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IMPLEMENTATION OF THE WATERSHED METHOD FOR SEGMENTING PADANG TRADITIONAL CUISINE IMAGES TO IMPROVE CULINARY OBJECT RECOGNITION ACCURACY

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Abstract

This study examines the implementation of the Watershed method for segmenting images of traditional Padang cuisine with the aim of improving culinary object recognition accuracy. Padang dishes possess complex visual characteristics, where multiple food components such as rice, side dishes, chili sauce, and vegetables are presented on a single plate. These elements often overlap and exhibit similar colors and textures, making image segmentation challenging when using conventional methods. Therefore, the Watershed algorithm was selected due to its ability to separate objects based on intensity variations and object contours, even when boundaries are unclear or blurred. The research process begins with image data collection from a publicly available Kaggle dataset containing various Padang food images. The preprocessing stage includes RGB to grayscale conversion, Gaussian blur filtering, and histogram equalization to enhance image quality and reduce noise. Subsequently, thresholding is applied to produce binary images, followed by distance transform to identify object cores. Marker determination is then performed to distinguish foreground and background regions, which serve as the basis for the Watershed segmentation process. The Watershed algorithm operates by simulating water flooding from predefined markers until meeting points form object boundaries. Experimental results show that the method can generate clear separation lines between food objects in visually complex scenes. However, quantitative evaluation reveals that the segmented foreground area remains relatively small, indicating that further optimization is required. Overall, the Watershed method demonstrates potential for handling overlapping objects and unclear boundaries, and can serve as a foundation for future culinary image analysis systems.

Keywords: image segmentation; watershed; padang cuisine; digital image processing; segmenting images.

1. INTRODUCTION

Padang cuisine is one of Indonesia's culinary heritages, characterized by its rich flavors, aromas, and highly distinctive visual appearance [1], [2]. Originating from the Minangkabau region of West Sumatra, this cuisine is widely recognized not only in Indonesia but also internationally as a symbol of the country's culinary diversity [3], [4]. Iconic examples of Padang dishes include rendang, gulai ayam (chicken curry), dendeng balado, and sambal ijo, all of which exhibit unique characteristics in terms of color, texture, and presentation. The visual appearance of each dish often reflects the ingredients, cooking processes, and spices used, making images of Padang cuisine rich in visual and semantic information within the context of digital image processing [5].

Image segmentation is a fundamental stage in digital image processing that aims to divide an image into homogeneous regions based on certain criteria such as color, intensity, or texture. Its purpose is to extract significant objects within an image so that they can be further analyzed, for example in recognition or classification processes. In the culinary context, image segmentation plays an important role in isolating different food elements within a single photograph, such as separating side dishes, vegetables, and accompaniments on a plate of nasi Padang. However, the complex visual characteristics of food, overlapping objects, and similarities in color among food components make image segmentation a challenging task in food image processing [6]–[8].

The main challenge in recognizing images of Padang cuisine lies in the low segmentation accuracy caused by extensive object overlap and unclear contours. Simple segmentation techniques based on thresholding or k-means clustering often fail to separate food components precisely. This limitation causes food image recognition systems to struggle in accurately identifying objects, which in turn degrades the performance of artificial intelligence–based applications such as food classification, culinary recommendation systems, or augmented reality applications for culinary tourism. In this context, a more adaptive segmentation approach is required, one that is capable of considering spatial structures and detailed intensity gradients within the image [9].

Previous research conducted by [10] reported that the detection of lung cancer nodules in CT scan images is challenging due to the irregular shapes of nodules and their frequent overlap with surrounding tissues. To address this issue, the Watershed algorithm was employed to achieve more accurate separation of nodule regions. The segmentation process involved preprocessing, binarization, and the application of the Watershed algorithm. The results demonstrated that this method was capable of effectively isolating nodules from other structures, achieving a similarity level of 91.97% with the ground truth images based on the Jaccard index.

As a potential solution, the Watershed algorithm can be implemented to improve the segmentation accuracy of Padang cuisine images. Watershed is a mathematical morphology [11], [12], based segmentation technique that models an image as a topographic surface, where object boundaries are identified through a flooding analogy that fills image basins. This technique is effective in detecting edges and contours comprehensively, particularly in images containing multiple elements with blurred or overlapping boundaries. By integrating preprocessing steps such as edge enhancement and gradient-based filtering, the implementation of the Watershed algorithm is expected to produce more accurate segmentation results, thereby supporting the development of intelligent and context-aware culinary object recognition systems, especially for Padang cuisine, which exhibits high visual complexity [13].

2. RESEARCH METHOD

2.1. Image Segmentation

Image segmentation is a process in digital image processing that aims to divide an image into several distinct and separate regions so that each region can be analyzed more easily. The primary objective of image segmentation is to separate the desired objects or features in an image from the background or other irrelevant parts [14]. This process plays a crucial role in various image processing applications, such as object recognition, medical image analysis, as well as manufacturing and surveillance systems. One of the most commonly used image segmentation methods is threshold-based segmentation (thresholding). This method works by converting a grayscale image into a binary image, where pixels with intensity values higher than a predefined threshold are classified as objects, while pixels with lower intensity values are considered background. Although this method is simple and computationally efficient, it may produce less accurate results when the contrast between the object and the background is low [13].

2.2. Watershed Method

The Watershed method is one of the image segmentation techniques used to divide an image into several regions or segments based on the distinctive topographic structure of the image. In the context of image processing, this technique treats an image as a topographic surface or landscape, where each pixel is considered a point with a certain height or intensity value [15]. The segmentation process using the Watershed method can be described as the flow of water into valleys, separating different regions based on existing contours or boundaries. In simple terms, the Watershed technique divides an image into more homogeneous regions, where each object in the image is regarded as a separate area divided by "valleys" or "separating lines." In an image, these "valleys" correspond to areas with low intensity values, while objects or regions with higher intensity values are viewed as peaks or distinct regions [6]. The basic process of the Watershed method can be described as follows:

1. Construction of Image Topography
   The image is first processed to construct a topographic representation of pixel intensities. The image is considered to consist of "mountains" and "valleys," where intensity values represent topographic heights.
2. Determination of Marker Points (Seeds)
   Initial points or markers are typically selected either manually or through automatic detection techniques to initiate the segmentation process. These points serve as sources for the water flow.
3. Simulation of Water Flow
   The Watershed technique then simulates water flowing from the marker points toward the valleys (areas with low intensity values). The water fills these valleys, and the process stops when object boundaries are encountered, namely at the separating lines that connect two different objects.
4. Object Separation
   Finally, after the water flow simulation is completed, different objects in the image are separated based on the boundaries formed by the separating lines or "watershed lines."

Mathematically, the Watershed method does not have a single explicit and simple formula as found in some other techniques (e.g., thresholding). Instead, its fundamental concept is implemented algorithmically based on topographic image processing. The mathematical formulation of the Watershed method can be described through the following steps:

1. Image Gradient
   To generate a topographic image, the image gradient is first computed, which measures the change in pixel intensity around a certain point. The gradient can be calculated using operators such as Sobel or Prewitt.

$$\text{Gradien}(x, y) = \sqrt{\left(I_x^2 + I_y^2\right)} \qquad (1)$$

where:

I_x : derivative of the image with respect to the x-axis (horizontal).
I_y : derivative of the image with respect to the y-axis (vertical).
(x, y) : coordinate position in the image.

2. Watershed Transformation
In the water flow simulation, the process starts from predefined marker points or seeds (usually located on the objects to be separated), and water is "poured" from these points toward the valleys (areas with low intensity values). At each pixel, the segment or object to which it belongs is determined based.

$$\text{label}(x, y) = \arg\min\left(\text{distance}(x, y)\right) \qquad (2)$$

where :

$\text{label}(x, y)$: the resulting label or segment assigned to the pixel at position (x, y).
$\text{distance}(x, y)$: the distance to the nearest marker point (seed).

3. Separation Using Watershed Lines
After the water flow simulation is completed, the boundaries between different objects or segments are defined by watershed lines. These lines act as separators between low-intensity regions (valleys) that connect different objects or regions, and they typically appear along boundaries where the image gradient is sufficiently high.

3. RESULTS AND DISCUSSION

The implementation of the Watershed method in the image segmentation process of traditional Padang cuisine. The discussion covers how this method operates in separating food objects from the background, the effectiveness of the resulting segmentation, as well as an analysis of the successes and challenges encountered during the experiments. The Watershed method was chosen due to its capability to handle images with blurred or overlapping object contours, which are common characteristics in the visual appearance of Padang cuisine. This technique is also suitable for food images containing multiple visual elements such as rice, side dishes, sambal, and vegetables served on a single plate. This discussion aims to determine whether the Watershed method is able to significantly improve segmentation accuracy compared to conventional segmentation methods.

3.1. Image Data Collection

The initial stage in the image segmentation process is the collection of visual data to be used as the research object. In this study, images of traditional Padang cuisine were obtained from a publicly available dataset on the Kaggle platform, accessible at: https://www.kaggle.com/datasets/faldoae/padangfood. The dataset contains a representative collection of Padang food images, covering various types of dishes such as rendang, gulai ayam (chicken curry), dendeng balado*, and* sambal ijo. The images in this dataset exhibit variations in terms of shooting angles, lighting conditions, and backgrounds, which are crucial for evaluating the robustness of the segmentation method under diverse real-world conditions. This visual diversity enables the system to be tested on highly complex images that closely resemble real serving conditions of Padang cuisine. In addition, the dataset is equipped with labels for each food category, which are useful for the evaluation and classification stages after the segmentation process is completed. Therefore, the Kaggle dataset serves as a valid and relevant data source to support this research on image segmentation using the Watershed method.

Figure 1. Example of the Dataset

3.2. Preprocessing Citra

One of the initial stages in digital image processing is preprocessing, which aims to improve image quality so that it is better prepared for subsequent processing stages. One of the main steps in preprocessing is the conversion of images from the RGB (Red, Green, Blue) format to grayscale. RGB images are color images composed of three primary color channels, whereas grayscale images consist of a single channel with intensity values ranging from black (0) to white (255). This conversion is performed to simplify visual information without losing the main structural characteristics of objects in the image. In the context of Padang cuisine image segmentation, the transformation to grayscale is essential because the Watershed method is based on differences in pixel intensity rather than color information. This process also helps reduce computational complexity and processing time, as only one channel is processed instead of three channels in RGB images. With a clear grayscale image that emphasizes contrast differences, the segmentation process can be performed more effectively and accurately.

Figure 2. RGB Image

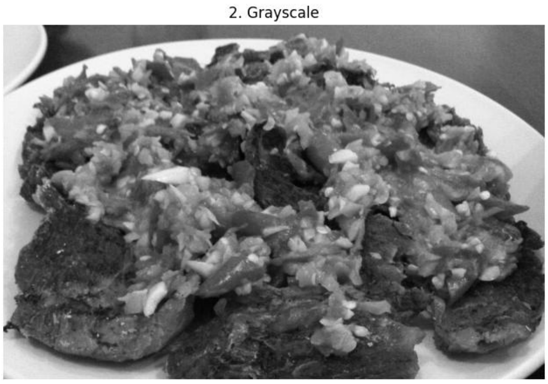

Figure 3. Grayscale

Figure 3 illustrates the result of converting a color image (RGB) into grayscale format. At this stage, all color information is transformed into grayscale levels that represent the light intensity of each pixel, ranging from black (low intensity values) to white (high intensity values). This conversion aims to simplify visual data so that it becomes more efficient for subsequent processing steps, such as segmentation. In the context of visually complex Padang cuisine images, the transformation to grayscale helps emphasize intensity differences among objects such as side dishes and sambal without being affected by color variations. Although the image loses color information, the structural features and texture details of the food objects remain clearly visible, such as meat pieces and the distribution of spices on the surface.

3. Gaussian Blur

Figure 4. Gaussian Blur

Figure 4 above shows the result of applying Gaussian Blur after converting the image to grayscale. Gaussian Blur is a filtering technique used to reduce noise or small disturbances in an image by smoothing pixel transitions. This process operates using a Gaussian distribution function, where each pixel is replaced by a weighted average of its neighboring pixels, resulting in a softer and more blurred appearance. In the Padang cuisine image, the Gaussian Blur effect helps suppress fine details such as sambal granules or spices that may interfere with the segmentation process, while still preserving the main contours of food objects, such as pieces of meat.

3.3. Application of Thresholding and Distance Transform

This stage is conducted to prepare the image for further processing in the segmentation pipeline. After the image undergoes preprocessing, a thresholding process is applied to convert the grayscale image into a binary image. This transformation aims to visually separate the main objects from the background. Subsequently, a distance transform is applied to map the distances between pixels within the object regions, which is useful for identifying core areas or the foreground. The results of these two processes form the basis for determining the regions that will be used as markers in the segmentation process using the Watershed method.

4. Histogram Equalization

Figure 5. Histogram Equalization

Figure 5 illustrates the result of applying the histogram equalization technique to a grayscale image. This technique aims to improve image illumination quality by equalizing the distribution of pixel intensity values. In this context, histogram equalization helps enhance the contrast between bright and dark regions of the food objects. This enhancement makes the boundaries between elements in the image, such as meat and sambal, more visually distinct. With improved contrast, important features within the image can be more easily identified by the digital image processing system, particularly during the segmentation stage.

Figure 6. Thresholding

Figure 6 shows the result of the thresholding process, a technique used to convert a grayscale image into a binary image. In a binary image, each pixel has only two possible values: black (0) or white (255), which visually represent the distinction between objects and the background. At this stage, the thresholding method aims to separate important regions in the food image, such as meat pieces, spices, and sambal, from irrelevant areas. White regions represent the object areas (foreground), while black regions indicate the background or areas that are not part of the main objects. Although the thresholding result may still appear coarse and merged across different parts, this step serves as a crucial initial stage in preparing the image for further segmentation using methods such as Watershed.

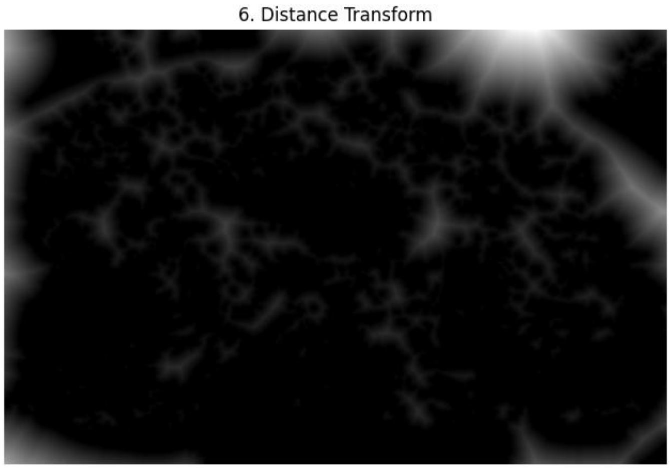

Figure 7. Distance Transform

Figure 7 shows the result of applying the distance transform to the binary image obtained from the thresholding process. The distance transform calculates the distance from each white pixel (object) to the nearest black pixel (background) and represents it as intensity gradients. Pixels that are farther from the object boundaries have higher values and are visualized as brighter regions, while pixels closer to the object edges appear darker. In this image, bright patterns resembling light spots can be observed, indicating the centers of mass of the food objects. These points are subsequently used to mark the foreground regions (object cores) spatially. The distance transform is particularly useful in the segmentation process because it helps distinguish objects that are close to each other or overlapping, which are difficult to separate using conventional thresholding alone.

3.4. Determination of Marker Points

After the thresholding and distance transform processes, the next stage is the determination of marker points. Markers serve as initial indicators that distinguish between object regions (foreground) and background regions in the image. The selection of markers is crucial because it provides the basis for the Watershed algorithm to initiate the segmentation process based on a water flow simulation. Foreground regions are typically identified from the results of the distance transform, which indicate the centers of mass of the objects, while background regions are obtained through dilation operations on the binary image. With well-defined markers, the system can more accurately recognize object boundaries and reduce the risk of over-segmentation caused by noise or blurred contours.

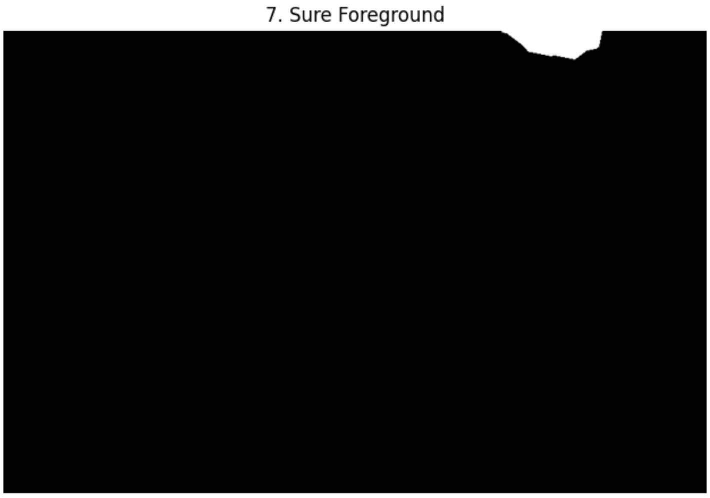

Figure 8. Foreground

Figure 8 presents the result of identifying the *sure foreground* areas, which represent the core regions of the food objects. These areas are obtained from the distance transform results that have undergone further thresholding, so that only pixels with the highest distance values are retained. In the context of segmentation, the sure foreground serves as the primary marker that guides the flooding of surrounding regions in the Watershed algorithm. The white regions in the image indicate pixels that are considered object centers, while the black areas represent regions that have not yet been classified. Identifying the foreground areas is crucial to prevent over-segmentation or misclassification between objects and the background, particularly in complex images such as Padang cuisine, which contain multiple overlapping visual elements.

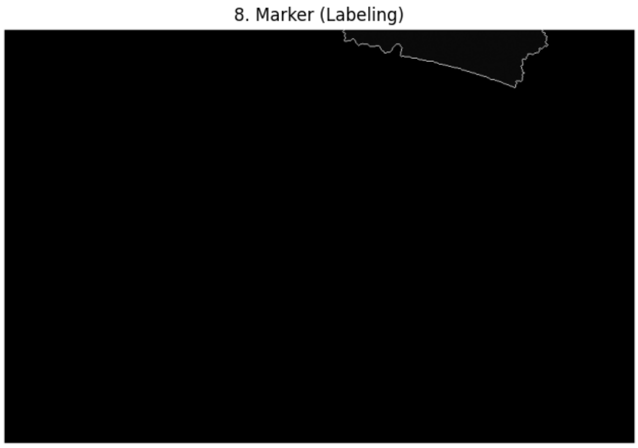

Figure 9. Marker

Figure 9 illustrates the results of the marker labeling stage, where the system assigns initial labels to the foreground and background areas within the image. This process is a crucial component in the implementation of the Watershed algorithm, as the markers serve as reference points for the "water flow" paths used to separate one object from another. In the figure, a thin bright line can be observed at the upper part of the image, indicating regions that have been identified as part of the object (foreground). The remaining areas are still shown in black, representing regions that have not yet been included in the markers. Although only a small portion of the area is labeled, this step forms a fundamental basis for constructing accurate segmentation between culinary objects.

3.5. Implementation of the Watershed Algorithm

After the markers are determined, the next stage is the application of the Watershed algorithm as the core of the image segmentation process. At this stage, the algorithm is executed to simulate the flow of water that floods the image starting from the previously defined marker points. The water is assumed to flow from each marker region until it meets the flow originating from other markers, and these meeting points automatically form the boundaries between objects. Through this mechanism, the Watershed algorithm is able to produce the final segmentation in the form of clear separating lines between food objects, even when the objects are in contact with each other or have similar colors and textures.

Figure 10. Final Segmentation

Figure 10 shows the final result of the segmentation process using the Watershed algorithm. After the foreground and background markers are defined, the algorithm operates by simulating the flooding of the image from the marker points until the flows meet, forming boundary lines or separating contours. In this segmentation result, the separating boundaries are indicated by thin red lines that divide several regions of the food image. These lines represent the boundaries between food objects, even though the objects may visually appear to overlap or have very similar colors. Using this approach, the system is able to identify and separate food elements more accurately, which is essential for object recognition or culinary classification tasks.

3.6. Segmentation Success Percentage

The segmentation success percentage is a quantitative indicator used to evaluate the effectiveness of an algorithm in separating the main objects (foreground) from the background in an image. This value is calculated by comparing the area of the successfully segmented objects with the total area of the image. The higher the percentage, the greater the system's ability to recognize and label relevant objects. This evaluation is important as an initial benchmark, particularly when ground truth data are not yet available for comparison. It can therefore be used to determine whether the segmentation process performs optimally or whether a significant amount of object information is still being lost.

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Luas Area Objek Tersegmentasi: 2888 piksel
Total Luas Citra: 483054 piksel
Persentase Segmentasi Foreground: 0.60%
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Figure 11. Segmentation Result

Based on the experimental results, the area of objects successfully segmented was recorded as 2,888 pixels out of a total image area of 483,054 pixels. From this calculation, the foreground segmentation percentage was only 0.60%. This value indicates that the object area identified by the system is relatively small compared to the overall image. This result suggests that the segmentation process has not yet performed optimally. Possible contributing factors include uneven lighting conditions, low contrast in object textures, or suboptimal threshold parameter settings. Therefore, further adjustments in preprocessing steps or feature enhancement are required to enable the system to recognize and separate food objects more effectively.

3.7. Discussion

The experimental results demonstrate that the Watershed algorithm is capable of separating food objects in Padang cuisine images by exploiting intensity gradients and spatial structure, particularly in cases where object boundaries overlap or appear visually ambiguous. The stepwise preprocessing pipeline, consisting of grayscale conversion, Gaussian smoothing, histogram equalization, thresholding, distance transform, and marker extraction, plays a critical role in guiding the Watershed process toward meaningful segmentation boundaries. Visual inspection of the final segmentation results indicates that the algorithm successfully delineates object contours even when color similarity and spatial proximity would hinder simpler segmentation techniques.

However, quantitative evaluation based on the foreground area percentage reveals that the segmentation performance remains limited, with only 0.60% of the total image area identified as foreground. This relatively low value suggests that the current parameter configuration and preprocessing strategy are not yet optimal for fully capturing the complex visual structure of Padang cuisine images. Factors such as uneven illumination, subtle texture differences between food components, and conservative threshold settings likely contribute to the under-segmentation observed in the results. In particular, aggressive noise suppression and strict foreground selection may have caused the loss of relevant object regions during marker determination.

Despite these limitations, the study highlights the potential of the Watershed method as a foundation for culinary image segmentation, especially in scenarios involving overlapping objects. The findings indicate that further improvements can be achieved through adaptive thresholding, illumination normalization, multi-scale marker extraction, or the integration of color and texture features. Overall, this research provides valuable insights into the challenges of segmenting complex food images and establishes a basis for future work aimed at enhancing segmentation accuracy to support robust food recognition and classification systems.

4. CONCLUSION

This study demonstrates the application of the Watershed algorithm for segmenting Padang cuisine images through a structured preprocessing pipeline, including grayscale conversion, Gaussian Blur, histogram equalization, thresholding, distance transform, and marker determination. The experimental results show that the Watershed method is able to produce clear boundary lines between food objects, even in conditions where objects overlap or share similar visual characteristics. This indicates that the algorithm is conceptually suitable for handling complex food images with dense object composition.

Nevertheless, quantitative evaluation reveals that the segmentation performance is still limited, as indicated by the low foreground segmentation percentage of 0.60% relative to the total image area. This result suggests that the current configuration has not yet optimally captured the relevant object regions, likely due to factors such as uneven lighting, low contrast between objects and background, and suboptimal threshold and marker parameters. As a consequence, a significant portion of object information may be lost during preprocessing and marker selection.

In conclusion, while the Watershed algorithm shows potential as a segmentation approach for complex culinary images, further refinement is required to improve its effectiveness. Future work should focus on optimizing preprocessing parameters, employing adaptive or multi-threshold techniques, and incorporating additional features such as color and texture information. These improvements are expected to enhance segmentation accuracy and support more reliable food object recognition and classification in subsequent processing stages.

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