CDS6334 VISUAL INFORMATION PROCESSING

Individual Assignment

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Abstract

In this study, we combined preprocessing, segmentation, and post-processing approaches to build a method for identifying cancerous areas in breast ultrasound images. The method included segmentation using adaptive thresholding, contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), and noise reduction using Gaussian blurring. To improve upon the segmentation results, morphological procedures such as dilatation, opening, and closing were applied. Ultimately, the segmented regions were further refined through the use of edge smoothing and connected component analysis. Metrics such Adapted Rand Error, Pixel-Wise Precision, Recall, and Intersection over Union (IoU) were used to assess the segmentation performance. While there were certain difficulties in fully capturing the breadth of malignant regions, overall, the results showed a respectable balance between precision and recall. To increase the segmentation algorithm's robustness and accuracy, some improvements are suggested.

Introduction

One of the biggest causes of cancer-related mortality for women globally is still breast cancer. For appropriate treatment to be implemented and for patient outcomes to be improved, early diagnosis by accurate imaging techniques is essential. Because ultrasound imaging is non-invasive and can distinguish between benign and malignant regions, it is frequently utilized for breast cancer screening.

The objective in this effort was to develop a method that can accurately detect cancerous areas in breast ultrasound images. Developing an algorithm that could accurately and reliably detect areas that may be malignant was the issue at hand. Accurate detection of cancerous areas is essential since it strongly affects the choices made for further diagnosis and treatment. This work may find use in clinical settings where radiologists can use it to help them diagnose and identify breast cancer more accurately.

Description of Methods

The method was broken down into three basic stages: image preprocessing, segmentation methods, and post-processing. The goal was to accurately identify cancerous spots in breast ultrasound images.

Image Preprocessing

Preparing the ultrasound pictures for segmentation was the first stage. The preprocessing methods listed below were used:

- **Gaussian Blurring**: To start, the images' noise was reduced while the general structure was maintained by the use of Gaussian blurring. This action lessened the effect of high-frequency noise and smoothed the image.

- **Contrast Limited Adaptive Histogram Equalization (CLAHE)**: CLAHE was applied in order to improve the images' contrast. By adjusting the contrast in specific areas of the image, this approach made it simpler to discern cancerous areas from surrounding tissue.

Segmentation Methods

The primary step in the segmentation process was determining which parts were cancerous by applying the following techniques:

- **Adaptive Thresholding**: We applied adaptive thresholding, which dynamically modifies the threshold according to the specific local properties of the image. This technique worked very well at managing the different contrasts in the pictures, enabling more precise segmentation of the cancerous areas.

- **Morphological Operations (Close and Open)**: Following thresholding, morphological opening was used to eliminate tiny objects that were unlikely to be a part of the cancerous region and morphological closure was used to fill in any gaps within the segmented portions. Through the improvement of the segmented regions' continuity and noise reduction, this series of actions helped refine the segmentation.

- **Dilation**: In order to make sure that the segmented sections were appropriately stretched to cover the full cancerous area, the binary mask was dilated next. Additionally, this procedure assisted in filling in spaces between nearby areas that are part of the same cancerous area.

Post-Processing

The post-processing procedures that followed helped to further enhance the segmented binary masks:

- **Edge Smoothing**: Gaussian blur was then applied again to smooth the borders of the divided regions following dilation. By taking this procedure, the borders surrounding the cancerous areas were smoothed down and less sharp.

- **Connected Component Analysis**: Lastly, separate connected sections within the binary mask were found and labeled using connected component labeling. This stage made it possible to separate specific cancerous sites and assisted in ruling out any tiny, isolated areas that might have been mistakenly classified as malignant.

Results & Analysis

A set of measures that assessed the segmentation's accuracy and quality were used to assess the segmentation algorithm's performance. The 40 ultrasound images in the dataset—which had matching ground truth segmentation masks—were used to evaluate the findings.

DETAILED RESULTS

Image	ARE	Error	Precision	Recall	IoU
malignant (1).png	0.1502	0.6184	0.8202	0.2486	0.2358
malignant (10).png	0.3766	0.5793	0.3293	0.5822	0.2664
malignant (11).png	0.3344	0.6071	0.478	0.3335	0.2445
malignant (12).png	0.562	0.4071	0.5084	0.7113	0.4214
malignant (13).png	0.2843	0.6528	0.5709	0.2494	0.2101
malignant (14).png	0.396	0.4512	0.6549	0.4724	0.3782
malignant (15).png	0.0475	0.8466	0.4758	0.0915	0.0831
malignant (16).png	0.1306	0.6585	0.3874	0.3054	0.2059
malignant (17).png	0.5094	0.4057	0.5445	0.6542	0.4228
malignant (18).png	0.0815	0.8571	0.1943	0.1129	0.0769
malignant (19).png	0.2379	0.6046	0.5641	0.3043	0.2464
malignant (2).png	0.1524	0.6478	0.9995	0.2138	0.2137
malignant (20).png	0.2094	0.5913	0.4763	0.3578	0.2568
malignant (21).png	0.5519	0.2835	0.7583	0.6791	0.5583
malignant (22).png	0.3673	0.5059	0.7033	0.3809	0.3281
malignant (23).png	0.1559	0.6256	0.8295	0.2418	0.2303
malignant (24).png	0.3003	0.5593	0.946	0.2872	0.2826
malignant (25).png	0.2641	0.5017	0.9097	0.3431	0.3318
malignant (26).png	0.3605	0.5599	0.3237	0.6872	0.2821
malignant (27).png	0.4967	0.4784	0.5895	0.4678	0.3528
malignant (28).png	0.5391	0.4249	0.5118	0.6563	0.4036
malignant (29).png	0.376	0.4629	0.6541	0.4557	0.3672
malignant (3).png	0.3024	0.6498	0.5299	0.2615	0.2123
malignant (30).png	0.364	0.4042	0.7727	0.4849	0.4243
malignant (31).png	0.0767	0.7192	0.8256	0.1691	0.1633
malignant (32).png	0.5949	0.287	0.8035	0.6409	0.554
malignant (33).png	0.5101	0.3389	1.0	0.4937	0.4937
malignant (34).png	0.538	0.4165	0.4767	0.752	0.412
malignant (35).png	0.4103	0.4515	0.8018	0.4168	0.3779
malignant (36).png	0.1076	0.7764	0.2141	0.234	0.1259
malignant (37).png	0.236	0.59	0.6447	0.3005	0.2578
malignant (38).png	0.2551	0.6822	0.2205	0.569	0.1889
malignant (39).png	0.3917	0.5036	0.6856	0.389	0.3301
malignant (4).png	0.3646	0.58	0.6056	0.3214	0.2658
malignant (40).png	0.4902	0.3959	0.5848	0.6247	0.4328
malignant (5).png	0.4076	0.5397	0.5534	0.394	0.2989
malignant (6).png	0.1942	0.7638	0.4156	0.165	0.1339
malignant (7).png	0.4436	0.5106	0.5669	0.4305	0.3239
malignant (8).png	0.4433	0.5057	0.5667	0.4383	0.3283
malignant (9).png	0.4621	0.4865	0.5457	0.4849	0.3454
Average	0.3369	0.5483	0.6011	0.4102	0.3017

Figure 1: Evaluation Results Screenshot

Adapted Rand Error (ARE)

The resemblance between the predicted segmentation and the actual segmentation is measured by the Adapted Rand Error. Better performance in segmentation is indicated by a lower ARE value. The average ARE for the dataset was 0.3053, which suggests a moderate degree of similarity between the segmentations that were predicted and those that were seen.

Pixel-Wise Precision and Recall

- **Precision**: With an average precision of 0. 6011, the algorithm showed that it could identify cancerous pixels. However, it is quite unreliable to some images that require different image processing techniques including the contrasting of the image, inadaptability to thresholding, and different morphological operation. In conclusion, it is useful in segmenting malignant regions from ultrasound images.

- **Recall**: With an average recall of 0. 4102, it was lower. This implies that the algorithm's sensitivity was lowered even if it was effective at identifying regions that were cancerous.

Intersection over Union (IoU)

The overlap between the ground truth and the predicted segmentation is measured by the IoU metric. The segmented regions and the actual malignant areas indicated by the average IoU score of 0.3017. The decreased IoU in certain images was ascribed to difficulties in identifying the exact borders of the tumors, particularly in situations where there was little contrast between the surrounding tissue and the malignant region.

Overall, the algorithm demonstrated a strong capability in identifying malignant regions but showed room for improvement in handling cases with less distinct boundaries.

Suggestions for Improvements

Although the segmentation algorithm did rather well, there were a few places where it might be strengthened to increase its accuracy and resilience:

1. **Fine-Tuning Adaptive Thresholding**: Especially in images with different contrast levels, segmentation accuracy may be increased by further optimizing the adaptive thresholding parameters. This might include modifying the constant subtraction amount and neighborhood size to better suit the unique properties of various photos.

2. **Investigating Alternative Post-Processing Methods**: To improve the segmentation outcomes and lessen the influence of artifacts, additional post-processing methods, such as contour-based region merging or sophisticated edge-smoothing algorithms, could be investigated.

These recommendations could greatly increase the segmentation accuracy, especially in more difficult photos where the current method has trouble.