# Beyond Thresholding: A Geometry-Aware Approach for Pectoral Muscle Removal in MLO Mammograms


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***Abstract*—In this project, our main goal was to isolate the breast tissue from MLO mammograms. This involves separating the tissue from the black background, removing artifacts, and most importantly, cutting out the pectoral muscle. Dealing with the MLO view is difficult because the pectoral muscle looks very similar to the actual breast tissue in terms of brightness. To solve this, we designed a hybrid method. We used Otsu's thresholding to get the main shape and then applied a Hough Line Transform to specifically find the muscle's straight edge. After that, we added some cleaning steps to remove small noise. We tested our code on a sample image and got a Dice Score of about 0.94, which shows that our approach works well compared to the ground truth.**



***Index Terms*—Mammography, Segmentation, Pectoral Muscle, Hough Transform, Image Processing.**


## I. Introduction

Early detection is key to fighting breast cancer, and mammography is the most common tool for this. For automated systems (CAD) to work, they need to know exactly where the breast tissue is [1]. But this is not easy because mammograms are noisy and often have labels or muscles that look like tissue.

We focused specifically on the MLO view. The hardest part here is the pectoral muscle in the top corner. It is bright and dense, just like the glandular tissue we want to keep. Standard methods often fail to separate them. So, in this study, we built a pipeline that improves the image quality first, and then uses geometry-based logic to find and cut the muscle line.

## II. Methodology

Our algorithm follows three steps: Preprocessing, Main Segmentation (with muscle removal), and Cleanup.

### A. Preprocessing

Original mammograms are usually too dark or low-contrast. If we try to segment them directly, the results are poor.

- We used **CLAHE** (Clip Limit: 2.0) to make the tissue details pop out more clearly [2].
- Then, we applied a **Median Filter** ($5\times5$). This helped us get rid of the "salt-and-pepper" noise without blurring the important edges too much.

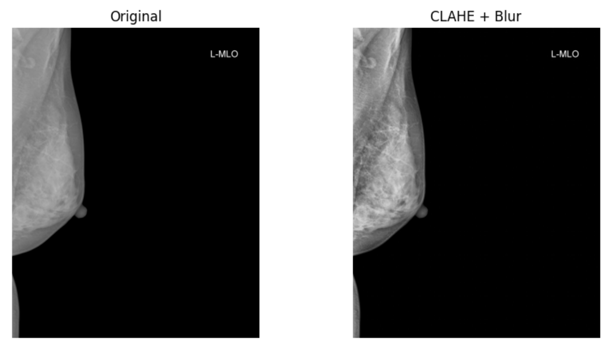


Fig. 1. Preprocessing effect. Left: Raw input. Right: Enhanced image.

### B. Initial Segmentation

To simply separate the breast from the black background, we utilized **Otsu's Thresholding** [3]. This gave us a binary mask. We also used morphological closing to fill in any small black holes inside the white tissue area.

### C. Removing the Pectoral Muscle

This was the most challenging step. The muscle usually looks like a triangle. We used a "Hybrid" strategy to catch it:

1) *Focus Area:* We only looked at the top-left corner (ROI). There is no point in searching for the muscle in the rest of the image.
2) *Finding Edges:* Inside this corner, we ran a Canny edge detector to find sharp transitions.
3) *Finding the Line:* We used the Probabilistic Hough Transform [4]. However, finding lines wasn't enough; we had to filter them. We told the algorithm to only accept lines that are diagonal (between $-85°$ and $-20°$). This filtered out random noise.
4) *The Cut:* Once we found the best line, we extended it to the borders and turned everything above it to black.
5) *Backup Plan:* Sometimes, the edge is too soft, and Hough fails. If that happens, our code switches to a

fallback method: it looks at the pixel intensity in the top row and estimates a geometric cut.

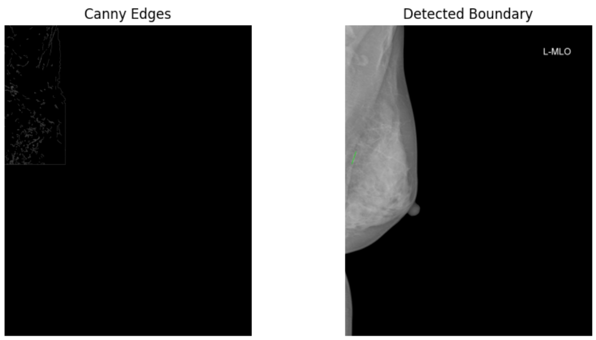


Fig. 2. Muscle detection logic. Left: Edges in ROI. Right: Green line shows the detected muscle boundary.

### D. Post-Processing (Cleanup)

Even after cutting the muscle, there were some leftovers.

- We cut off the bottom part of the image (below row 2600) to remove tape artifacts.
- We used "Connected Component Analysis." Basically, we checked all the white blobs in the mask and kept only the biggest one. This automatically removed the nipple (if it was detached) and other floating noise.

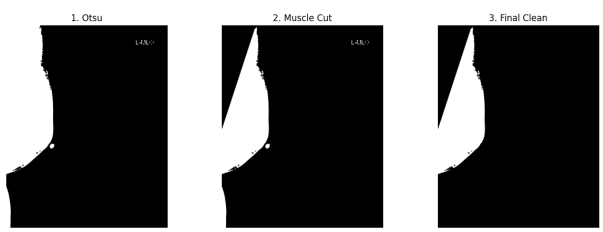


Fig. 3. Step-by-step mask evolution. (a) Otsu only. (b) Muscle removed. (c) Final cleaned result.

## III. Results and Discussion

We compared our final mask with the Ground Truth provided in the dataset. To measure success, we used Dice Score, Jaccard Index, and Pixel Accuracy.

TABLE I
FINAL METRICS

| **Metric** | **Value** |
|---|---|
| Dice Coefficient | 0.9487 |
| Jaccard Index (IoU) | 0.9024 |
| Pixel Accuracy | 0.9875 |

As seen in Table I, we achieved a Dice score of $\approx 0.95$. This means our result overlaps heavily with the expert's mask. Fig. 4 shows the visual comparison. The error map (bottom-right) shows that the differences are mostly at the skin border. This is expected because X-ray edges can be fuzzy.

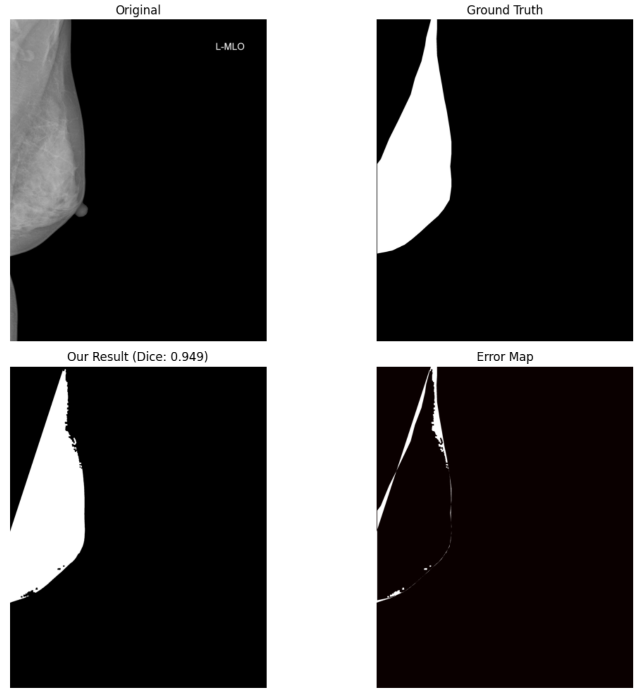


Fig. 4. Comparison. Bottom-left is our result, Top-right is Ground Truth. They are nearly identical.

## IV. Software Implementation

We implemented the proposed method using Python 3.9 and the OpenCV library. The interface is designed to be simple and effective.

First, the user is greeted by the home screen where they can select and upload the mammogram image (Fig. 5).

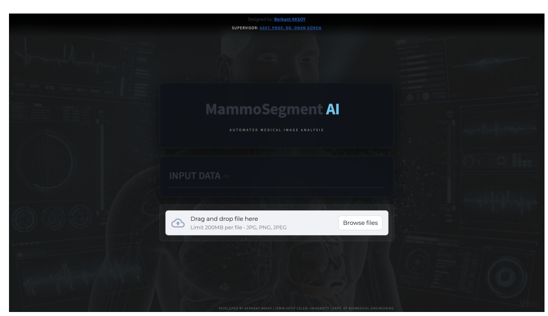


Fig. 5. Home Screen: Initial upload interface.

Once the image is loaded, the system processes it. The processing view displays the file details and prepares the segmentation pipeline (Fig. 6).

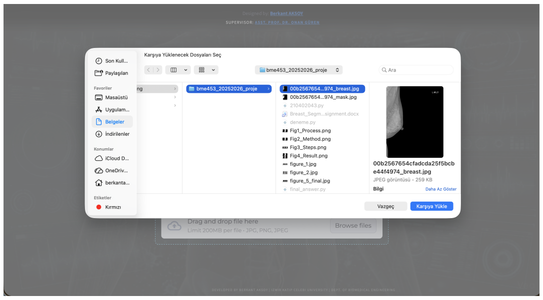


Fig. 6. Processing View: Image analysis in progress.

Finally, the output is generated. The result screen allows the user to compare the original image with the final segmented mask side-by-side (Fig. 7).


Fig. 7. Result Output: Final segmented mask.

## V. Conclusion

In this assignment, we built an automated tool to clean up MLO mammograms. By combining a simple intensity check (Otsu) with a geometric rule (Hough Transform), we managed to remove the pectoral muscle effectively. The final mask is clean and accurate. Future work could involve fitting a curve to the muscle instead of a straight line to handle more complex cases.

Finally, to ensure reproducibility, the full source code and documentation are publicly available[1].

## References


[1] H. D. Cheng, X. Cai, X. Chen, L. Hu and X. Lou, "Computer-aided detection and classification of microcalcifications in mammograms: a survey," *Pattern Recognition*, vol. 36, no. 12, pp. 2967-2991, 2003.

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[3] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62-66, 1979.

[4] R. O. Duda and P. E. Hart, "Use of the Hough transformation to detect lines and curves in pictures," *Communications of the ACM*, vol. 15, no. 1, pp. 11-15, 1972.


[1]Project Repository: https://github.com/berkantaksyy/MammoSegment-AI/