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A Morphology Processing Approach For Image Processing In Cancer Diagnosis

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Abstract

Early tumor detection is critical for improving cancer treatment outcomes, enabling less invasive and more cost-effective interventions. However, limited access to pathologists and high patient volumes reduce diagnostic efficiency, particularly in underserved regions, underscoring the urgency for computational support tools. While deep learning has shown promise in tumor detection, it requires extensive annotated datasets, high computational resources, and long processing times, making it less feasible in certain contexts.This study introduces a lightweight image processing approach for detecting tumors in Hematoxylin and Eosin (H&E)–stained histopathology images without deep learning. Using data from the PAIP 2023 Tumor Cellularity challenge, the proposed method applies histogram equalization, bilateral filtering, morphological transformations, bitwise operations, and an improved algorithm adapted from prior research. The method achieves IoU (Intersection of Union) of 0.93 compared to pathologist-determined ground truth. The results indicate that this approach can serve both as a standalone segmentation tool and as a preprocessing stage for deep learning pipelines, enhancing accessibility, reducing computational costs, and supporting broader adoption of computer-aided pathology in resource-limited settings.

Keywords : *Image Processing, Morphology Operation, Tumor Detection.*

1. INTRODUCTION

The early detection of tumors is a critical component in cancer diagnosis and treatment, as timely identification of early-stage tumors can significantly improve patient outcomes and survival rates [1]. Traditionally, tumor detection is performed manually by pathologists through the visual examination of histopathological tissue images. However, this manual process faces inherent limitations [2], [3], including slow processing speed, potential delays in diagnosis, and reliance on the subjective interpretation of the examiner.

To overcome these challenges, numerous studies have explored computer-assisted approaches for tumor detection [4], [5]. Computational methods, particularly those leveraging artificial intelligence (AI), machine learning (ML), and image processing, have demonstrated potential to enhance both the accuracy and efficiency of tumor analysis. In histopathology, hematoxylin and eosin (H&E) staining is commonly used to prepare tissue samples for microscopic examination, after which computational algorithms, such as deep learning, can be applied to distinguish between normal and abnormal tissue regions based on morphological and structural characteristics, including cell shape, texture, intensity, and spatial distribution [6].

A commonly used metric in tumor assessment is tumor cellularity, defined as the proportion of tumor cells within the tumor bed [7]. In manual practice, pathologists evaluate tissue images, identify tumor regions, and calculate tumor cellularity scores, those process is both time-consuming [7], [8] and

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impractical for large-scale datasets. This reinforces the need for automated solutions. Previous research has shown promising results with deep learning; for example, Ortega achieved a sensitivity of approximately 88% when detecting tumors from H&E images [9], while Xu reported detection accuracy of 99.9% for non-tumor images and 94.8% for tumor images, with reduced evaluation time compared to manual assessment [10]. Deep learning has been applied to various cancer types frequently identified by the World Health Organization as high-risk, including breast, lung, colon, rectum, prostate, skin, and stomach cancers [11], with notable applications in breast [12], [13], lung [14], [15], colon [16], [17], rectum [18], [19], prostate [20], [21], skin [22], [23], and stomach [22], [24] tumor detection.

Despite these achievements, deep learning approaches present certain drawbacks. Zaidi [25] highlighted that while deep learning models excel in object recognition and achieve high overall accuracy, they may underperform in real-time detection tasks, particularly in terms of processing speed. Furthermore, deep learning requires substantial computational resources and large annotated datasets to achieve optimal performance [26], [27]. In scenarios with limited training data, such as in the PAIP 2023 challenge, where only 53 training samples were provided, deep learning is less likely to produce reliable results.

In light of these limitations, alternative approaches such as pixel-based image analysis offer potential advantages, including reduced computational requirements and faster processing times, while avoiding the dependence on large-scale annotated datasets. This research investigates such an approach for tumor cellularity estimation in the PAIP 2023 dataset, aiming to provide a computationally efficient method for pre-processing histopathological images, which could also serve as input for deep learning models in future studies.

2. METHOD

Starting from the collection of training data, this section discusses the algorithm used in this study, the environment, the proposed algorithm process, research trends on related topics and their strengths and weaknesses, the algorithm analysis, and finally how this experimental scenario looks like.

2.1. Data Gathering

Gathering data for research purposes can be done through direct observation or through public data. Through direct observation, researchers can easily control the data used for research. However, the disadvantage of the direct observation method is that it requires a lot of power and much data needed. Public data is now data that is already available, eliminating the need for researchers to search for data for research purposes.

Table 1. Specification Dataset PAIP 2023

Dataset	Image Size	Pancreas	Colon
Training		50	3
Validtion	1024 X 1024	10	-
Testing		20	20

This research is research based on a challenge, namely PAIP 2023. So, the research data was provided by the organizers of the challenge. Data were acquired using a Leica Aperio AT2 or GT450 Whole Slide Imaging Scan with H&E staining. The images are in PNG format with a size of 1024 x 1024 pixels. The captured images show the pancreas and colon organs at 20x or 40x magnification. The images were recorded by Seoul National University Hospital (SNUH) from January 2005 to June 2019. The data will be used as training data to develop the algorithm for this study. The amount of data recorded is at Table 1.

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In the given challenge, the differences to images with 20x or 40x magnification are not discussed. However, the 20x image is about 0.5 mpp (microns per pixel) while the 40x image is 0.26 mpp.

The data set used as training data is training data. The training data is used to analyze whether the algorithm agrees with the given basic truth. The comparison between research results and ground truth is explained in the experiment scenario.

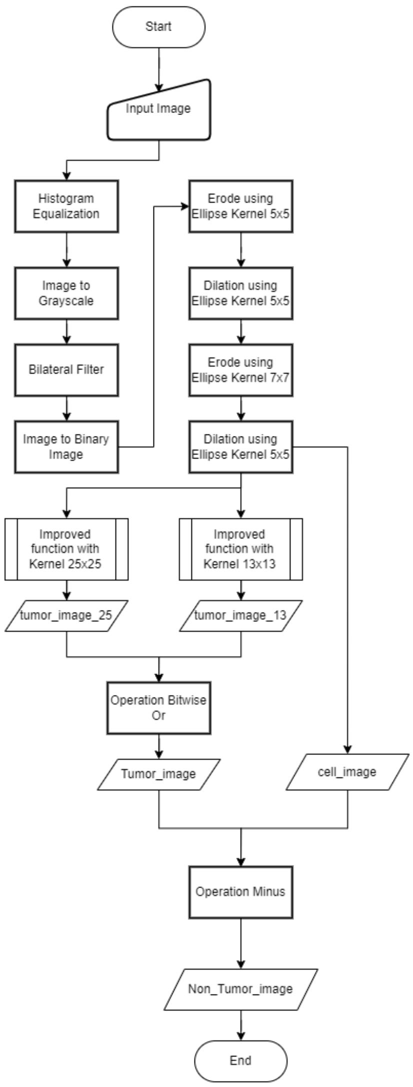

Figure 1. Main Algorithm

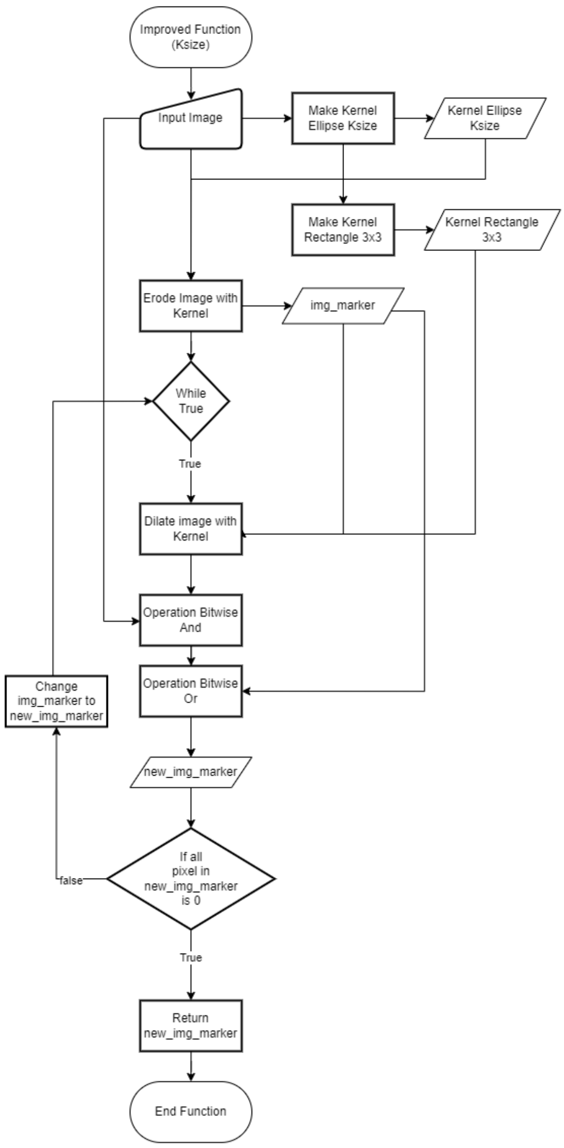

Figure 2. Improved Function from Wang

2.2. Algorithm

The developed algorithm at **Kesalahan! Sumber referensi tidak ditemukan.** mainly uses the OpenCV library with the programming language Python as seen at **Kesalahan! Sumber referensi tidak ditemukan.**. Using OpenCV library for various operations on images like histogram equalization, image-to-grayscale, bilateral filter, morphological operations, and bitwise operations. The morphology operations used are dilation, erosion, opening, and closing operations. Bitwise operations are now used to perform OR, AND, and XOR operations. The AND and XOR operations are performed using a modified, improved morphological bandpass filter algorithm and its application to circle detection. The kernel used in the Operation Morphology process is the ellipse kernel.

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The input to this algorithm is an image derived from an H&E stained scan of a tissue or organ. This image is then processed into a binary image showing the area of the tumor cells. The white areas are cells. Cells can be tumor cells or non-tumor cells.

This algorithm first recognizes all cells. Then, Then, by modifying the referred algorithm from study [28] a region is created that is a tumor cell. The image containing all the cells is reduced in size by the resulting image from the algorithm change. The result is an image containing non-tumor cells. So, there are three outputs of this algorithm, namely images of all cells, tumor cells and non-tumor cells.

The method proposed in this research uses only the pixel process. The image is pre-processed to improve image quality, such as histogram equalization and bilateral filtering. Next, the image undergoes pixel processing, ranging from morphological operations to improvised algorithms in biomedical settings.

2.3. Environment

The implementation of this study uses the Python programming language with the Google Colab IDE. The Python programming language is used because it supports data and image analysis. The pandas library is used for data analysis. The OpenCV library is now used for image analysis. It uses the Google Colab IDE as it supports displaying images that come from the OpenCV library.

2.4. Morphology Image Processing

Morphological image processing is one of the operations in image processing. Morphological operations are widely used in the biomedical world as a pre-processing process [29] Mardani's studies on the segmentation of retinal blood vessels show good results compared to previous studies. Mardani uses the morphology operation to eliminate image noise and improve image quality.

2.5. Improved Morphological Band-Pass Filtering Algorithm and Its Application in Circle Detection

Morphological bandpass filtering is a feature extraction method. This method uses a specific shape of a structural element according to the shape of the feature to be extracted. In a study conducted by Wang [28], as shown at **Kesalahan! Sumber referensi tidak ditemukan.**, a new method to perform morphological bandpass filtering was proposed. During his research, he found that the proposed method gave good results in terms of time and accuracy in industrial settings. The application of the algorithm proposed by Wang is suitable for detecting circles in a laser beam. Laser light detection is useful for monitoring a machine in industry where research is being conducted.

The method proposed by Wang uses image processing morphology operations. In its research, the proposed algorithm uses opening, closing, dilation and erosion operations. There is also a subtraction operation between images.

When detecting tumors on an H&E image, the image of the cancer cells is circular or elliptical[30], [31]. Therefore, this study will adapt the algorithm created by Wang based on the properties of circular tumor cells. The algorithm was adapted to the data used, namely the data provided by the challenge organizers. The development and modification of the algorithm proposed by Wang for this study is as follows.

The input of the modified function is the kernel size. This kernel size is the size of the structure element used for morphology operations. The kernel type is kernel square. The purpose of this function is not to obtain circular features, as is the case with Wang, but to identify tumor cells and non-tumor cells.

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2.6. Deep Learning for Tumor Detection and its Pro-Cons

Many researchers have conducted studies on tumor detection. Several studies have shown good results regarding the accuracy of tumor detection. It is predicted that the use of deep learning as a tool to detect tumors from H&E images will continue to increase in the future. In a study conducted by Ortega, it was found that using deep learning to detect tumors resulted in a high sensitivity score of around 88% [9]. Ortega also stated that deep learning will be a promising tool in the future. Another study conducted by Xu using a neural network [10] approach found up to 99.9% accuracy for non-tumor images and 94.8% for tumor images. Xu compared the proposed method with the detection results performed by pathologists. Xu's research results show good accuracy with fast detection time.

The WHO states on the official website that there are seven types of tumors that are quite common. The seven tumor types even reach the cancer stage. The seven are breast, lungs, colon, rectum, prostate, skin, and stomach [11]. There are several studies on the use of Deep Learning for Cancer, such as Breast [12], [13], Lung [14], [15], Colon [16], [17], Rectum [18], [19], Prostate[20], [21], Skin [22], [23], and Stomach [22], [24]

In a study comparing deep learning models conducted by Zaidi [25]. It is said that deep learning is good at recognizing objects from an image. This is evidenced by the good average accuracy of the deep learning model. However, there are other issues with implementing object detection, particularly when it comes to real-time detection issues. The results show the poor performance of deep learning models in detection, especially in terms of speed.

On the other hand, Deep Learning comes after Machine Learning, so it can be said that Deep Learning is a subfield of Machine Learning. One of the problems with using Machine Learning and Deep Learning is that significant resources are required for model development. With a small amount of data, it is possible that the model created does not provide optimal results. The solution to this problem is to use a different approach, such as the pixel-based approach.

The purpose of this research is to develop an algorithm that will speed up the tumor analysis process by detecting tumors. Therefore, the shortcomings of the deep learning model are replaced by other methods such as the pixel-based algorithm.

2.7. Algorithm Analysis

The use of image processing algorithms in this research is because the algorithm is mostly executed sequentially with few iterations. While other approaches like deep learning require many iterations to train the mode with training data. This improves the approach of the image processing algorithm in terms of time. However, the deep learning approach is still superior in terms of accuracy.

To measure the accuracy of this research, Intersection over Union (IoU) is used. IoU is often used to compare two images, especially binary images. The result of the algorithm proposed in this article is a binary image. The binary image resulting from the algorithm is compared to the ground truth, which is also a binary image. Therefore, the use of IoU can be a measure of the accuracy of the algorithm in this ground truth research.

2.8. Experiment Scenario

The purpose of this research is the algorithm to detect tumors using the pixel method and calculate the TC value from the detection results. Then, as already explained, the research data is public data provided by the organizer. Therefore, this research focuses on developing an algorithm to detect tumors from H&E images.

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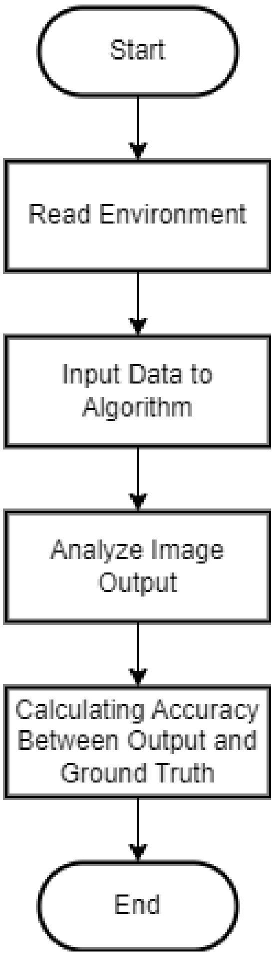

Figure 1. Experiment Scenario

In Figure 1, the experimental scenario starts with the reading environment. This is done so that the IDE used is consistent with research [32]. Setting up the IDE can take the form of installing the required libraries. Next, enter data into the algorithm. Here the algorithm was created and receives input in the form of images. The input image is an H&E image of the organ tissues of the pancreas and colon. The algorithm processes the image and produces a binary image output. The resulting binary image is a binary image of tumor, non-tumor, and all cells in the image. The image analysis is done visually between the image generated by the algorithm and the ground truth provided by the challenge organizer. To subsequently obtain quantitative results, a comparison between the image generated by the algorithm and the ground truth is carried out using Intersection over Union (IoU) formula. IoU is used because naïve solution will never occur [33]. Naïve solution can be when the accuracy of calculating the image segmentation of the Region of Interest is low, and the rest runs for the background. So, using pixel-by-pixel precision counts the background and true negatives. True negatives are not counted in the IoU. For IoU formula on (1)

$$IoU = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

Where A and B are images to be compared for similarity. The result of the formula is the accuracy value of the degree of similarity of the two images. If the IoU value is closer to 1, the two images will be more similar and vice versa.

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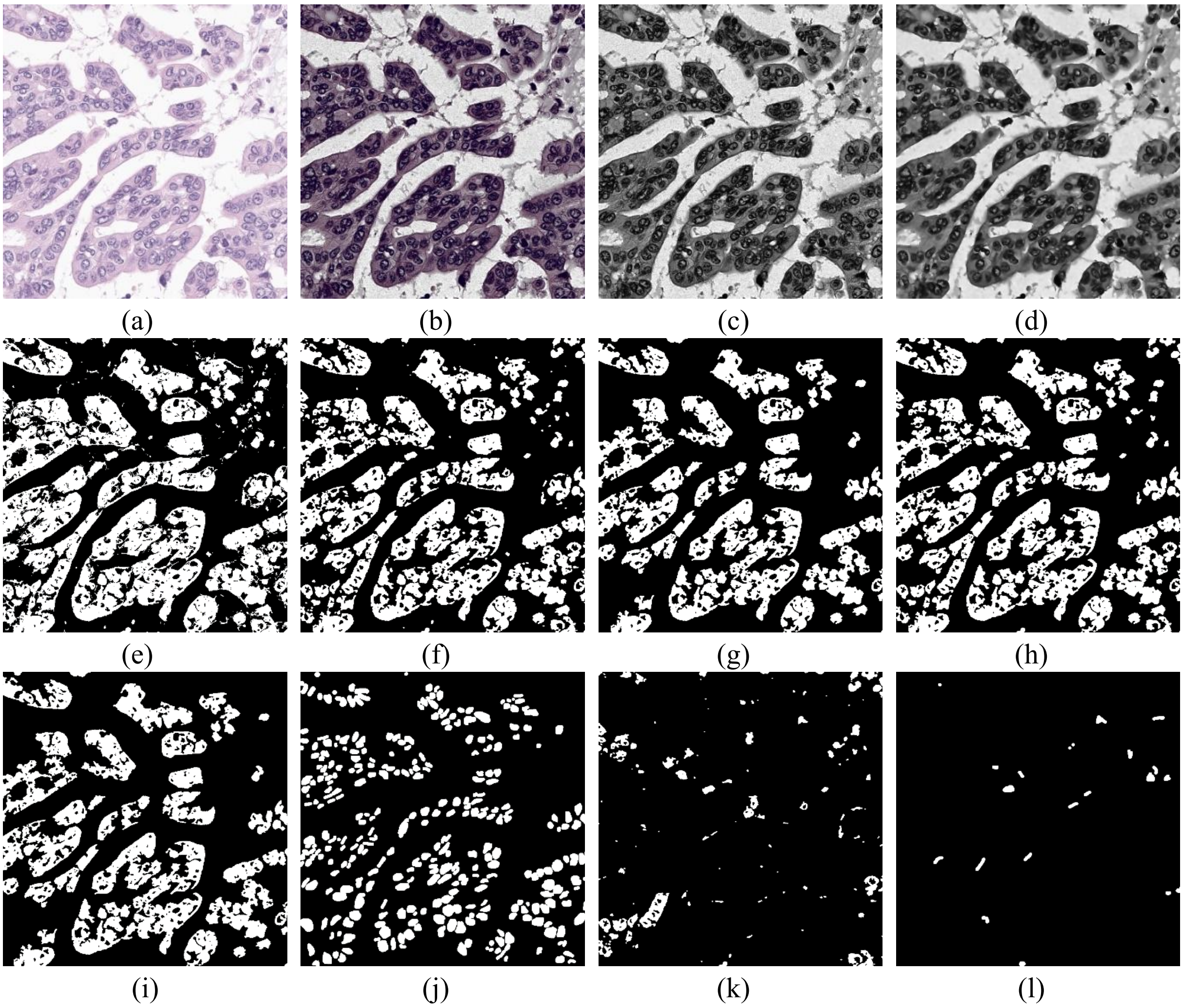

Figure 2. Algorithm Process Sequence

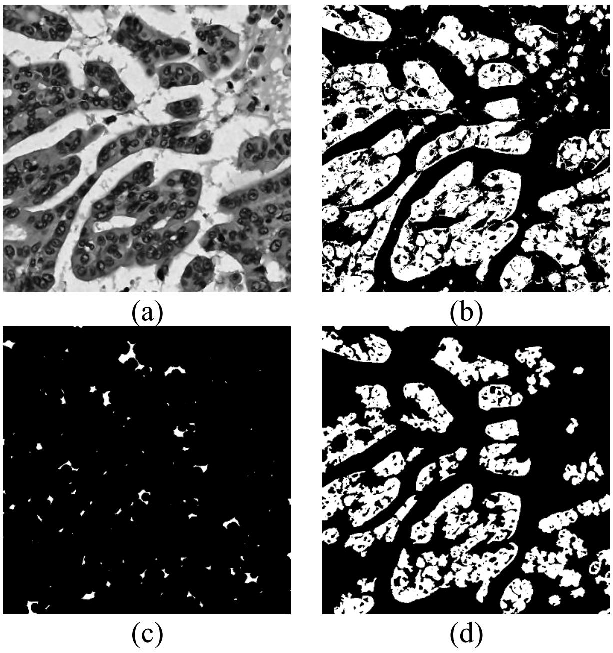

Figure 3. Modification Function from Wang with Kernel Size 25x25

3. RESULT

Figure 4 presents the sequential image processing workflow from the original scanned histopathology section to the final segmentation maps for tumor and non-tumor cells. The input image (Figure 4.a), stained with Hematoxylin and Eosin (H&E), is first enhanced using histogram equalization applied to the luminance channel in the YCbCr color space, improving contrast between tissue structures. The image is then converted to grayscale (Figure 4.c), followed by bilateral filtering (Figure 4.d) to reduce noise while preserving edge definition.

Subsequently, thresholding at a fixed value of 100 produces a binary image (Figure 4.e), enabling morphological operations such as dilation, erosion, opening, and closing to be performed. The result is a mask representing all detected cells, shown in Figure 4.f, with cell regions in white.

To identify tumor cells specifically, an improvised function adapted from Wang's method is applied. The process involves extrusion with kernel sizes of 25×25 (Figure 4.g) and 13×13 (Figure 4.h) to target tumors of varying nuclear sizes. These results are combined using a bitwise OR operation to form a tumor segmentation map (Figure 4.i). Non-tumor cells are obtained by subtracting the tumor mask from the total cell mask, resulting in Figure 4.k.

The Intersection over Union (IoU) metric is used for evaluation. Tumor cell segmentation (Figure 4.i vs. ground truth Figure 4.j) achieves an IoU of 0.43, while non-tumor segmentation (Figure 4.k vs. Figure 4.l) yields an IoU of 0.04. Figure 5 illustrates the extrusion process in detail: the grayscale image (Figure 5.a) is binarized (Figure 5.b), eroded with a 25×25 kernel (Figure 5.c), and then iteratively expanded without exceeding the original binary mask, producing Figure 5.d with reduced noise.

4. DISCUSSION

The results demonstrate that the proposed segmentation pipeline, incorporating the modified Wang algorithm, effectively isolates tumor cells despite histological variability in size and morphology. The combination of two kernel sizes like 25×25 for capturing larger contiguous structures and 13×13 for finer detail. This approach enhances tumor segmentation accuracy while mitigating the limitations of using a single kernel size.

The IoU score of 0.43 for tumor segmentation indicates moderate overlap with the ground truth, suggesting that the method captures most tumor nuclei but may miss irregular or fragmented regions. Conversely, the low IoU of 0.04 for non-tumor segmentation reflects challenges in differentiating small tumor clusters from larger non-tumor nuclei. This misclassification could stem from morphological similarities or noise introduced during thresholding and morphological operations.

From a methodological standpoint, bilateral filtering combined with histogram equalization successfully enhances feature visibility while preserving structural boundaries critical for morphological processing. However, the fixed thresholding approach may be overly simplistic for histopathological images with variable staining intensity. Adaptive thresholding or color deconvolution could improve binary mask quality.

Biomedically, accurate separation of tumor and non-tumor cells is essential for quantitative pathology applications such as tumor burden estimation, grading, and treatment response assessment. While the current framework shows promise, its limitations, particularly in non-tumor segmentation, suggest that integrating machine learning-based refinement stages or adaptive morphological parameters could further improve robustness across diverse tissue samples.

5. CONCLUSION

This study demonstrates that image processing techniques can serve as an effective and interpretable method for detecting tumors in H&E-stained histopathological images. By leveraging traditional operations such as histogram equalization, bilateral filtering, morphological transformations, and threshold-based segmentation, it is possible to achieve meaningful separation between tumor and non-tumor regions without relying on deep learning. Such methods offer advantages in terms of transparency, computational efficiency, and independence from large-scale annotated datasets, making them particularly valuable in settings where data scarcity or interpretability concerns are significant. In addition to providing a standalone segmentation approach, the methodology presented here can also function as a robust preprocessing stage for more complex automated analysis pipelines.

Looking ahead, the image processing framework established in this research can form the foundation for hybrid workflows that integrate conventional feature extraction with modern deep learning models. By supplying deep learning architectures with cleaner, more representative input data, many of the known limitations of deep learning, such as overfitting, noise sensitivity, and reduced generalizability. Future work could enhance the presented approach through adaptive parameter tuning, incorporation of advanced texture or shape descriptors, and integration with color deconvolution techniques to isolate histological stain components. These improvements have the potential to further increase segmentation accuracy and consistency, ultimately contributing to more reliable, interpretable, and clinically applicable tumor detection systems.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest either between the authors or with the research object discussed in this paper.

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