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Image retrieval with SNN-based multi-level thresholding

SNN tabanlı çok seviyeli eşikleme ile görüntü erişimi

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Abstract

Image retrieval is defined as indexing similar or identical images in a digital image database. Various feature vectors obtained from the images are used while searching for a similar digital image. However, processing all pixels of the images requires costly algorithms. In addition, it is a possible issue that the images used in retrieval approaches are of different sizes. For this reason, pixel-level operations are insufficient when comparing images. Therefore, it requires vectorial structures that represent images. The process of obtaining these vectorial structures is called feature extraction, and it is one of the most important stages of content-based image retrieval. On the other hand, the histogram is the most basic feature vector that is independent of the dimensions of the image and can be easily calculated. In gray-level images, the size of the histogram is suitable for use as a feature vector. However, three different channels in color images contain too much data to be used as feature vectors. The data of 3 separate histograms are reduced using various thresholding processes and feature vectors are extracted. Therefore, reducing the vector size is an inevitable operation. In this study, a new multi-thresholding method based on the Spiking Neural Network model, inspired by the human visual system, is proposed. With the proposed model, 3 threshold values are determined for each of the RGB color channels, and each color channel is divided into 4 parts. Thus, the color palette of the image is quantized to 64 different colors and a feature vector with 64 elements is obtained. The proposed method was compared with the commonly used multilevel thresholding methods. The results obtained showed that the proposed method is quite successful.

Keywords: Color quantization, Content-based image retrieval, Multilevel thresholding, Spiking neural network

Öz

Görüntü erişimi, dijital bir görüntü veri tabanından benzer veya özdeş görüntülerin indekslenmesi olarak tanımlanır. Benzer bir dijital görüntü aranırken görüntülerden elde edilen çeşitli öznitelik vektörleri kullanılır. Çünkü görüntülerin pikselleri üzerinde işlem yapmak maliyetli algoritmalar gerektirir. Ayrıca, erişim yaklaşımlarında kullanılan görüntülerin farklı boyutlarda olması olası bir problemdir. Bu nedenle, görüntüleri karşılaştırırken piksel düzeyindeki işlemler yetersiz kalmaktadır. Görüntüleri temsil eden vektörel yapılar gereklilik olarak karşımıza çıkmaktadır. Bu vektörel yapıları elde etme sürecine özellik çıkarımı denir ve içerik tabanlı görüntü erişiminin en önemli aşamalarından biridir. Histogram ise görüntünün boyutlarından bağımsız ve kolaylıkla hesaplanabilen en temel öznitelik vektörüdür. Gri seviyeli görüntülerde histogramın boyutu öznitelik vektörü olarak kullanıma uygundur. Ancak, renkli görüntülerdeki üç farklı kanal, özellik vektörleri olarak kullanılmak için çok fazla veri içerir. Bu nedenle vektör boyutunu küçültmek kaçınılmaz bir işlemdir. Bu çalışmada, insan görsel sisteminden esinlenerek İğnecikli Sinir Ağı modeline dayalı yeni birçok-seviyeli eşikleme yöntemi önerilmiştir. Önerilen model ile RGB renk kanallarının her biri için 3 ayrı eşik değeri belirlenmiş ve her bir renk kanalı 4 parçaya bölünmüştür. Böylece elde edilen renk paleti ile renk uzayı 64 farklı renge indirgenir. Önerilen yöntem, görüntü erişimi için yaygın olarak kullanılan çok seviyeli eşikleme yöntemleri ile karşılaştırılmıştır. Elde edilen sonuçlar önerilen yöntemin başarısını açıkça göstermektedir.

***Anahtar kelimeler**: Renk niceleme, İçerik tabanlı görüntü erişimi, Çok seviyeli eşikleme, İğnecikli sinir ağı*

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1. Introduction

1. Giriş

In recent years, with the development of science and technology, the use of digital images in many fields such as medicine, military, art, and education has led to the creation of large image databases. Retrieving the desired images in the aforementioned data sets has been a crucial issue. Early work for image retrieval was text-based. This approach, which is based on the indexing of each image with words, has the disadvantage that it is both insufficient and dependent on human perception in describing the images. Therefore, content-based image retrieval (CBIR) has become a field of computer vision that researchers have been interested in (Lai and Chen, 2011; Deveraj et al., 2020). CBIR systems are approaches that take into account the visual content of images such as color, shape, and texture. Commercial applications such as Qbic (Barber et al., 1994) VisualSEEK (Smith & Chang, 1997) and Virage (Gupta & Jain, 1997) are examples of typical CBIR. CBIR consists of two stages: feature extraction and similarity measurement. Feature extraction is the representation of the features of images by vectors. So it is a basic and important process of CBIR. An effective CBIR approach can be realized with the high representation ability of the feature vectors obtained. Color is a descriptor for feature extraction and it is commonly used in CBIR (Mojsilovic & Rogowitz, 2001) and the histogram is an important representation method that shows the frequency of colors. Also, the color histogram is one of the most commonly used feature vectors (Desealers, 2003; Long & Feng, 2003; Alamdar & Keyvanpour, 2011; Messing et al., 2001). Related vector is a powerful feature because it is easy to calculate, and is resistant to rotation and scaling. However, while the histogram is obtained with a single color channel in gray-level images, it is necessary to process three different color channels in color images. Moreover, there are 2^{24} different colors in the RGB color space. Processing on an image defined in RGB color space will be high computational complexity. Color reduction approaches have been developed to overcome the complexity and computational cost problem. The main purpose of color quantization approaches is to reduce the color diversity in the image by collecting similar colors under the same group.

There are several CBIR approaches based on histogram and color reduction in the literature. Smith and Chang developed an image retrieval approach using the distance between histograms (Smith & Chang, 1996). Küçüktunç and Zamalieva proposed a rule-based CBIR They defined 26 rules in their work and created the histogram vector by obtaining 15 colors from the images (Kucuktunc & Zamalieva, 2009). Konstantinidis et al. proposed a system with fuzzy logic based on 27 rules in the L*a*b* color space and calculates the similarity with the histogram intersection criterion. They represented images with 10 different colors in their approach (Konstantinidis et al., 2005). Islam et al. (2021) combined many feature vectors. In their approach using deep features, a novel feature vector was proposed by concatenating the histogram vector. Liu and Yang (2013) a novel feature vector developed which called color difference histograms. A conventional histogram only counts the number or frequency of pixels. However, the unique feature of the color difference histogram is that they count color differences between two points under different backgrounds in relation to colors and edge orientations. Some of the remarkable approaches in CBIR architectures are also based on neural networks. Neural network algorithms, which have become prominent in recent years, also attract attention in retrieval studies. However, there isn't any imaging study using the spiking neural network-based approach that models the human visual system.

Although the first psychophysical studies on HVS date back to the 1980s (Hilderth, 1983), the first HVS-based approach in the field of image processing was developed in 1993 using a double-layer network design for edge and boundary detection (Manjunath & Chellappa, 1993). Studies have shown that spiking neural networks (SNNs) very successfully simulate biological image processing in HVS (Ghosh-Dastidar & Adeli, 2009; Kunkle & Merrigan, 2002). There are many edge detection studies based on biological neural system models in the literature (Wu et al., 2007; Clogenson et al., 2011; Kerr et al., 2011a; Kerr at al., 2011b).

Since SNNs are known to be quite successful in detecting edges by modeling HVS, a new multi-thresholding method based on the bio-inspired Spiking Neural Network model is proposed in this study. With the proposed model, 3 different threshold values are determined for each of the RGB color channels in color images. In this way, each color channel is divided into 4 parts. Thus, the color palette of the image is reduced to 64 different colors and a feature vector of 64 elements is obtained. The proposed method was compared with the multilevel thresholding methods, which are widely used for CBIR, with the help of the Precision and Recall metrics.

2. Color quantization with multi-level thresholding

2. Çoklu eşikleme ile renk indirgeme

Multi-level thresholding is one of the methods used to segment images into homogeneous regions. These techniques are also preferred in color reduction approaches. Color reduction, in other words, vector quantization approaches are one of the frequently used methods in CBIR. Image process algorithms operate faster by combining similar colors in the extraction of low-level features. The capability of the reduced image to represent the original confirmations the performance of the reduction algorithm. These approaches take place in two stages. First, a color palette is created. Then, the output image is reconstructed with this color palette (Márquez-de-Silva et al., 2008).

LBG (Linde et al., 1980) is still one of the methods used for color reduction for CBIR (Chen, Chang, & Hsu, 2020). Approaches such as Otsu, Kapur, and the center of gravity of the Histogram (CoG) are preferred for multi-level thresholding. However, related techniques have also been used in color reduction. LBG algorithm takes an input vector set, which reduces its representation to a sub-vector set. Thus, a vector set with l elements is reduced to a vector set with k elements (k<l). Initially, randomly determined cluster centers are updated according to their distance from the pixel.

Otsu thresholding technique is based on the calculation of variance between classes. The mentioned optimization approach aims to determine the value that maximizes the variance between classes (Huang & Wen, 2021). Kapur, on the other hand, is a commonly used approach for segmentation. The method, also known as Kapur Entropy, estimates the threshold values that maximize local entropies on the gray level histogram (Satya, Kalyani & Sakthivel, 2021). Similarly, CoG is an approach that calculates the repetitive average over the probabilities of the colors. This approach uses the threshold values in which the centers of gravity of the histogram are determined as the critical points between the classes (Demirci & Okur, 2019).

Otsu, Kapur, and CoG are techniques that perform effective segmentation on gray level images. Approaches used in multi-level thresholding are also included in the literature to segment the color space. Kılıçaslan et al. (2018, 2020) divided the color space into sub-cubes with related techniques in their studies. Afterward, they assigned a single color value to the remaining colors in the sub-prisms. Thus, for a colored RGB image, they combined the information from 3 color channels and represented them with a single color. As a result, a one-dimensional histogram is presented by the color reduction in the proposed approach.

3. Conductance-based integrate and fire neuron model

3. Kondüktans tabanlı topla ve ateşle nöron modeli

The structure of neurons was mathematically modeled for the first time in 1952 by Hodgkin and Huxley (HH) (Hodgkin & Huxley, 1952). The HH model consists of equations expressing the generation of action potentials (Nelson, 2004). Instead of the highly complex HH neuron model, Integrate and Fire (IF), FitzHugh-Nagumo (FHN), and Izhikevich models were proposed that minimize computational costs (Nagumo et al., 1962; Fitzhugh, 1969; Gerstner & Kistler, 2002; Izhikevich, 2003). The IF model stands out with its features such as simplicity, easy applicability, and low computational complexity (Vemuru, 2020). The variation of the membrane potential $v(t)$ of the Conductance based IF model used in this study is given below.

$$c_m \frac{dv(t)}{dt} = g_l(E_l - v(t)) + \frac{w_{ex} g_{ex}(t)}{A_{ex}}(E_{ex} - v(t)) \qquad (1)$$

where c_m refers to membrane capacitance, g_l membrane conductivity, and E_l inverse potential of the membrane. E_{ex} is the reverse potential of excitatory synapses. w_{ex} indicates the weight of the synapse and A_{ex} is the membrane surface area of the synapse. The variable g_{ex} is the conductivity of the excitatory synapse. When the membrane potential $v(t)$ exceeds the threshold voltage, an action potential is generated and then $v(t+1)$ is reset to the initial value. Figure 1 shows the spikes formed by an output neuron with a spike train coming from the neuron to which it is synaptically connected.

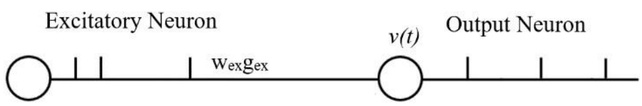

Figure 1. Synaptic connection and spike trains of IF neuron model.
Şekil 1. *Sinaptik bağlantı ve topla ve ateşle nöron modelinin iğnecik dizisi*

4. Image retrieval with SNN based color quantization

4. SNN tabanlı renk indirgeme ile görüntü erişimi

In this study, a network model shown in Figure 2 is proposed for SNN-based vector quantization. The proposed SNN consists of three layers. The first layer is the receptive layer that contains as many receptors as the number of pixels in the image. Neurons in the intermediate layer produce spikes according to the gray level value coming from each pixel in the image. The output layer, to which each of the neurons in the intermediate layer is connected, also consists of output neurons. The firing number of each output neuron corresponds to the gray level value in the output image. All synaptic connections of neurons within the SNN are excitatory.

If the gray level value of a pixel at (x, y) position is large enough, it will enable the $M_{x,y}$ neuron to produce spike(s). As the gray level value increases, the frequency of generating spikes will also increase. The resulting spike train is transmitted to the $O_{x,y}$ neuron in the Output layer via the excitatory synaptic connection. Depending on the number of excitatory spikes from the $M_{x,y}$ neuron, the increase in the membrane potential of the $O_{x,y}$ neuron will also cause spike generation at certain intervals. In the proposed model, (x, y) represents the coordinate of the receptor corresponding to each pixel in RF. The peak conductivity values of the receivers are calculated by equation (2) with the help of the $G_{x,y}$ gray level values of the pixels

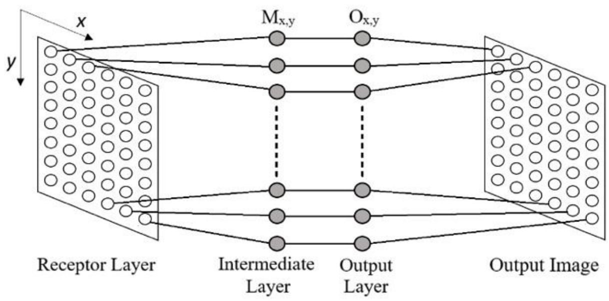

Figure 2. Proposed SNN structure
Şekil 2. Önerilen SNN modeli

$$q_{ex} = \alpha G_{x,y} \quad (2)$$

where $g_{x,y}$ is the gray level value of the pixel at (x, y) coordinate. The α coefficient ensures that the gray level value is between 0 and 1 and its value is accepted as 1/255 in this study. The spike train of each $M_{x,y}$ neuron in the intermediate layer is calculated with the help of the following equations.

$$\frac{g_{ex}(t)}{dt} = -\frac{1}{\tau_{ex}} g_{ex}(t) + \frac{w_{ex} q_{ex}}{A_{ex}} \quad (3)$$

where τ_{ex} is the time constants for all synapses. In the calculation of the time-dependent membrane potential of the neuron, the following equation, which is the analytical solution of equation (1), was used (Vemuru, 2020):

$$I_{ex} = -g_{ex} E_{ex} \quad I_l = g_l E_l \quad (4)$$

$$v_M = (\frac{1}{g_l})\{(-\exp(\frac{g_l t}{c_m}))(I_{ex} + 70 g_l + I_l) + I_{ex} + I_l\} \quad (5)$$

The spike is generated when the membrane potential of an $M_{x,y}$ neuron reaches the threshold voltage, and then the neuron returns to its initial state. The Spike Train formed by these spikes is obtained by equation (6).

$$S_{M_{x,y}(t)} = \begin{cases} 1 & \text{if neuron } i \text{ fires a spike at time } t \\ 0 & \text{if there is no spike at time } t \end{cases} \quad (6)$$

In the output layer, there is one $O_{x,y}$ output neuron to which each $M_{x,y}$ neuron is excitatory synaptically connected. Equations (7), (8) and (9) are used for each $O_{x,y}$ neuron.

$$\frac{g_{out}(t)}{dt} = -\frac{1}{\tau_{out}} g_{out}(t) + \frac{S_{M_{x,y}}(t)}{A_{ex}} \quad (7)$$

$$I_{out} = -g_{out} E_{out} \quad (8)$$

$$v_O = (\frac{1}{g_l})\{(-\exp(\frac{g_l t}{c_m}))(I_{out} + 70 g_l + I_l) + I_{out} + I_l\} \quad (9)$$

where gout is the time-varying conductivity, τ_{out}, the time constant. Spike trains for all $O_{x,y}$ neurons are also calculated using equation (6). The number of spikes $F_{O_{x,y}}$ produced by neuron $O_{x,y}$ during T time in the output layer is found by equation (10).

$$F_{O_{x,y}} = \sum_{t=0}^{T} S_N(t) \tag{10}$$

In the tests, it is seen that the FN results for the gray level value between 0-255 appear in the range of 0-3. Thus, by applying the same approach to three of the RGB channels of each pixel, each color channel is reduced to 4 levels and the image to 64 different color values. The RGB color space reduced to 64 colors is shown in Figure 3. Each color belongs to a different cluster of $C = \{C_0, C_1, C_2, \cdots, C_{63}\}$. th is the thresholding value which calculated by SNN.

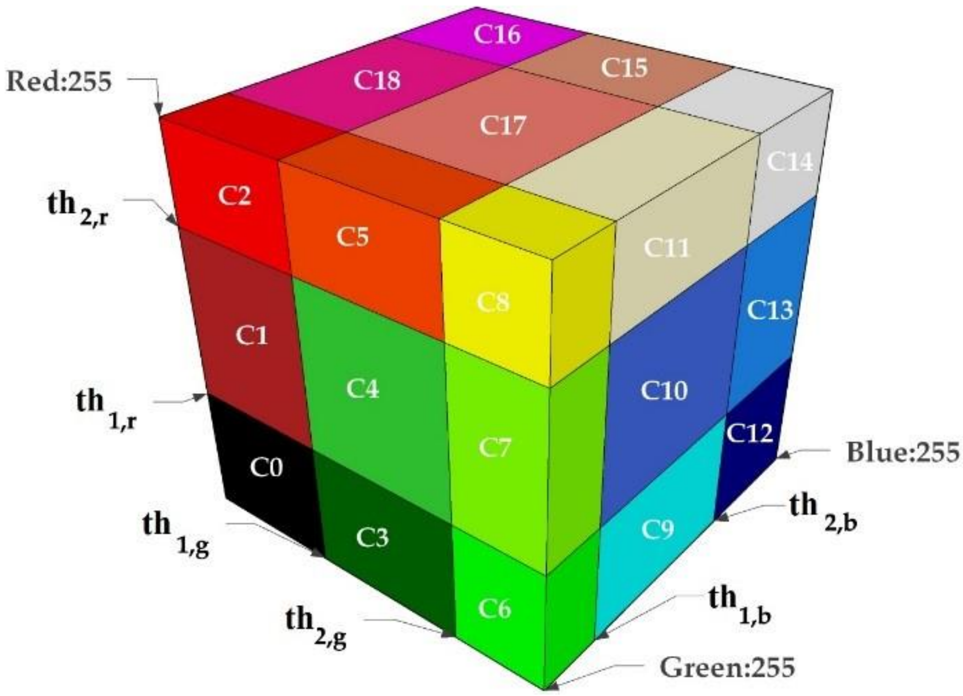

Figure 3. RGB color space reduced to 64 colors (Kılıçaslan et al., 2020; Rahkar Farshi et al., 2018)
Şekil 3. 64 renge indirgenmiş RGB renk uzayı (Kılıçaslan et al., 2020; Rahkar Farshi et al., 2018)

Table 1 demonstrates the quantized images obtained by different methods. Images in the table are randomly selected from the Corel 1K dataset. While the original images are included in the first row of Table 1, the other rows contain the thresholding results obtained by LBG, Otsu, Kapur, CoG, and the proposed method, respectively.

Table 1. Quantized images with different algorithms
Tablo 1. Farklı algoritmalarla indirgenen görüntüler

Org.	
LBG	

Table 1. Continue
Tablo 1. *Devamı*

Otsu	
Kapur	
CoG	
Prop.	

5. Experimental results and discussion

5. Deneysel sonuçlar ve tartışma

The proposed method is based on the multi-level thresholding technique. Therefore, the adaptation of the experiments has been examined by making comparisons with different thresholding techniques. The color space is segmented with all thresholding techniques. Then, feature vectors representing color images have been obtained. Related feature vectors are used for image retrieval. Corel 1K dataset has been used for the proposed retrieval approach. Corel 1K dataset is used frequently in CBIR studies. It consists of 10 different classes and each class has 100 images.

Proposed algorithm consists of two stages. In the first stage, the codebook is constructed with the proposed SNN model for color reduction. The developed network model was performed in MATLAB using the following parameters: $c_m = 1$ μF/mm^2, $E_l = -44.42$ mV, $g_l = 0.003$ μS/mm^2, $\tau_{ex} = 4$ ms, $E_{ex} = 36.78$ mV, $v_{\text{reset}} = -70$ mV, $A_{ex} = 0.0141$ mm^2, $T = 100$ ms, $dt = 0.1$ ms, and $w_{ex} = 0.0025$. The weights of the synapses were approximately calculated according to (Wu et al., 2007). The other step is to perform CBIR with feature vectors extracted from SNN.

Image retrieval architecture consists of two basic stages. The first is feature extraction and the second is similarity measurement. The similarity measurement phase is critical. The feature extracted by the proposed method is a one-dimensional histogram. For this reason, frequently used histogram similarity metrics such as Canberra, Chebyshev, Chi-Square, Cosine, Intersection, and L1 were used to measure similarity. The use of different metrics made the experiments more effective and consistent. The performances of the methods have been evaluated with Precision and Recall values. Equation 11 and Equation 12 show the formulas for the Precision and Recall metrics, respectively.

$$Precision = \frac{N_R}{N_T} \tag{11}$$

$$Recall = \frac{N_R}{N_C} \tag{12}$$

where N_R and N_T are the numbers of retrieved relevant images and all retrieved images for each query image, respectively. N_C is the number of images in each category of the dataset.

Precision values (%) of the proposed method according to different metrics are shown in Table 2. The highest precision values were obtained from the Canberra metric. For this reason, the Canberra similarity metric was used in comparisons with other methods. On the other hand, it was observed that especially Intersection and L1 distance metrics produced very close results. When Table 2 is examined, the precision values decrease as the number of retrieved images increases. This situation is an expected result. In addition, the different performance of different similarity metrics indicates that the similarity measurement step is crucial. In addition, the superior performance of the Canberra results showed that the feature vectors extracted with the developed approach were more compatible.

Table 2. Precision results (%) of proposed method
Tablo 2. Önerilen metodun kesinlik sonuçları (%)

Precision (%)	10	20	30	40	50	60	70	80	90	100
Canberra	70.03	63.18	59.06	55.97	53.36	51.13	49.19	47.59	46.11	44.67
Chebyshev	58.38	50.59	46.24	43.45	41.41	39.69	38.18	36.98	35.85	34.86
Chi-Square	64.23	57.15	52.79	49.60	47.06	44.99	43.15	41.63	40.31	39.03
Cosine	63.27	56.36	52.39	49.59	47.27	45.28	43.61	42.18	40.87	39.52
Intersection	68.79	61.60	57.46	54.26	51.72	49.46	47.65	45.98	44.55	43.16
L1	68.77	61.59	57.45	54.26	51.72	49.47	47.65	45.98	44.55	43.17

Table 3 shows the Precision and Recall values obtained for the top 10 images. According to the results obtained, the lowest values were obtained with LBG. The disadvantage of the LBG approach is that it reduces the color space with random initial values. This causes different feature vectors to be produced for the same image. Kapur and Otsu techniques produced similar results. In addition, both optimization methods were approximately 23% more successful than LBG. CoG is the most successful of the traditional methods. The method in question produced 28% superior results compared to LBG and approximately 5% superior to Otsu and Kapur. The proposed method, on the other hand, left all the traditional methods behind. The developed algorithm is more powerful with a precision of 70%. In addition, experimental findings and results indicated that the proposed method produced feature vectors that represent images better than other methods. In Figure 4, the Precision (%) graph is given according to the number of images retrieved. Similar to the results in Table 3, although the number of retrieved images increased, the success order did not change. The proposed method gave more successful results than the traditional methods.

Table 3. Precision and recall results (%) of threshold methods for top 10 images
Tablo 3. İlk 10 görüntü için eşikleme metotlarının kesinlik ve hassasiyet değerleri

Method	LBG	Otsu	Kapur	CoG	Prop.
Precision(%)	41.16	64.86	63.89	69.30	70.03
Recall(%)	4.12	6.49	6.39	6.93	7.00

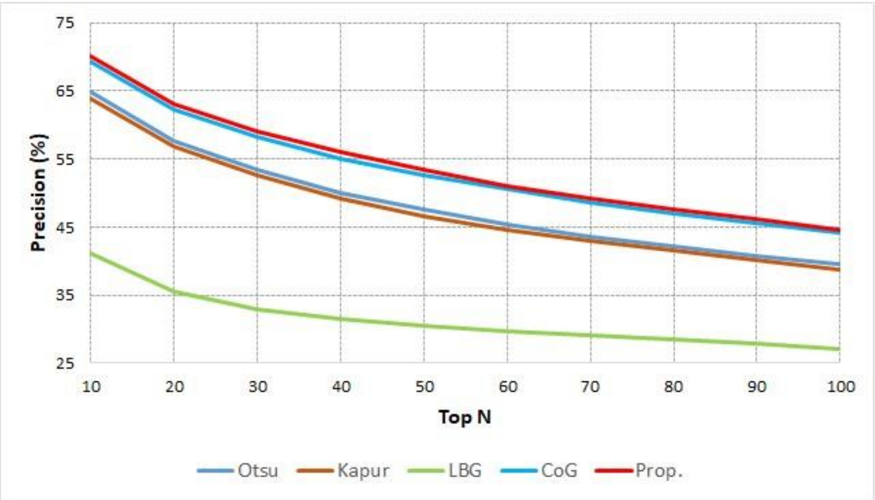

Figure 4. Average precision (%) performances of threshold methods
Şekil 4. Eşikleme tekniklerinin ortalama kesinlik performansları (%)

In Table 4, there are examples of retrieved images against various query images in the database. For example, there is a bus image among the images retrieved in response to the image in the first line in the Africans category. Similarly, 2 of the images corresponding to the bus image in the second row are quite irrelevant. For the horse image in the third line, one of the retrieved images shows a sunbathing couple. In the food image in the 4th line, it is striking that all the first 7 images are related. The most important reason for this situation is that only reduced color information is used for retrieval.

Table 4. Query and retrieved image examples
Tablo 4. Sorgu görüntü ve getirilen görüntüler

Query Image   Retrieved Images

With the proposed method, color quantization was made based on SNN simulating the human visual system. Although the success of the proposed method seems to be lower than many retrieval studies in the literature, it should be noted that only color reduction is used. All recently developed techniques use larger feature vectors (Yuan, & Liu, 2020; Kayhan, & Fekri-Ershad, 2021; Singhal, Agarwal, & Pachori, 2021) that combine edge, pattern, and color information. In addition, the calculation of the similarities between the obtained features through linear metrics is seen as one of the factors that reduce success. For this reason, it is predicted that the success of the proposed method will increase by calculating the similarities of the feature vectors to be obtained by using edge and color information together with the help of machine learning techniques.

6. Conclusion
6. Sonuç

In this study, a new multi-thresholding method is proposed. The proposed method is based on the SNN model and is used to threshold the color channels of the images. Each color channel is divided into 4 parts and a vector with 64 elements is produced by reducing the colors of the image. This feature vector generated was used for CBIR. The proposed method was compared with the commonly used multilevel thresholding methods. The results showed that the proposed method can be used for CBIR. In the future, it is planned to carry out studies to increase the success of CBIR by using the proposed method with different features to be extracted from the images.

Author contribution
Yazar katkısı

Incetaş and Kılıçaslan formed the structure, experiments and core concept of the article. Akan has coded optimization techniques.

Declaration of ethical code
Etik beyanı

The authors declare that the materials and methods used in this study do not require ethical committee approval and/or legal-specific permission.

Conflicts of interest
Çıkar çatışması beyanı

The authors declare that there is no conflict of interest.

References
Kaynaklar

Alamdar, F. & Keyvanpour, M. (2011). A new color feature extraction method based on QuadHistogram. *Procedia Environmental*

Sciences, *10*, 777-783. https://doi.org/10.1016/j.proenv.2011.09.126

Barber, R., Flickner, M., Hafner, J., Niblack, W., Petkovic, D., Equitz, W. & Faloutsos, C. (1994). Efficient and effective querying by image content. *Journal of Intelligent Information Systems*, *3*(3-4), 231-262. https://doi.org/10.1007/BF00962238

Cambronero, J., Stanley-Marbell, P. & Rinard, M. (2018). Incremental color quantization for color-vision-deficient observers using mobile gaming data. *arXiv preprint arXiv:*1803.08420. https://doi.org/10.48550/arXiv.1803.08420

Clogenson, M., Kerr, D., McGinnity, T. M., Coleman, S. A. & Wu, Q. (2011). Biologically inspired edge detection using spiking neural networks and hexagonal images. *In International Conference on Neural Computation Theory and Applications* (pp. 381-384). SciTePress. https://doi.org/ 10.5220/0003682103810384

Chen, Y. H., Chang, C. C., & Hsu, C. Y. (2020). Content-based image retrieval using block truncation coding based on edge quantization. *Connection Science*, *32*(4), 431-448. https://doi.org/10.1080/09540091.2020.1753174

Deselaers, T. (2003). Features for image retrieval. [Master's thesis, University of Rhine-Westphalia Alsiche Technical University of Aachen].

Demirci, R., & Ümit, O. (2019). Renkli Görüntülerin Ortalama Tabanlı Çok Seviyeli Eşiklenmesi. *Düzce Üniversitesi Bilim ve Teknoloji Dergisi*, *7*(1), 664-676. https://doi.org/10.29130/dubited.471040

Devaraj, A. F. S., Murugaboopathi, G., Elhoseny, M., Shankar, K., Min, K., Moon, H. & Joshi, G. P. (2020). An Efficient Framework for Secure Image Archival and Retrieval System Using Multiple Secret Share Creation Scheme. *IEEE Access*, *8*, 144310-144320. https://doi.org/10.1109/ACCESS.2020.3014346

FitzHugh, R. (1969). Mathematical models of excitation and propagation in nerve. *Biological Engineering*, 1-85.

Gerstner, W. & Kistler, W. M. (2002). *Spiking neuron models: Single neurons, populations, plasticity*. Cambridge University Press.

Gervautz, M., Purgathofer, W. (1988). *A Simple method for color quantization: octree quantization. New Trends in Computer Graphics*. Springer. https://doi.org/10.1007/978-3-642-83492-9_20

Ghosh-Dastidar, S. & Adeli, H. (2009). Spiking neural networks. *International Journal of Neural Systems*, *19*(04), 295-308. https://doi.org/10.1142/S0129065709002002

Gupta, A. & Jain, R. (1997). Visual information retrieval. *Communications of the ACM*, *40*(5), 70-79. https://doi.org/10.1145/253769.253798

Heckbert, P. (1982). Color Image Quantization for Frame Buffer Display. *Computer Graphics*, *16*(2), 297-307. https://doi.org/10.1145/965145.801294

Hildreth, E. C. (1983). The detection of intensity changes by computer and biological vision systems. *Computer Vision, Graphics and Image Processing*, *22*(1), 1-27. https://doi.org/10.1016/0734-189X(83)90093-2

Hodgkin, A. L. & Huxley, A. F. (1952). A quantitative description of membrane current and its application to conduction and excitation in nerve. *The Journal of physiology*, *117*(4), 500-544.

Huang, C. Li X. & Wen, Y. (2021). AN OTSU image segmentation based on fruitfly optimization algorithm. *Alexandria Engineering Journal*, *60*(1), 183-188. https://doi.org/10.1016/j.aej.2020.06.054

Islam, S.M., Joardar, S., Dogra, D.P. (2021) Ornament Image Retrieval Using Multimodal Fusion. *SN COMPUT. SCI.*2,336. https://doi.org/10.1007/s42979-021-00734-1

Izhikevich, E. M. (2003). Simple model of spiking neurons. *IEEE Transactions on neural networks*, *14*(6), 1569-1572. https://doi.org/10.1109/TNN.2003.820440

Kayhan, N., & Fekri-Ershad, S. (2021). Content based image retrieval based on weighted fusion of texture and color features derived from modified local binary patterns and local neighborhood difference patterns. *Multimedia Tools and Applications*, *80*(21), 32763-32790. https://doi.org/10.1007/s11042-021-11217-z

Kerr, D., Coleman, S., McGinnity, M., Wu, Q. & Clogenson, M. (2011a, November). Biologically inspired edge detection. In 2011 *11th International Conference on Intelligent Systems Design and Applications (pp. 802-807).* IEEE.

Kerr, D., McGinnity, M., Coleman, S., Wu, Q. & Clogenson, M., (2011b, January) Spiking hierarchical neural network for corner detection, NCTA 2011 - *Proceedings of the International Conference on Neural Computation Theory and Applications, pp. 230-235.*

Kilicaslan, M., Tanyeri, U. & Demirci, R. (2020). Image Retrieval using One-Dimensional Color Histogram Created with Entropy. *Advances in*

Electrical and Computer Engineering, 20(2), 79-88. https://doi.org/10.4316/AECE.2020.02010

Kılıçaslan, M., Tanyeri, U., & Demirci, R. (2020). Tekrarlı Ortalama Yardımıyla Renk İndirgeme ve Görüntü Erişimi. *Düzce Üniversitesi Bilim ve Teknoloji Dergisi, 8*(1), 1042-1057. https://doi.org/10.29130/dubited.643351

Kılıçaslan, M., Tanyeri, U., & Demirci, R. (2018). Renkli Görüntüler İçin Tek Boyutlu Histogram. *Düzce Üniversitesi Bilim ve Teknoloji Dergisi, 6*(4), 1094-1107. https://doi.org/10.29130/dubited.413822

Konstantinidis, K., Gasteratos, A. & Andreadis, I. (2005). Image retrieval based on fuzzy color histogram processing. *Optics Communications, 248*(4-6), 375-386. https://doi.org/10.1016/j.optcom.2004.12.029

Kucuktunc, O. & Zamalieva, D. (2009). Fuzzy color histogram-based CBIR system. *Proceedings of 1st International Fuzzy Systems Symposium*, (pp.231-234).

Kunkle, D. R. & Merrigan C, (2002). *Pulsed Neural Networks and Their Application*. Computer Science Department, College of Computing and Information Sciences, Rochester Institute of Technology.

Lai, C. C. & Chen, Y. C. (2011). A user-oriented image retrieval system based on interactive genetic algorithm. *IEEE transactions on instrumentation and measurement, 60*(10), 3318-3325. https://doi.org/10.1109/TIM.2011.2135010

Linde, Y., Buzo, A. & Gray, R. (1980). An algorithm for vector quantizer design. *IEEE Transactions on communications*, 28(1), 84-95. https://doi.org/10.1109/TCOM.1980.1094577

Liu, G. H. & Yang J. Y. (2013) Content-based image retrieval using color difference histogram. *Pattern Recognition 46*(1), 188–198. https://doi.org/10.1016/j.patcog.2012.06.001

Liu, S., Wei, G., Song, Y. & Ding, D. (2017). Set-membership state estimation subject to uniform quantization effects and communication constraints. *Journal of the Franklin Institute, 354*(15), 7012-7027. https://doi.org/10.1016/j.jfranklin.2017.08.012

Long, F., Zhang, H. & Feng, D. D. (2003). Fundamentals of content-based image retrieval. *In Multimedia information retrieval and management* (pp. 1-26). Springer, Berlin, Heidelberg.

Manjunath, B. S. & Chellappa, R. (1993). A unified approach to boundary perception: edges, textures and illusory contours. *IEEE Transactions on neural networks, 4*(1), 96-108. https://doi.org/10.1109/72.182699

Márquez-de-Silva, S., Felipe-Riverón, E. & Fernández, L. P. S. (2008, September). A simple and effective method of color image quantization. *In Iberoamerican Congress on Pattern Recognition* (pp. 749-757). Springer, Berlin, Heidelberg.

Messing, D. S., Van Beek, P. & Errico, J. H. (2001, October). The mpeg-7 colour structure descriptor: Image description using colour and local spatial information. *In Proceedings 2001 International Conference on Image Processing (Cat. No. 01CH37205) (Vol. 1, pp. 670-673).* IEEE.

Mojsilovic, A. & Rogowitz, B. (2001, October). Capturing image semantics with low-level descriptors. *In Proceedings 2001 International Conference on Image Processing (Cat. No. 01CH37205) 1,* (pp. 18-21). IEEE.

Nagumo, J., Arimoto, S. & Yoshizawa, S. (1962). An active pulse transmission line simulating nerve axon. *Proceedings of the IRE, 50*(10), 2061-2070.

Nelson, M. E. (2004). Electrophysiological models. *Databasing the brain: from data to knowledge,* 285-301.

Patanè, G. & Russo, M. (2001). The enhanced LBG algorithm. *Neural networks, 14*(9), 1219-1237. https://doi.org/10.1016/S0893-6080(01)00104-6

Rahkar Farshi, T., Demirci R. & Mohammad-Reza F. (2018). Image clustering with optimization algorithms and color space. *Entropy, 20*(4), 296-314. https://doi.org/10.3390/e20040296

Sathya, P.D., Kalyani, R., & Sakthivel, V.P. (2021). Color image segmentation using Kapur, Otsu and minimum cross entropy functions based on exchange market algorithm. *Expert Systems with Applications, 172,* 114636. https://doi.org/10.1016/j.eswa.2021.114636

Singhal, A., Agarwal, M., & Pachori, R. B. (2021). Directional local ternary co-occurrence pattern for natural image retrieval. *Multimedia Tools and Applications, 80*(10), 15901-15920. https://doi.org/10.1007/s11042-020-10319-4

Smith, J. R. & Chang, S.F. (1996) Tools and techniques for color image retrieval, Proceedings of SPIE 2670. *Storage and Retrieval for Still Image and Video Databases IV*. (pp. 426-437). https://doi.org/10.1117/12.234781.

Smith, J. R. & Chang, S. F. (1997). VisualSEEk: a fully automated content-based image query system. *Proceedings of the fourth ACM international conference on Multimedia* (pp. 87-98).

Vemuru, K. V. (2020). Image Edge Detector with Gabor Type Filters Using a Spiking Neural Network of Biologically Inspired Neurons. *Algorithms*, *13*(7), 165. https://doi.org/10.3390/a13070165

Yuan, B. H., & Liu, G. H. (2020). Image retrieval based on gradient-structures histogram. *Neural Computing and Applications*, *32*(15), 11717-11727. https://doi.org/10.1007/s00521-019-04657-0

Wu, Q., McGinnity, M., Maguire, L., Belatreche, A. & Glackin, B. (2007, August). Edge detection based on spiking neural network model. *In International Conference on Intelligent Computing* (pp. 26-34). Springer, Berlin, Heidelberg.