# Image Segmentation Based on Color Dissimilarity

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*This study aims to develop a segmentation technique that can be used to detect objects in an image. The concept used is to imitate the human concept of recognizing an object based on its color difference. A color is considered different if it has different R, G or B values. Humans can only distinguish two colors clearly if they both have a DeltaE value of at least 8. The difference in DeltaE values is obtained from differences in the values of R, G or B, either alone or in pairs. The application of this concept to the segmentation technique has shown good results. This technique is able to give the same results and is good for images with JPG, PNG and BMP file types. To provide confidence in the performance of this method, a comparison is made with several segmentation methods. By measuring the similarity index using the Jaccard index, Sørensen–Dice index and BF Score, this color dissimilarity-based segmentation method has the best performance. Meanwhile, when measuring the processing time, this method has the second best performance. Thus, it can be concluded that this method is very suitable for detecting objects in an image.*

*Povzetek: Tehnika segmentacije je bila razvita z imitacijo človeškega koncepta prepoznavanja predmeta, in sicer na podlagi barvnih razlik. Barve se štejejo za različne, če imajo vrednost DeltaE najmanj 8, ki jo dobimo iz razlik v vrednostih R, G ali B barv samih ali v parih. Izvajanje te tehnike kaže enake rezultate za datoteke JPG, PNG in BMP in je v veliko pomoč pri postopku identifikacije predmeta.*

## 1 Introduction

Segmentation is the process of separating an object from other objects in an image based on certain characteristics. The purpose of image segmentation is to divide the image into sections / segments that have similar features or attributes. Based on his understanding, segmentation has the aim of finding specific characteristics possessed by an image. An image is separated based on certain criteria so that the image is divided into groups of areas with the same properties [1]. The segmentation process divides images into small areas to be analyzed and used to distinguish different types of objects in an image [2]. Image segmentation is one of the most important object recognition stages for the artificial vision system. Image segmentation is defined as a combination of sets containing pixel coordinates with certain features [3]. Therefore, segmentation is needed in the pattern recognition process. The complexity of object detection will occur when there are many potential object locations and only rough locations are available, which makes the process more difficult [4]. The better the quality of segmentation, the better the quality of pattern recognition. The creation of visual data is important in image processing. With the support of problem solving abilities and the application of other disciplines, it has encouraged further research to be carried out [5].

Each object has a variety of characteristics that can be used to recognize the object. The characteristics that are widely used include the shape, texture and color possessed by an object [6]. From the shape it has, an object can be recognized and distinguished from other objects [7]. Compared to the shape and texture characteristics, the color shows better stability and is not too sensitive when it is associated with playback and zooming of images. Color greatly contributes to the introduction of objects, both to objects related to certain colors or not [8]. Color is one of the most important features in image recognition by humans [9]. Color is also believed to improve the performance of memory [10]. Color also has a very important role in the process of object recognition by patients with Alzheimer's disease, in addition to other visual forms [11].

To recognize and distinguish them, a color usually has a name. However, sometimes colors that obviously look different, are identified by the same name. Vice versa, colors that are identified by different names, apparently have similarities [12]. The real problem is related to the identification of a color that refers to the name given, while there are many colors that are similar, approaching and appearing to be almost the same [13]. This happens because the process of color recognition itself, namely by referring to the primary color, and then the primary color is segmented and recognized by the identity of a particular name [14]. To avoid mistakes in identifying, colors are then identified in a three-dimensional color space, with modeling that refers to hardware and users. Modeling that refers to hardware includes RGB (Red Green Blue), CMY (Cyan Magenta Yellow) and YIQ. Whereas those referring to users include HLS (Hue Saturation Luminance), HCV, HSV (Hue Saturation value), HSB, MTM, CIE-LAB, and CIE-LUV [15]. In the storage process, most image file formats (JPEG, BMP, GIF) use the RGB color space. RGB color space is defined based on the values of the axes R, G and B [16].

Based on this modeling, there are actually millions of colors that can be identified [17]. If calculated from variations in the value of the axis R, G and B which are owned by a color, then there are 256x256x256 pieces of color, because each color has a value of the axis R, G and B varies between 0 – 255. But not all of these variations can be distinguished by our sense of sight. This of course will have an impact on our ability to identify an object in an image. The similarity of the color of the object, especially between background and foreground can cause errors in identifying the object [18]. Perception, recognition and memory of a color can affect our ability to recognize colors or objects [19].

# 2 Related works

## 2.1 Image segmentation

Image segmentation is the process of partitioning an image into several parts, so that it can change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation into meaningful objects is related to the same characteristics as color, intensity, texture and others. Image segmentation is used to identify objects and backgrounds in an image. Image segmentation is the process of assigning labels to each pixel in an image such that pixels with the same label share certain visual properties [20]. Several general purpose algorithms and techniques have been developed for image segmentation. Because there is no general solution to the problem of image segmentation, these techniques often must be combined with domain knowledge in order to effectively solve the problem of image segmentation for the problem domain [21]. In general, image segmentation algorithms can be categorized into region based segmentation, edge based segmentation, feature based segmentation, threshold based segmentation, graphical segmentation and model based segmentation [2].

Dividing the image into connected sets of pixels is the goal of image segmentation. The resulting collection, called a region, is defined based on visual properties extracted from local features. To reduce the gap between calculated and expected segmentation by users, a segmentation approach was developed by changing the color texture, to express visual complexity and show how it can be used to express homogeneity, distance, and measure of similarity [22].

There are various image segmentation techniques and algorithms that have been developed and applied. In general, these techniques and algorithms can be grouped into:

a. contextual and non-contextual technique, which underlies the grouping of its treatment of the features possessed by an image. In the contextual technique, the relationship between image features is very taken into account, while in the non-contextual technique it is completely ignored;
b. based on discontinuity and based on similarity, which is based on how to group the gray level intensity of the image. In the discontinuity-based technique, image partitioning is carried out when a sudden change occurs, while in the based on similarity technique, image certainty is carried out on the basis of the similarity of the gray level of the image;
c. structural, stochastic and hybrid techniques, the grouping of which is based on information on the structure of the image section, the image's discrete pixel value or a combination of both. Structural techniques are only based on the structure of the image section. Stochastic technique based on the discrete pixel values of the image. The hybrid technique combines both techniques, namely using discrete pixels and structural information together [23].

Regardless of the way they are grouped, each of these techniques has a different way from one another, which will be described in the following section.

*a) Threshold method*

This method is applied to a grayscale image, and is performed based on a certain threshold value. Based on a certain threshold value (T), the image is then converted into a binary image, colored black (0) or white (1), with the following conditions:

$$f(x, y) = \begin{cases} 1 \text{ if } f(x, y) > T \\ 0 \text{ if } f(x, y) \leq T \end{cases} \quad (1)$$

There are global and local (adaptive) variants, which are applied based on the properties possessed by an image. These variants are categorized based on how the threshold value is applied. In the global variant, the threshold value is applied to the entire image. Whereas in the local variant, the threshold value is used to determine whether a pixel is the foreground or background of an image, based on information about the surrounding pixels.

The advantage of this method is that it has a simple calculation and fast process. It's just that the results obtained will not be good if the image does not have a clear gray scale difference. The key to success and at the same time a weakness of this method lies in the accuracy of selecting/determining the threshold value [24].

*b) Edge based method*

This method performs a partition based on a significant change in the intensity of the image on a gray image with the aim of finding the pixels that are used as the boundaries of the region. There are two edge detection techniques that are often used, namely the gradient-based method and the gray histogram method [25]. The gradient-based method works based on sudden changes in the intensity of two regions, while the gray histogram method is based on separating the foreground from the background by selecting a certain threshold value [26]. The calculation of the gradient intensity estimation is carried out with various operators, which are also variants of this method. These types of operators are Robert, Sobel, Prewitt, Canny and Laplace [27]. In contrast to other operators, the Sobel operator is used to detect two-way edges (horizontal. vertical) [28]. To simplify image analysis and reduce data processing while retaining structural information [29], this method applies various detectors.

*c) Region based method*

This method works with the concept of the homogeneity of connected pixels in a region, which have the same characteristics, and are different from other regions [30]. Regional sorting is based on certain criteria, such as color, intensity or object. And to get a wider area coverage and consider the characteristics of existing pixels, then the method of segmentation growing region and region splitting and merging was developed [24].

In the region growing method, the formation of a region starts from a certain pixel point, then expands by adding pixels next to it that have similar properties, with a greater/stronger similarity level than other regions [31]. Properties that can be used to determine whether a pixel is included in an area or not include gray level, texture, color or shape. This method is very good for showing regional boundaries, but it has a difficult computational level and is not able to handle noise and uneven gray levels, so the results are not perfect.

In the region splitting and merging method, the segmentation process is carried out by sorting the image into four quadrants with certain homogeneity criteria, repeatedly until it is impossible to sort again. The results of this sorting are then combined as a result of segmentation [32][30].

*d) Clustering based method*

This method works on the basis of the pixels owned by an image, which are distinguished and classified with certain requirements and rules, using a mathematical algorithm [33]. Pixels will be grouped into a number of clusters based on their similarity of characteristics. The image will be divided into a number of clusters on the basis of the similarity of its pixel characteristics [34]. The grouping is done repeatedly to get the similarity of pixels in a cluster or the maximum difference between clusters [35].

There are two groups of clustering techniques, namely hard and soft clustering. Hard clustering emphasizes the differences between clusters, so that a pixel will only be joined in a cluster. In soft clustering, the grouping is done based on several similarity criteria, such as distance, connectivity or intensity, so it is very possible to join several clusters [36].

K-Means clustering is a popular and widely used clustering method. The algorithm is simple, the process is fast and works based on the proximity of the distance between the elements to the center of the cluster, to produce as many as K cluster data [37]. Distance calculations are carried out on various properties that form the basis for grouping [38]. With a predetermined number of clusters as many as K and a randomly assigned initial cluster center, pixels are grouped on the basis of their proximity. Each cluster obtained is then calculated on the average, and this value is used as the center of the new cluster. This process is then repeated until there are no more significant changes or a certain number of repetitions [39].

*e) Watershed based method*

This method assumes an image as a surface gradient topography [40], where the pixel of the image with the highest gradient will be the boundary area, like a river flow with a continuous boundary, without gaps [41]. Working by exploiting the similarity of an area and using a mathematical morphological approach and analogy such as flood-affected areas [42]. Starting from the part of the image with the minimum intensity as the watershed base point [43]. When it rains, the river flow will be flooded, with the area of waterlogging that changes according to the capacity of rainfall. In order to keep the puddles separate from puddles in other areas, a dam or water barrier is made.

This method has a good ability to separate the foreground and background of an image [44]. The computational complexity, sensitivity to blur and resulting in excessive image segmentation are the main drawbacks of this method.

*f) PDE based method*

This method performs segmentation by converting an image into a partial differential equation (PDE), and the results are determined based on the solution obtained. The change process is carried out based on the active contour in the form of a curve in the image [45]. To overcome the problem of surface topology of objects in the image, a function that represents the curve or surface as a set of zero levels for surfaces with higher dimensions is developed. In this way it turns out that a more accurate numerical implementation is obtained, so as to be able to solve topological problems better [46] [47]. The Level-Set method is quite simple and easy to adapt to calculate and analyze the interface changes of an image, either two or three dimensions [48].

The PDE method is believed to be able to overcome the geometric complexity of the image, and is able to provide results with better image texture contrast [49]. That is why this method is considered better than other methods. In addition to segmentation purposes, the PDE method is also suitable for denoising and enhancing image coherence [50].

*g) ANN based method*

This method of the human nervous system works with guidance and has the ability to learn like humans. In its implementation, it is trained with a number of training samples, just like a learning process [51]. The system receives input, processes and provides output based on a familiar concept or pattern.

Various learning algorithms, exploratory methods and analytical methods have been developed [52]. In general, it is categorized into two, namely supervised and unsupervised methods. In the supervised method, it takes the presence of experts in supervising and at the same time carrying out the learning process on the system. In the unsupervised method, the practical system works automatically.

One of the ANN methods that is considered feasible for image segmentation is the PCNN (Pulse-Coupled Neural Network) model [53]. The model inspired by the cat's visual system by simply modeling the cortical neurons in the visual area of the cat's brain [54], is believed to be able to produce good segmentation results, even though the input image is in poor condition.

## 2.2 Color perception and similarity

Content in the context of colors, shapes, textures and more from an image can actually be derived from the image itself. The technique applied is to extract image features by using the color similarity approach that is owned by an image [55]. The features of an image are extracted based on R, G and B values of the colors they have. With a mathematical approach using mean, median and standard deviation values for the values of R, G and B images, the content of an image can be known. Color imagery reveals information that is more meaningful to human observers than the gray scale. For this reason, an improved multiscale structural similarity index was developed which added a color comparison to the MSSIM gray scale criteria (Multiscale Structural Similarity index) [56].

Color descriptors are the most important features used in image analysis and retrieval. Because of its compact representation and low complexity, direct histogram comparison is a technique commonly used to measure color similarity. A measure of similarity is defined for the proposed color descriptor and is shown to be equivalent to the size of the quadratic histogram distance [57]. However, this has many serious weaknesses, including a high degree of dependence on the design of the color code book, sensitivity to quantization limits, and inefficiency in representing images with few dominant colors [58].

There are various types of distance and similarity measures available, and their selection is based on the context in which they are intended. In addition to the different designations, the range of values they have is also different [59]. This results in numerical values obtained from one measurement not always the same as another measurement [60]. In color image processing, color pixels are traditionally treated as geometric vectors in the Euclidean color space [61]. A color stimulus is then represented as a point in space. The difference in color ΔE between the two colors is calculated as the distance between the points that represent the color. Tolerance for color differences is determined on the basis of the range of this ΔE value. ΔE (Delta E, dE) shows the measure of changes in visual perception of two colors, and can be used as a measure to determine whether the human eye can see the difference in color. On a typical scale, the value of Delta E will range from 0 to 100. See Table 1.

Based on experiments comparing a color with other colors made from variations in the value of RGB colors, the results obtained that the two colors can be clearly distinguished by the eye, when both colors have a value of Delta E (ΔE) of 8. These results are obtained if both colors have a difference in the values of R, G or B of at least 8, or a difference in the two values of R and G, R and B or G and B of at least 6, or a difference in the three R, G, and B values of at least 5 [62].

## 2.3 Similarity index measurement

*a) Jaccard index*

Jaccard Similarity Index is a measure that shows the degree of similarity between two data sets, X and Y. The index value ranges from 0 to 1. The larger the index value obtained, the more similar the two data sets are [63]. The index value can be calculated by the following formula :

$$J(X,Y) = |X \cap Y| \,/\, |X \cup Y| \quad (2)$$

*b) Sørensen–Dice index*

The Sørensen–Dice index is a statistical tool used to measure the similarity between two data sets, X and Y. This measure is widely used to validate the algorithm of the image segmentation method. Index can be calculated by the formula:

$$QS = \frac{2|X \cap Y|}{|X|+|Y|} \quad (3)$$

The QS value ranges from 0 to 1, which can be expressed as the degree of similarity between the two data sets [64].

| Delta E | Perception |
|---|---|
| <= 1.0 | Not perceptible by human eyes. |
| 1 - 2 | Perceptible through close observation. |
| 2 - 10 | Perceptible at a glance. |
| 11 - 49 | Colors are more similar than opposite |
| 100 | Colors are exact opposite |

Table 1: Delta E and Color Perceptions.

*c) BF score*

The BF score produces a value with a range from 0 to 1. This value indicates the level of similarity of the object contour between the segmentation results and the ground truth of the image. Value is calculated by the formula:

$$\text{BFScore} = \frac{2 \text{ x Precission x Recall}}{(\text{Precession+Recall})} \quad (4)$$

Where :

- Precision is a ratio with a value of 0-1 which shows the comparison of the number of boundary points of the segmented image that is close to the boundary of ground truth to the length of the segmented image boundary.
- Recall is a ratio with a value of 0-1 which shows the comparison of the number of ground truth boundary points of the image that are close to the segmented image boundary to the length of the ground truth boundary [65].

# 3 Methodology

The initial idea of this research is based on the reality of how our process of recognizing an object in an image is influenced by our ability to distinguish a color. An object's pattern or shape will be identified when the eye is able to find a clear color difference between one field and another.

The working concept of the color dissimilarity-based segmentation method is to compare each color pixel in the image with the image next to it (right and bottom). If this comparison shows the color dissimilarity detected by the eye [62], then the pixel is changed to white.

An image can be represented as:

$$f(x,y,i) \in R^{m \times n \times 3} \quad (5)$$

This segmentation process will convert images into new images with the following working concepts:

$$(k_1 \cup k_2 \cup k_3) \rightarrow f(x,y,i) = 255 \quad (6)$$

where:

$k_1 = (\Delta R_{12} \cup \Delta R_{13} \cup \Delta G_{12} \cup \Delta G_{13} \cup \Delta B_{12} \cup \Delta B_{13}) \geq 9$

$k_2 = ((\Delta R_{12} \cap \Delta G_{12}) \cup (\Delta R_{12} \cap \Delta B_{12}) \cup (\Delta G_{12} \cap \Delta B_{12}) \cup (\Delta R_{13} \cap \Delta B_{13}) \cup (\Delta R_{13} \cap \Delta B_{13}) \cup (\Delta G_{13} \cap \Delta B_{13})) \geq 7$

$k_3 = ((\Delta R_{12} \cap \Delta G_{12} \cap \Delta B_{12}) \cup (\Delta R_{13} \cap \Delta G_{13} \cap \Delta B_{13})) \geq 6$

$R = f(x,y,1)$ ; $G = f(x,y,2)$ ; $B = f(x,y,3)$

$\Delta R_{12} = |f(x,y,1) - f(x,y+1,1)|$ ;

$\Delta R_{13} = |f(x,y,1) - f(x+1,y,1)|$

$\Delta G_{12} = |f(x,y,2) - f(x,y+1,2)|$ ;

$\Delta G_{13} = |f(x,y,2) - f(x+1,y,2)|$

$\Delta B_{12} = |f(x,y,3) - f(x,y+1,3)|$ ;

$\Delta B_{13} = |f(x,y,3) - f(x+1,y,3)|$

The converted image is then converted back into a binary image, black and white, with the following provisions:

$$b(v) = \begin{cases} 1, & b(v) < 0.9 \\ 0, & b(v) \geq 0.9 \end{cases} \quad (7)$$

Finally, this binary image is then processed further with a morphological process that aims to emphasize holes and eliminate small and unclear objects in the image. The type of morphological operation performed is the type of opening, with a pixel size limit of 5000.

# 4 Experiment result

In this study, as many as 10 images used with 3 different file formats, namely JPG, PNG and BMP. The selection of these three file formats is solely due to the consideration that this file format is the most widely and commonly used in storing digital images. Image stored in JPG, PNG and BMP file types is included in the raster type image category. A raster image (bitmap) is an image consisting of pixel points of various colors, which together form the image. Technically JPG is lossy compression, PNG is lossless compression and BMP is lossless but uncompressed. In quality, the image stored in these three file types is actually not much different and is practically not affected by the resolution. What distinguishes the three more on the file size. Because BMP is uncompressed, the file size is among the largest.

These ten image files were originally JPG image files, then saved back into PNG and BMP file formats, using the Paint version 2004 application on Microsoft Windows 10. Table 2 presents the results obtained from the segmentation process of the converted and saved images. with all three file formats. The results of segmentation obtained from the three types of different file formats are practically not much different, even almost the same. The difference in file types apparently does not greatly affect the results of the segmentation process.

The results shown in Table 2 are the best results resulting from several variations in the values of R, G and B, both alone and in pairs. The difference in the values of R, G and B used are 9 for the difference from the values of R, G or B, 7 for the difference from the value of RG, RB or GB, and 6 for the different values of the pairs of R, G, and B together. Increasing the value of this difference means finding a clear color difference between adjacent pixels. If the difference is smaller than specified, it will be considered to have the same color. On the other hand, this may not seem good for our eyesight, because the eye is not able to distinguish colors properly.

The results of segmentation expressly indicate that the object can be separated from its background. The resulting image is the ground truth of a segmented image. This of course is an advantage of this segmentation process, because it is able to produce something that can later be used as a basis for object detection in an image. The object can be detected directly from the segmentation results obtained.

In plain view, the results obtained from this method look quite good, especially if it is associated with the purpose of developing this method is to detect the presence of an object in an image. The question that arises then is whether this method has a good performance when compared to other methods?

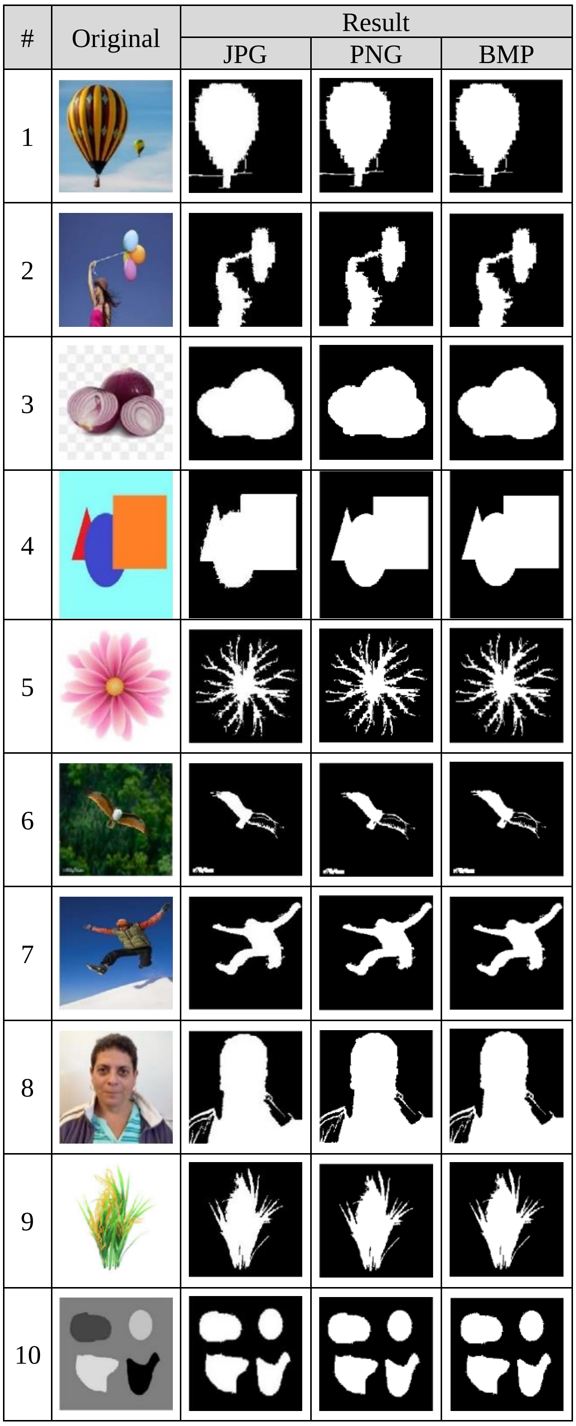



Table 2: Image and Segmentation Results Based on Color Dissimilarity.

To find out what the performance of this method is, further testing is carried out by comparing this method with the Threshold, Edge, Region growing, KMeans, Watershed, Fuzzy C-Mean and Pulse Coupled Neural Network [66] methods. The test was carried out using 21 sample images that were randomly selected from the DUTS Image Dataset [6], and the results can be seen in Table 3.

In this testing process, there are two things that are compared, namely the quality of the segmented image compared to the ground-truth sample image and the execution time of each method. The measurement of the quality of the results is measured using the Jaccard index, Sørensen–Dice index and BF score, which is calculated using the *jaccard(I1,I2)*, *dice(I1,I2)* and *bfscore(I1,I2)* functions, while the execution time is performed using the *tic* and *toc* functions. All functions used are MATLAB functions. Comparison of the performance of each tested method can be seen in Figure 1.

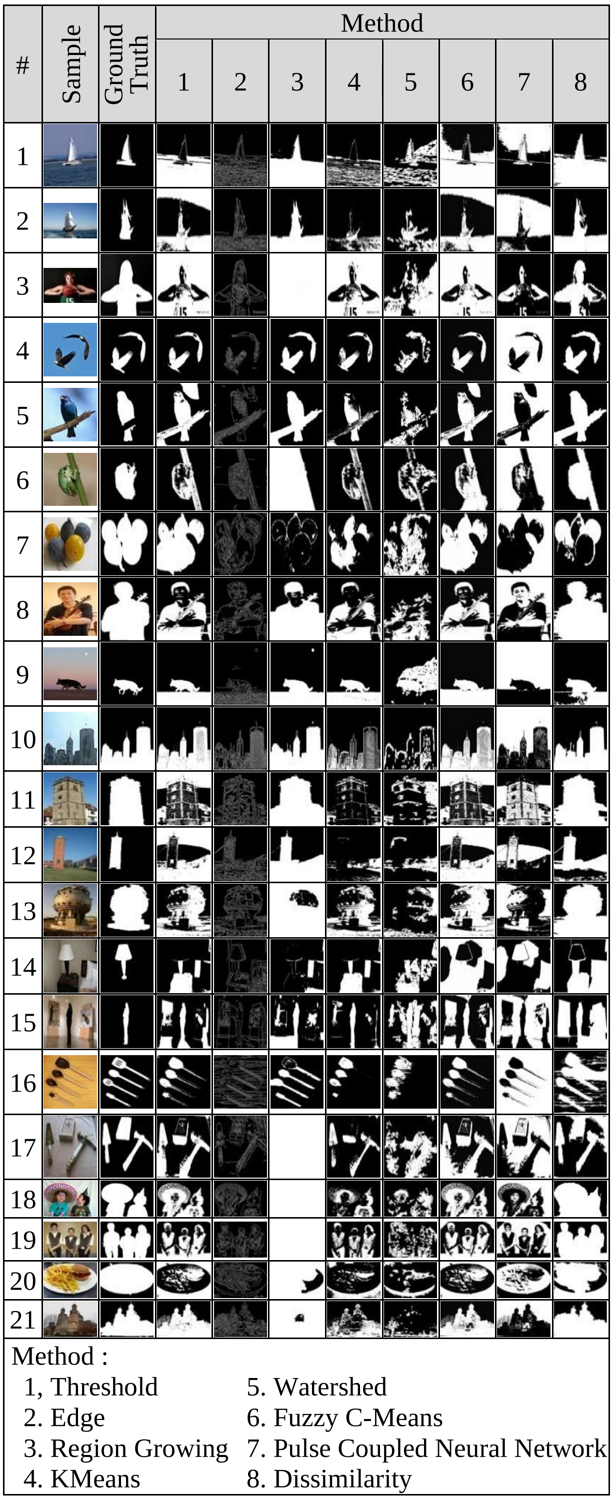
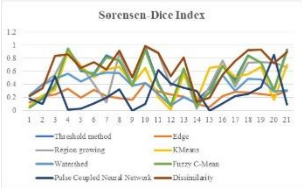
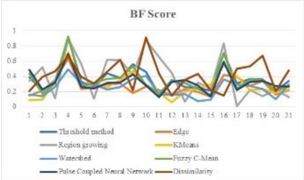



Table 3: Comparison of Image Segmentation Results.


a. Jaccard Index




b. Sørensen–Dice Index




c. BF Score


e. Execution Time

Figure 1: Test Results Comparison.

| Method | Jaccard (%) | Dice (%) | BFS (%) | Time (Sec) |
|---|---|---|---|---|
| Threshold method | 42.3166667 | 53.7981 | 37.1281 | 0.17948143 |
| Edge | 13.5742857 | 23.53714 | 26.8381 | 0.92272905 |
| Region growing | 43.9447619 | 56.36333 | 39.79667 | 5.35255476 |
| KMeans | 34.3761905 | 47.46524 | 28.49619 | 4.0992381 |
| Watershed | 24.5971429 | 38.15667 | 24.43429 | 3.11750238 |
| Fuzzy C-Mean | 41.052381 | 52.58286 | 35.00476 | 16.2354019 |
| Pulse Coupled Neural Network | 16.1590476 | 24.6419 | 32.47619 | 312.957779 |
| Dissimilarity | 55.5214286 | 66.99524 | 41.70571 | 0.83928 |

Table 4: Average Value of Test Results.

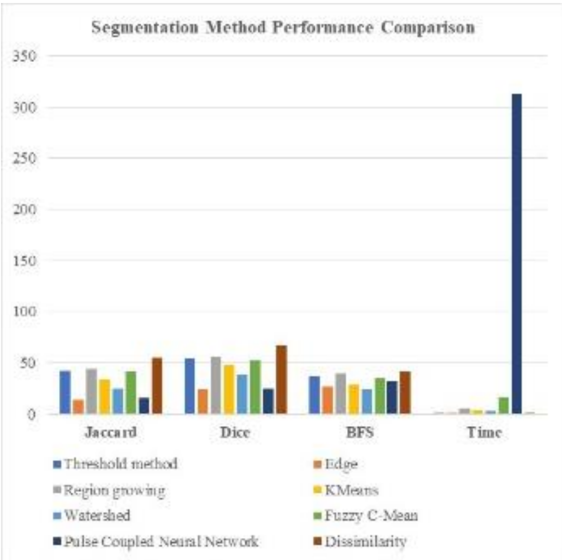



Figure 2: Performance Comparison.

In Figure 1 it can be seen that all methods show inconsistent performance and are strongly influenced by the complexity of the sample image. However, if we refer to the average value of the test results presented in Table 3, it appears that this color dissimilarity based segmentation method has the best performance. Based on the quality of the results (see Table 4), this method shows the results with Jaccard index = 55.521%, Sørensen–Dice index = 66.995% and BF Score = 41.706%, the largest value compared to other methods. In terms of the quality of the segmentation results, this method can be declared to have the best performance. In terms of execution time, this method is also relatively good. With an average execution time = 0.839 seconds, this method is in second place, and is beaten by the Threshold method. Although it does not have the fastest execution time, this method includes a very fast execution time. The Figure 2 shows the general performance comparison of all the tested methods.

## 5 Conclusion and future works

Image segmentation using the proposed method, which is based on color dissimilarity in an image, was able to sort the image well. The sharpness of sorting is greatly influenced by variations in the values of R, G and B of the adjacent pixels, both individually and in pairs. The greater the difference in the values of R, G and B themselves and their combinations will provide clearer object separation. This is certainly very easy in identifying objects.

Noting the results shown by this segmentation method are so clear, it is certain that this method can be used to separate an object from another object in an image. The development of this color dissimilarity based method will be used as a method of identifying objects in an image. The results of comparison with other methods also show that this segmentation method shows better performance in terms of quality results, with relatively fast execution times.

## References

[1] Y. Song and H. Yan, "Image Segmentation Techniques Overview," in *2017 Asia Modelling Symposium (AMS)*, 2017, pp. 103–107, doi: 10.1109/AMS.2017.24.

[2] J. S. D. Rasi, "A Survey on Image segmentation algorithms," *Int. J. Comput. Trends Technol.*, vol. 35, no. 4, pp. 170–174, 2016, doi: 10.14445/22312803/IJCTT-V35P132.

[3] F. Garcia-Lamont, J. Cervantes, A. López, and L. Rodriguez, "Segmentation of images by color features: A survey," *Neurocomputing*, vol. 292, pp. 1–27, May 2018, doi: 10.1016/j.neucom.2018.01.091.

[4] A. Chaudhuri, "Hierarchical Modified Fast R-CNN for Object Detection," *Informatica*, vol. 45, no. 7, 2021, doi: 10.31449/inf.v45i7.3732.

[5] I. Azam and S. A. Khan, "Feature extraction trends for intelligent facial expression recognition: A survey," *Informatica*, vol. 42, no. 4, 2018, doi: 10.31449/inf.v42i4.2037.

[6] I. J. Sumana, M. M. Islam, D. Zhang, and G. Lu, "Content based image retrieval using curvelet transform," in *Multimedia Signal Processing, 2008 IEEE 10th Workshop on*, 2008, pp. 11–16, doi: 10.1109/MMSP.2008.4665041.

[7] M. Safar, C. Shahabi, and X. Sun, "Image retrieval by shape: a comparative study," in *Multimedia and Expo, 2000. ICME 2000. 2000 IEEE International Conference on*, 2000, vol. 1, pp. 141–144, doi: 10.1109/icme.2000.869564.

[8] I. Bramão, A. Reis, K. M. Petersson, and L. Faísca, "The Role of Color Information on Object Recognition: A Review and Meta-Analysis," *Acta Psychol. (Amst).*, vol. 138, no. 1, pp. 244–253, 2011, doi: 10.1016/j.actpsy.2011.06.010.

[9] K. Yang, S. Gao, C. Li, and Y. Li, "Efficient color boundary detection with color-opponent mechanisms," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2013, pp. 2810–2817, doi: 10.1109/CVPR.2013.362.
[10] S. S. Guan and P. S. Hung, "Influences of psychological factors on image color preferences evaluation," *Color Res. Appl.*, vol. 35, no. 3, pp. 213–232, 2010, doi: 10.1002/col.20570.
[11] R. L. Adlington, K. R. Laws, and T. M. Gale, "Visual processing in Alzheimer's disease: Surface detail and colour fail to aid object identification," *Neuropsychologia*, vol. 47, no. 12, pp. 2574–2583, 2009, doi: 10.1016/j.neuropsychologia.2009.05.004.
[12] A. Byrne, "Color and Similarity," *Philos. Phenomenol. Res.*, vol. 66, no. 3, pp. 641–665, May 2003, doi: 10.1111/j.1933-1592.2003.tb00282.x.
[13] H. S. Faridul, T. Pouli, C. Chamaret, J. Stauder, A. Tremeau, and E. Reinhard, "A Survey of Color Mapping and its Applications," *Eurographics 2014-State Art Reports*, pp. 43–67, 2014, doi: 10.2312/egst.20141035.
[14] N. R. Pal and S. K. Pal, "A review on image segmentation techniques," *Pattern Recognit.*, 1993, doi: 10.1016/0031-3203(93)90135-J.
[15] P. Kaur, S. Thakral, and M. Singh, "Color Based Image Retrieval System," *IOSR J. Comput. Eng.*, 2012, doi: 10.9790/0661-0150105.
[16] S. V Sakhare and V. G. Nasre, "Design of feature extraction in content based image retrieval (CBIR) using color and texture," *Int. J. Comput. Sci. Informatics*, vol. 1, no. 2, pp. 57–61, 2011, doi: 10.47893/ijcsi.2012.1029.
[17] S.-C. Cheng and C.-K. Yang, "A fast and novel technique for color quantization using reduction of color space dimensionality," *Pattern Recognit. Lett.*, vol. 22, no. 8, pp. 845–856, 2001, doi: 10.1016/S0167-8655(01)00025-3.
[18] X. Zhang and J. Yang, "The analysis of the color similarity problem in moving object detection," *Signal Processing*, 2009, doi: 10.1016/j.sigpro.2008.10.027.
[19] H. Zimmer and A. Steiner, "Colour Specificity in Episodic and in Perceptual Object Recognition with Enhanced Colour Impact," *Eur. J. Cogn. Psychol.*, vol. 15, no. 3, pp. 349–370, 2003, doi: 10.1080/09541440303603.
[20] F. Yi and I. Moon, "Image segmentation: A survey of graph-cut methods," in *2012 International Conference on Systems and Informatics (ICSAI2012)*, 2012, pp. 1936–1941, doi: 10.1109/ICSAI.2012.6223428.
[21] N. M. Zaitoun and M. J. Aqel, "Survey on Image Segmentation Techniques," 2015, doi: 10.1016/j.procs.2015.09.027.
[22] B. Sowmya and B. Sheela Rani, "Colour image segmentation using fuzzy clustering techniques and competitive neural network," *Appl. Soft Comput.*, vol. 11, no. 3, pp. 3170–3178, Apr. 2011, doi: 10.1016/j.asoc.2010.12.019.
[23] S. Inderpal and K. Dinesh, "A Review on Different Image Segmentation Techniques," *IJAR*, vol. 4, 2014, doi: 10.15373/2249555x/apr2014/200.
[24] P. Sivakumar and S. Meenakshi, "A Review on Image Segmentation Techniques," *Int. J. Adv. Res. Comput. Eng. Technol.*, vol. 5, no. 3, pp. 641–647, 2016, doi: 10.1016/0031-3203(93)90135-J.
[25] W. Khan, "Image Segmentation Techniques: A Survey," *J. Image Graph.*, vol. 1, no. 4, pp. 166–170, 2013, doi: 10.12720/joig.1.4.166-170.
[26] L. Zhengdong, "A Garment Image Segmentation Method Based on Salient Region and JSEG," *JSW*, vol. 10, no. 11, pp. 1274–1282, 2015, doi: 10.17706/jsw.10.11.1274-1282.
[27] S. Salimzadeh and S. Kandulu, "Teeth Segmentation of Bitewing X-Ray Images Using Wavelet Transform," *Informatica*, vol. 44, no. 4, 2020, doi: 10.31449/inf.v44i4.2774.
[28] Y. Yao, "Image segmentation based on Sobel edge detection," in *2016 5th International Conference on Advanced Materials and Computer Science (ICAMCS 2016)*, 2016, pp. 141–144, doi: 10.2991/icamcs-16.2016.27.
[29] J. Canny, "A computational approach to edge detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-8, no. 6, pp. 679–698, 1986, doi: 10.1109/TPAMI.1986.4767851.
[30] H. G. Kaganami and Z. Beiji, "Region-based segmentation versus edge detection," in *2009 Fifth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, 2009, pp. 1217–1221, doi: 10.1109/IIH-MSP.2009.13.
[31] P. Qiong, "An Image Segmentation Algorithm Research Based on Region Growth," *J. Softw. Eng.*, vol. 9, no. 3, pp. 678–679, 2015, doi: 10.3923/jse.2015.673.679.
[32] W.-X. Kang, Q.-Q. Yang, and R.-P. Liang, "The comparative research on image segmentation algorithms," in *Education Technology and Computer Science, 2009. ETCS'09. First International Workshop on*, 2009, vol. 2, pp. 703–707, doi: 10.1109/ETCS.2009.417.
[33] Z. Wang and M. Yang, "A fast clustering algorithm in image segmentation," in *Computer Engineering and Technology (ICCET), 2010 2nd International Conference on*, 2010, vol. 6, pp. V6-592-V6-594, doi: 10.1109/ICCET.2010.5486041.
[34] S. Tongbram, B. A. Shimray, and L. S. Singh, "Segmentation of image based on k-means and modified subtractive clustering," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 3, pp. 1396–1403, 2021, doi: 10.11591/ijeecs.v22.i3.pp1396-1403.
[35] A. K. Jain, M. N. Murty, and P. J. Flynn, "Data clustering: a review," *ACM Comput. Surv.*, vol. 31, no. 3, pp. 264–323, 1999, doi: 10.1145/331499.331504.
[36] N. Dhanachandra and Y. J. Chanu, "A Survey on Image Segmentation Methods using Clustering Techniques," *Eur. J. Eng. Res. Sci.*, vol. 2, no. 1, p. 15, 2017, doi: 10.24018/ejers.2017.2.1.237.

[37] M. Luo, Y.-F. Ma, and H.-J. Zhang, "A Spatial Constrained K-Means Approach to Image Segmentation," in *Information, Communications and Signal Processing, 2003 and Fourth Pacific Rim Conference on Multimedia. Proceedings of the 2003 Joint Conference of the Fourth International Conference on*, 2003, vol. 2, pp. 738–742, doi: 10.1109/ICICS.2003.1292554.

[38] A. R. Hedar, A. M. M. Ibrahim, A. E. Abdel-Hakim, and A. A. Sewisy, "K-means cloning: Adaptive spherical K-means clustering," *Algorithms*, vol. 11, no. 10, 2018, doi: 10.3390/a11100151.

[39] R. Jain and R. S. Sharma, "Image segmentation through fuzzy clustering: A survey," in *Advances in Intelligent Systems and Computing*, 2019, vol. 741, pp. 497–508, doi: 10.1007/978-981-13-0761-4_48.

[40] J. Tang, "A color image segmentation algorithm based on region growing," in *Computer engineering and technology (iccet), 2010 2nd international conference on*, 2010, vol. 6, pp. V6-634-V6-637, doi: 10.1109/ICCET.2010.5486012.

[41] H. Xu, G. Lin, and M. Wang, "A Review of Recent Advances in Image Co-Segmentation Techniques," *IEEE Access*, vol. 7, pp. 182089–182112, 2019, doi: 10.1109/ACCESS.2019.2960162.

[42] S. Umaa Mageswari, M. Sridevi, and C. Mala, "An Experimental Study and Analysis of Different Image Segmentation Techniques," *Procedia Eng.*, vol. 64, pp. 36–45, 2013, doi: 10.1016/j.proeng.2013.09.074.

[43] A. Bleau and L. J. Leon, "Watershed-based segmentation and region merging," *Comput. Vis. Image Underst.*, 2000, doi: 10.1006/cviu.1999.0822.

[44] M. H. Rahman and M. R. Islam, "Segmentation of color image using adaptive thresholding and masking with watershed algorithm," in *2013 International Conference on Informatics, Electronics and Vision (ICIEV)*, 2013, pp. 1–6, doi: 10.1109/iciev.2013.6572557.

[45] J. Wei and L. Chan, "An Image Segmentation Method Based on Partial Differential Equation Models.," *Int. J. Simulation--Systems, Sci. Technol.*, vol. 17, no. 36, 2016, doi: 10.5013/IJSSST.a.17.36.46.

[46] J. Sliž and J. Mikulka, "Advanced image segmentation methods using partial differential equations: a concise comparison," in *2016 Progress in Electromagnetic Research Symposium (PIERS)*, 2016, pp. 1809–1812, doi: 10.1109/PIERS.2016.7734800.

[47] Xin-Jiang, Renjie-Zhang, and Shengdong-Nie, "Image segmentation based on PDEs model: A survey," 2009, doi: 10.1109/ICBBE.2009.5162922.

[48] B. Zhou, L. I. Y. Xiao, and R. Liu, "Image segmentation with partial differential equations," *Inf. Technol. J.*, vol. 9, no. 5, pp. 1049–1052, 2010, doi: 10.3923/itj.2010.1049.1052.

[49] A. Sofou and P. Maragos, "Generalized flooding and multicue PDE-based image segmentation," *IEEE Trans. Image Process.*, 2008, doi: 10.1109/TIP.2007.916156.

[50] E. Yoruk and C. B. Akgul, "Color image segmentation using PDE-based regularization and watershed transformation," in *Proceedings of the IEEE 12th Signal Processing and Communications Applications Conference, 2004.*, 2004, pp. 518–521, doi: 10.1109/siu.2004.1338579.

[51] H.-D. Cheng, X. H. Jiang, Y. Sun, and J. Wang, "Color Image Segmentation: Advances and Prospects," *Pattern Recognit.*, vol. 34, no. 12, pp. 2259–2281, 2001, doi: 10.1016/S0031-3203(00)00149-7.

[52] T. Tianhao and W. Tianzhen, "An ANN-based clustering analysis algorithm with dynamic data window," in *Control and Automation, 2005. ICCA'05. International Conference on*, 2005, vol. 1, pp. 581–586, doi: 10.1109/icca.2005.1528185.

[53] S. Carata and V. Neagoe, "A Pulse-Coupled Neural Network approach for image segmentation and its pattern recognition application," in *2016 International Conference on Communications (COMM)*, 2016, pp. 61–64, doi: 10.1109/ICComm.2016.7528317.

[54] J. Lian *et al.*, "An Overview of Image Segmentation Based on Pulse-Coupled Neural Network," *Arch. Comput. Methods Eng.*, vol. 28, no. 2, pp. 387–403, 2021, doi: 10.1007/s11831-019-09381-5.

[55] R. V. R. Chary, D. R. Lakshmi, and K. V. N. Sunitha, "Feature Extraction Methods for Color Image Similirity," *Adv. Comput.*, vol. 3, no. 2, pp. 147–157, 2012, doi: 10.5121/acij.2012.3215.

[56] M. Hassan and C. Bhagvati, "Structural Similarity Measure for Color Images," *Int. J. Comput. Appl.*, vol. 43, no. 14, pp. 7–12, Apr. 2012, doi: 10.5120/6169-8590.

[57] Y. Deng, B. S. Manjunath, C. Kenney, M. S. Moore, and H. Shin, "An efficient color representation for image retrieval," *IEEE Trans. Image Process.*, vol. 10, no. 1, pp. 140–147, 2001, doi: 10.1109/83.892450.

[58] A. Mojsilovic, H. Hu, and E. Soljanin, "Extraction of perceptually important colors and similarity measurement for image matching, retrieval and analysis," *IEEE Trans. Image Process.*, vol. 11, no. 11, pp. 1238–1248, Nov. 2002, doi: 10.1109/TIP.2002.804260.

[59] V. Shijina, A. Unni, and S. J. John, "Similarity measure of multiple sets and its application to pattern recognition," *Informatica*, vol. 44, no. 3, 2020, doi: 10.31449/inf.v44i3.2872.

[60] D. J. Weller-Fahy, B. J. Borghetti, and A. A. Sodemann, "A Survey of Distance and Similarity Measures Used Within Network Intrusion Anomaly Detection," *IEEE Communications Surveys and Tutorials*, vol. 17, no. 1. pp. 70–91, 2015, doi: 10.1109/COMST.2014.2336610.

[61] S. S. Harshvardhan, S. Kiran, and S. Kumari, "Color Texture Segmentation using Binary Tree Cluster Quantization Technique," *Int. J. Innov. Res. Comput. Commun. Eng.*, vol. 6, no. 6, pp. 5820–5827, 2015, doi: 10.15680/ijircce.2015. 0306109.

[62] I. G. M. Karma, "Determination and Measurement of Color Dissimilarity," *Int. J. Eng. Emerg. Technol.*, vol. 5, no. 1, pp. 67–71, 2020,

doi: 10.24843/ijeet.2020.v05.i01.p13.

[63] R. Real and J. M. Vargas, "The probabilistic basis of Jaccard's index of similarity," *Systematic Biology*, vol. 45, no. 3. pp. 380–385, 1996, doi: 10.1093/sysbio/45.3.380.

[64] A. Carass *et al.*, "Evaluating white matter lesion segmentations with refined Sørensen-Dice analysis," *Sci. Rep.*, vol. 10, no. 1, pp. 1–19, 2020, doi: 10.1038/s41598-020-64803-w.

[65] E. Fernandez-Moral, R. Martins, D. Wolf, and P. Rives, "A New Metric for Evaluating Semantic Segmentation: Leveraging Global and Contour Accuracy," in *IEEE Intelligent Vehicles Symposium, Proceedings*, 2018, vol. 2018-June, pp. 1051–1056, doi: 10.1109/IVS.2018.8500497.

[66] J. Hernández and W. Gómez, "Automatic Tuning of the Pulse-Coupled Neural Network Using Differential Evolution for Image Segmentation," in *Mexican Conference on Pattern Recognition*, 2016, pp. 157–166, doi: 10.1007/978-3-319-39393-3_16.