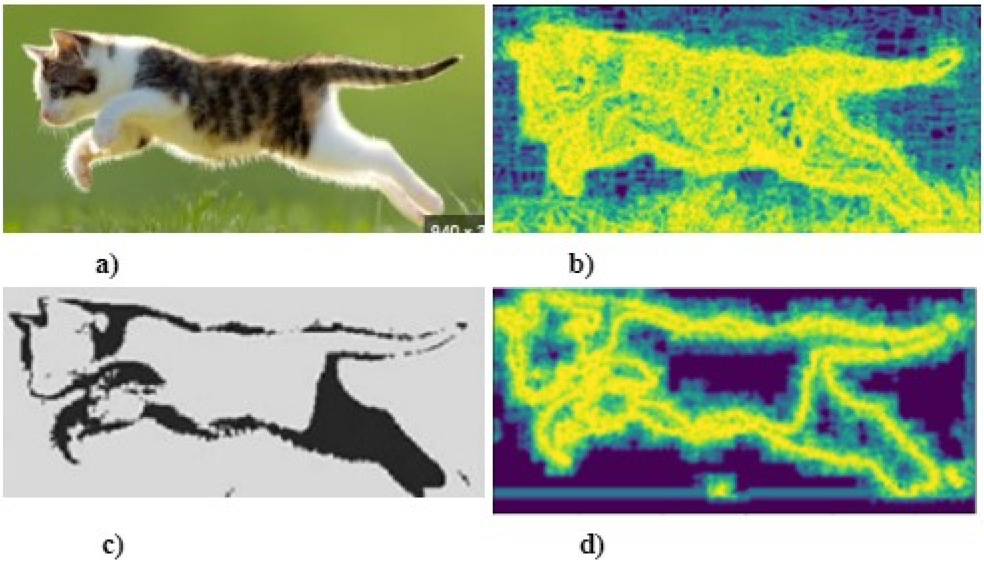

Figure 9: a) original image. b) entropy of the original image. c) SOM2+k-means_convolution. d)Entropy of SOM2+k-means_convolution

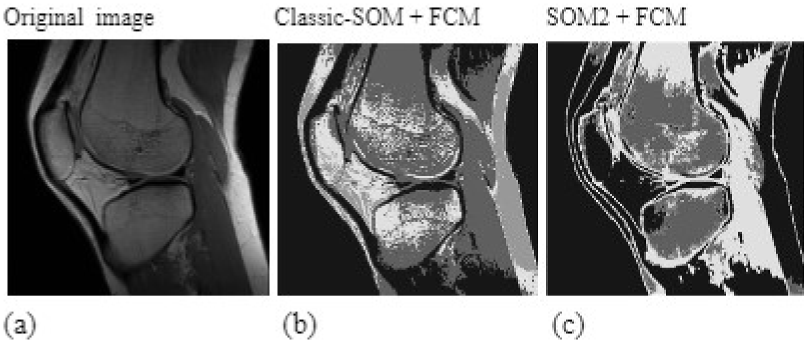

Figure 10: From left to right; the original image and image segmentation with classic SOM + FCM and on the left with SOM2 + FCM.

Table 4: Entropy result of the original image and classic model and proposed method

Mean-Entropy	
Original photo	6.77
Classic SOM+K-means convolution	5.37
SOM2+K-means convolution	5.12

Table 5: The comparison of the Classic model with a proposed model in entropy reduction of the input image.

Mean-Entropy		
Classic SOM+FCM	32%	10.13
SOM+FCM	52%	10.41
Classic SOM+K-means convolution	26%	9.02
SOM2+K-means convolution	33%	12.46

Based on Table. 5, the difference between the classic and proposed model is depicted in image entropy reduction. According to the results, the SOM2+FCM performs better than SOM2+Kmeans convolution. Moreover, the standard deviation of SOM2+K-means convolution is more than SOM2+FCM, which means the SOM2+FCM entropy reduction result is more uniform than SOM2+k-means.

Both proposed models had better performance than classic models, but In a comparison, SOM2+FCM with classic SOM+FCM has got a better result than SOM2+K-means with classic SOM-Kmeans convolution. In order of the running time the classic model is faster than new methods, on average the processing is 1.37 times faster

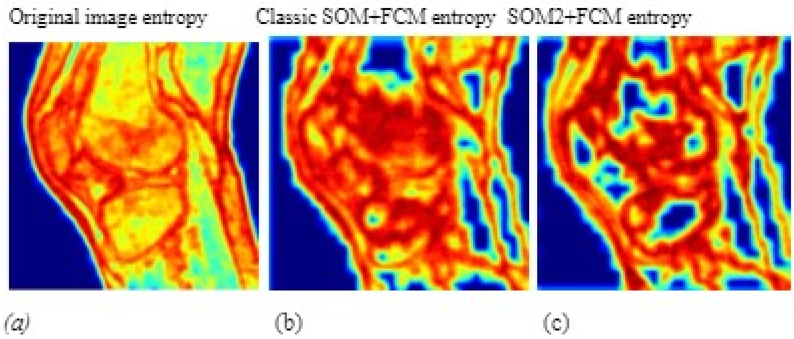

Figure 11: From left to right, (a) the entropy of the original image (b) and classic SOM+FCM and (c)SOM2+FCM

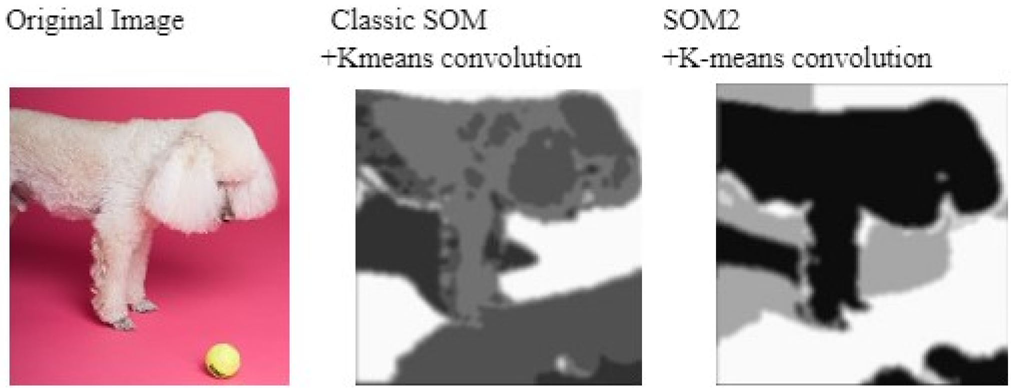

Figure 12: From left to right, the original image and image segmentation with classic SOM + K-means and on the left with SOM2 +Kmeans convolution.

than the novel model.

In summary, the following table displays the detailed and differences between all algorithms which we used.

Table 6: Review and Comparison table between articles methods

Name of original method	Article detail	Description
SOM Kohonen	Kohonen (1990) [17]	Works on continues unsupervised data
Novel SOM	Ghaseminezhad (2011) [18]	Improving SOM for discrete simple tabulate dataset
SOM2+FCM /Kmean+convolution	proposed model	Using Novel SOM with FCM and Kmeans convolution for-soft and hard image segmentation

Name of method	Article detail	Max Space Complexity	Entropy reduction performance
Classic SOM+FCM	Dehghanian(2019) [9]	$O(n^2)$	32%
Classic SOM+Kmeans	Prezelj(2022) [27]	$O(n^2)$	26%
SOM2+FCM	proposed model	$O(m^3)$	52%
SOM2+kmeans+convolution	proposed model	$O(m^3)$	33%

6. Summary and Conclusion

The novel SOM2 had been presented before for classic tabulate and simple data sets; this time, we have used it for digital image segmentation; in such cases, we have discussed the main differences between classic data sets and image pixels and the problem of classic SOM [16] in discreet data sets. This paper introduces the segmentation using novel SOM2 with a combination of FCM when we want a soft segmentation and a combination with K-means convolution kernel if we consider hard image segmentation.

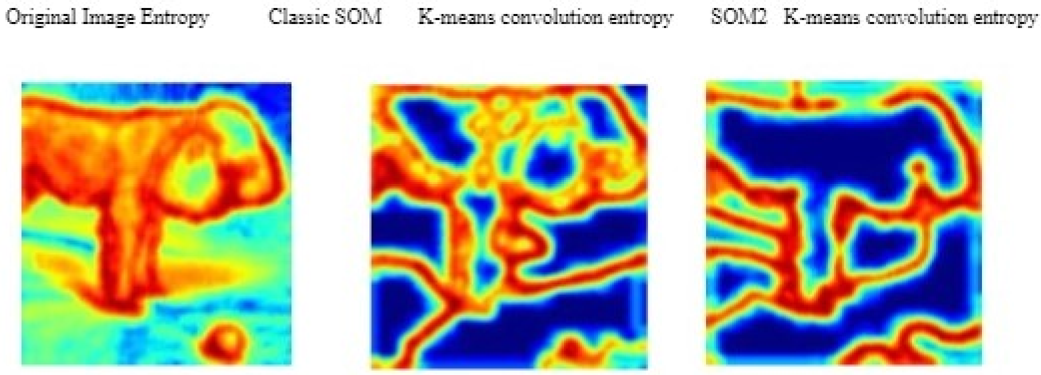

Figure 13: The entropy of original and classic and proposed segmentation.

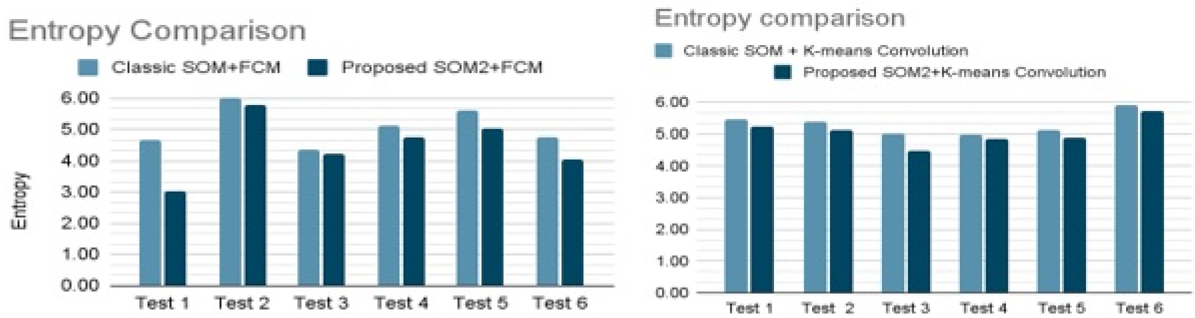

Figure 14: The left chart is an entropy comparison of classic SOM+FCM and SOM2+FCM for four tests, and the right chart is an entropy comparison of classic SOM+Kmeans Convolution and SOM2+k-means Convolution.

The main goal and innovation idea of the proposed model is to use novel SOM [11] for image processing as hard and soft segmentation with noise and entropy reduction without any damage to the main information of the image's contents and to show how combining new SOM with FCM for soft segmentation and combining with K-means convolution for hard segmentation can noise reduction with entropy criteria better than classic SOM + FCM and SOM+K-means convolution combining. In the result, we have shown that SOM2+FCM can reduce entropy by 1.58 times better in comparison to classic SOM+FCM [9]. On the other side, SOM2+Kmeans convolution can reduce entropy by 1.14 times better in comparison to classic SOM+kmeans [27].

In the results, we have tested models with various image types, such as medical images and images from nature and animals. Our main goal is entropy reduction to lighten the image [24]. We have visually shown the main entropy results and compared them with the original image by the entropy benchmark. Moreover, to better understand the main differences between the proposed and classic models, we compared them in terms of noise and entropy reduction with charts and depicted entropy results.

As a result, when wanting a soft segmentation, the proposed SOM2+FCM on average 52% reduced the entropy of the original image but classic SOM+FCM by 32%. Furthermore, in terms of hard segmentation, the proposed SOM2+k-means convolution can 33% reduce the entropy without damaging the main information of the original image, but SOM+k-means with 26%. Accordingly, the results show us that soft segmentation (SOM2+FCM) performs better than hard segmentation (SOM2+K-means convolution).

Our proposed model lets us opt the soft or hard segmentation, and with the map size of SOM2, we can define the density segmentation; when our map size is large, the segmentation would be with less density by contrast to when our map would be little the density of segmentation would be high. The profit of our segmentation model is that it lets us decide which degree and type (hard or soft)segmentation we consider. This method works on natural images when front ground information is substantial such as medical images and natural scenery, but the proposed model is not suitable and convenient for the image with sensible details such as fingerprint and cracks detection when the interioir of content is very important. besides the method is suitable for semantic segmentation but not for instance segmentation.

The advantage of the previous model over this model is running time, in fact, on average 1.37 times can process faster than novel SOM.

The application of our proposed model is for preparing images for modelling and analysis models or classification and prediction in deep learning; by lighting the images from noises and reduction of the entropy, the images are prepared as a satisfied preprocessing model for deep learning. Because the prediction needs successful preprocessing, in such a case, the data sets in the duration of the preprocessing should be cleaned from outliers and noises, which we have focused on in this paper.

As future offers, this method can be tested for satellite photos. And reduce the running time without damaging the performance.

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