A Comparative Study of Cellular Automata and Alternative Algorithms in Medical Imaging

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***Abstract*—This study aims to replicate and compare (enhance) the cellular automata-based algorithm for medical image processing presented by Wongthanavasu and Tangvoraphonkchai (2007). By applying different image processing techniques, we seek to improve image quality and reduce computational time. The preliminary results indicate significant improvements in both areas.**

Keywords—Image Processing, Medical Imaging, Cellular Automata (CA), Edge Detection (Canny), CLAHE, Median Filtering, Breast Cancer Detection.

I. Introduction

Medical image processing is essential for an accurate diagnosis, particularly in detecting breast cancer through mammograms. Wongthanavasu and Tangvoraphonkchai's (2007) Cellular Automata Based Algorithm and its Application in Medical Image Processing has shown promise in this field. However, there is potential for further improvement in image quality and computational efficiency. This paper focuses on replicating the original model and introducing enhancements to address these aspects.

II. Related Work

Various studies have explored preprocessing techniques for mammographic image enhancement, focusing on noise reduction and feature preservation. Cellular Automata (CA) have gained attention due to their computational efficiency and local processing capabilities. Wongthanavasu and Tangvoraphonkchai’s (2007) cellular automata-based application demonstrated the potential of CA in medical image processing, particularly in mammographic analysis. Their approach utilized Von Neumann’s neighborhood for noise filtering and edge detection, effectively enhancing microcalcifications in mammograms. By iteratively updating pixel values based on their four direct neighbors, their method balanced noise reduction with the preservation of diagnostically significant features, such as white spots indicative of early-stage breast cancer [1].

Our work took significant motivation from Zheng et al. (2007), who highlighted the importance of feature-based classification for breast tumor detection using dynamic contrast-enhanced MR images [2]. Their method complements mammographic analysis by focusing on the segmentation and classification of tumors, emphasizing the role of geometric features and intensity variations. This approach inspired our methodology to prioritize the detection and classification of diagnostically relevant regions.

More recently, Ascencio-Piña et al. (2024) extended the application of CA to image segmentation tasks, showcasing its adaptability across different types of medical imaging [3]. Their work reinforced CA’s capability to handle diverse preprocessing requirements, such as noise resilience and edge enhancement, which are critical for effective image analysis.

III. Methodology

CA Algorithm:

The methodology focuses on replicating and extending the Cellular Automata (CA) framework originally proposed by Wongthanavasu and Tangvoraphonkchai (2007). The CA algorithm operates on a grid where each cell represents a pixel in the image, and its value is updated based on the values of its neighboring cells. Specifically, the algorithm employs a Von Neumann neighborhood structure, which considers the four immediate neighbors (top, bottom, left, right) of a cell.

At each iteration, the pixel value is updated using a set of predefined rules that balance noise reduction with the preservation of important features. This iterative process is repeated until a convergence criterion is met. The steps involved in the methodology are as follows:

A. *Gray Level Edge Detection:*

Convert the mammogram image into a grayscale edge map using the CA algorithm. This enhances the magnitude of local differences in pixel intensities between regions, highlighting boundaries.

Algorithm 4 Spot Detection

Input: Original image I, Binary edge map B
Output: Detected spots S
Initialize $S \leftarrow 0$
Subtract B from I to isolate bright spots
for each pixel $p \in I - B$ **do**
  if $p >$ spot threshold **then**
    Add p to S
Return: Detected spots S

Fig. 1. The algorithm for gray level edge detection, which enhances local intensity differences in the mammogram image.

B. *Binary Edge Detection:*

Apply the CA algorithm to the grayscale edge map, converting it into a binary edge map. This step isolates significant edges using a thresholding technique.

Algorithm 2 Binary Edge Detection

Input: Grayscale edge map E
Output: Binary edge map B
Initialize $B \leftarrow 0$
for each pixel $p \in E$ **do**
  if $p >$ threshold **then**
    Set $p \in B$ to 1
  else
    Set $p \in B$ to 0
Return: Binary edge map B

Fig. 2. The algorithm for binary edge detection, converting a grayscale edge map into a binary edge map by applying a threshold.

C. *Noise Filtering:*

Utilize CA-based noise filtering to remove high-frequency noise while preserving key structures in the image. This ensures diagnostically relevant features are not lost.

Algorithm 3 Noise Filtering

Input: Noisy image I
Output: Denoised image $I_{filtered}$
Initialize $I_{filtered} \leftarrow I$
for each pixel $p \in I$ **do**
  Compute neighborhood $N(p)$ using Von Neumann structure
  Identify the majority class C_{target} in $N(p)$
  Update p using the average of C_{target}
Return: Denoised image $I_{filtered}$

Fig. 3. The noise filtering algorithm, which removes high-frequency noise while preserving key structures in the image.

D. *Spot Detection:*

Enhance and identify white spots (potential lesion) by subtracting the edge map from the original image. Apply an intensity threshold to isolate these regions, aiding in the detection of potential breast cancer indicators.

Fig. 4: The algorithm for spot detection, isolating bright regions that may indicate potential tumors in mammograms.

A New Tumor Detection Algorithm:

To improve upon the original methodology, we propose a new approach that integrates additional preprocessing and segmentation techniques. The approach involves a multi-stage pipeline designed to preprocess images, segment regions of interest, and identify potential tumor areas. The methodology comprises three key phases: preprocessing, image segmentation, and tumor region identification.

A. *Preprocessing*

The mammogram images are converted to grayscale to reduce complexity. Salt-and-pepper noise is added to simulate real-world imperfections, followed by median filtering to remove noise while preserving edges. Contrast enhancement using CLAHE improves visibility in areas with subtle intensity variations.

Algorithm 1 Grayscale Conversion and Preprocessing

Input: Original mammogram image I
Output: Preprocessed grayscale image $I_{preprocessed}$
Convert I to grayscale using `rgb2gray` function.
Add salt-and-pepper noise to simulate real-world imperfections.
Apply median filtering using a disk-shaped structuring element to remove noise while preserving edges.
Enhance contrast using Contrast Limited Adaptive Histogram Equalization (CLAHE).
Return: Preprocessed image $I_{preprocessed}$

Fig. 5. An algorithm for preprocessing, including grayscale conversion, noise addition, median filtering, and contrast enhancement to prepare the mammogram image for segmentation.

B. *Image Segmentation*

Adaptive thresholding creates a binary mask, highlighting potential tumor regions. The Canny edge detection algorithm is then applied to refine boundaries and improve region delineation.

Algorithm 2 Image Segmentation

Input: Preprocessed grayscale image $I_{preprocessed}$
Output: Binary mask M with detected edges
Apply adaptive thresholding (`threshold_local`) to create a binary mask highlighting brighter regions.
Detect edges in the binary mask using the Canny edge detection algorithm to refine region boundaries.
Return: Binary mask M

Fig. 6. Algorithm for segmenting the enhanced image using adaptive thresholding and edge detection to isolate regions of interest.

C. Tumor Region Identification

Bright areas in the image are isolated to generate a tumor mask. Connected regions are labeled, and irrelevant regions are filtered based on size thresholds, ensuring only significant tumor-like regions are retained.

Algorithm 3 Tumor Region Identification

Input: Binary mask M
Output: Detected tumor regions R
Generate a tumor mask by isolating the brightest areas in M.
Label connected regions in the tumor mask.
for each labeled region r in R **do**
  Compute region properties such as area and bounding box.
  Filter regions based on area thresholds to remove noise and irrelevant regions.
Return: Filtered tumor regions R

Fig. 7. Algorithm for tumor region identification, involving tumor mask creation, region labeling, and filtering based on area thresholds to highlight potential tumors.

IV. IMPLEMENTATION / RESULT

CA Algorithm:

The replication of Wongthanavasu and Tangvoraphonkchai's (2007) Cellular Automata (CA) framework focused on edge detection, noise filtering, and white spot detection in mammogram images. The results for each stage of the algorithm are summarized below:

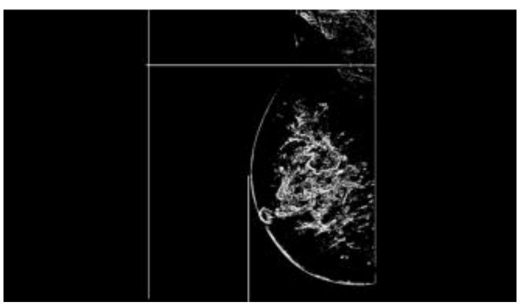

Fig. 8. Gray level edge detection highlighting intensity gradients in the mammogram image to delineate boundaries of regions of interest.

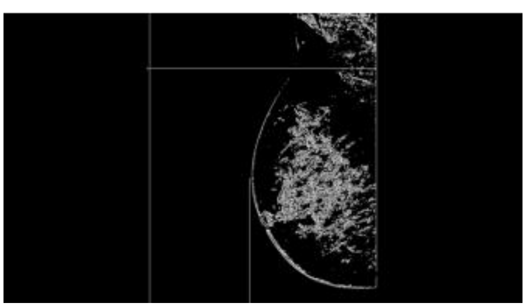

Fig. 9. Binary edge detection isolating significant edges from the grayscale edge map using a thresholding technique.

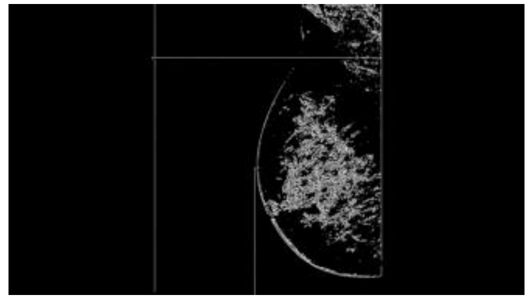

Fig. 10. Binary image with simulated salt-and-pepper noise (Original paper:2%) to mimic real-world imaging imperfections.

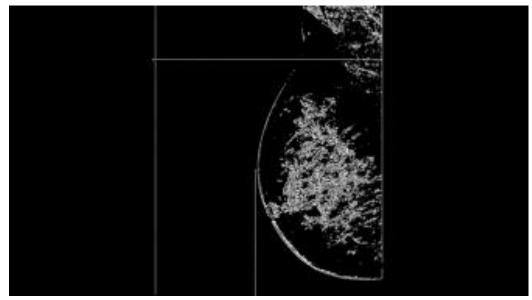

Fig. 11. Noise filtering results showing the removal of high-frequency noise while preserving image structures.

Fig. 12. Spot detection results identifying bright regions potentially corresponding to microcalcifications in the mammogram image.

A New Tumor Detection Algorithm

The algorithm involves preprocessing mammogram images with grayscale conversion, artificial noise addition, and noise filtering to enhance image quality. Segmentation is achieved through adaptive thresholding and edge detection to isolate regions of interest. Tumor regions are identified by generating a mask, labeling connected regions, and filtering out irrelevant areas based on size criteria.

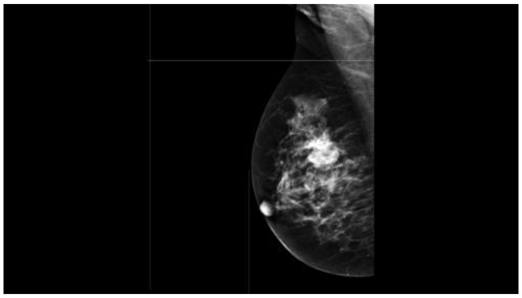

Fig. 13. Original Grayscale Image highlights the structural details of the mammogram for tumor detection.

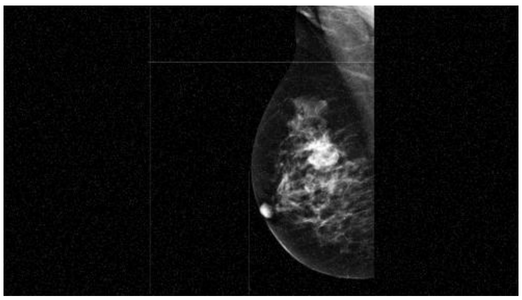

Fig. 14. The grayscale image after introducing salt-and-pepper noise with a noise rate of 3%.

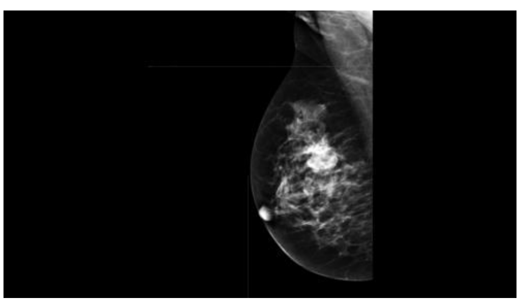

Fig. 15. The noisy image after applying a median filter with a disk-shaped structuring element. Shows significant reduction in noise while preserving the edges and details

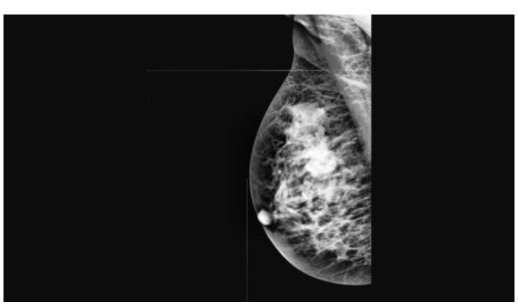

Fig. 16. The denoised image processed with CLAHE. Improved local contrast and enhances subtle intensity variations in the mammogram

Fig. 17. The edge-detected image using the Canny edge detection algorithm. Captures the boundaries of significant regions in the mammogram

Fig. 18. Binary mask generated by isolating the brightest regions in the enhanced image. Highlights the potential tumor regions based on intensity thresholds.

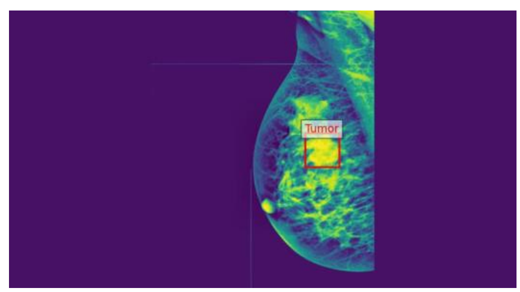

Fig. 19. Final output with detected tumor regions annotated using bounding boxes

Comparison / Evaluation

Two methods for detecting tumors in mammography pictures are closely compared in this study. The CA algorithm's poor sensitivity to intensity fluctuations makes it difficult to detect delicate regions, like benign tumors, even though it can capture basic structural boundaries. On the other hand, the suggested approach performs well by utilizing various preprocessing techniques such as adaptive segmentation, contrast improvement, and noise removal. As a result, it can precisely identify and label both benign and malignant tumors, exhibiting exceptional performance in handling subtle and delicate imaging problems. This contrast highlights the suggested method's practical usability and robustness for thorough tumor detection.

Fig. 20. The image primarily highlights the overall structural edges of the breast but fails to isolate or identify any tumor region, including the benign tumor

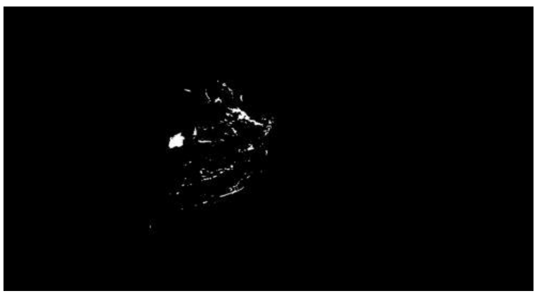

Fig. 21. The current approach successfully highlights the benign tumor due to its robust segmentation process and sensitivity to subtle intensity differences

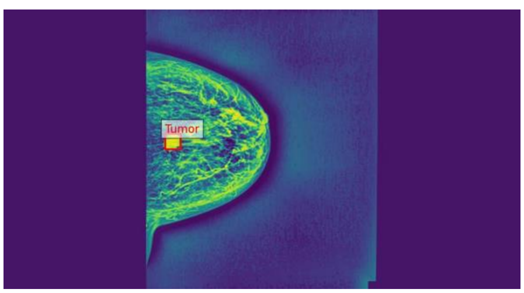

Fig. 22. The image is annotated to clearly indicate the tumor region

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We would like to express our sincere gratitude to our professor, Maria Helguera, for her guidance and support throughout this research. Her suggestion to introduce artificial noise into the images significantly enhanced the robustness of our methodology by simulating real-world conditions. This input was instrumental in improving the performance of our preprocessing and noise removal techniques.

CONTRIBUTIONS

This work was a collaborative effort between Saruultugs and Kushal. Saruultugs focused on replicating the previous paper and constructing the framework for this study. Kushal contributed by exploring alternative methods to improve and compare the performance of the replicated model. This division of labor ensured a thorough and systematic exploration of the research objectives.

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