

Automatic Segmentation of Breast Thermal Images Using Mask R-CNN

José Antonio Rivas-Navarrete¹, A. Paola Romero-Carmona², Hayde Peregrina-Barreto^{2,*}

¹ Universidad Autónoma de Zacatecas, Zacatecas, Mexico

² Instituto Nacional de Astrofísica, Óptica y Electrónica, Puebla, Mexico

j.rivas@uaz.edu.mx, {paola.romero, hperegrina}@inaoep.mx

Abstract. Clinical thermography has been widely proposed as a complementary tool for the early detection of breast cancer due to its non-invasive nature, low cost, and absence of ionizing radiation. However, one of the main technical challenges is accurately segmenting the breast region (BR), as the thermal similarity surrounding it can bias analysis. This study presents an automated approach for segmenting the BR in infrared thermal images using the Mask R-CNN neural network. The model was trained on a set of breast thermograms labeled with manually annotated masks. The resulting automatic segmentation enables accurate isolation of the region of interest (RoI), minimizing the influence of irrelevant areas and supporting a more objective thermal analysis. Evaluated using the DICE coefficient, the system achieved an average value of $90.98\% \pm 3\%$, demonstrating its effectiveness in potential applications for computer-aided diagnosis systems and standardizing thermal image analysis for breast health.

Keywords. Breast thermography, image segmentation, mask R-CNN.

1 Introduction

Breast cancer is a high cause of cancer-related death among women worldwide. The World Health Organization reported in 2022, 2.3 million new cases of breast cancer diagnosis in women, and approximately 670,000 deaths were recorded as a result of the disease [17]. The standard methods for breast cancer detection include mammography, ultrasound, and magnetic resonance imaging [7]. However, these procedures can be expensive, invasive and involve exposure to ionizing radiation.

Therefore, the development of complementary techniques to facilitate the early detection of the disease is required.

One such technique is infrared thermography, which has emerged as a non-invasive, low-cost, and radiation-free alternative for detecting thermal anomalies associated with underlying physiological processes, such as angiogenesis [8].

The use of clinic thermography, particularly in the study of breast cancer risks, is related to the angiogenesis process.

Angiogenesis is a biological mechanism through which new blood vessels form around tumor tissue to meet the increased demand for oxygen and nutrients of cancer cells. This process increases blood flow and metabolic activity in the affected region, increasing skin surface temperatures. These thermal differences can be captured using infrared cameras, making thermography a potentially useful complementary tool for the clinical analysis of the disease [3, 5]. Despite its advantages, the clinical use of thermography still presents limitations.

The analysis of thermal images (thermograms) typically requires the involvement of trained experts, which can introduce subjectivity and inter-observer variability. Furthermore, the lack of standardized interpretation criteria hinders its widespread adoption in conventional clinical settings. In response to these limitations, approaches based on artificial intelligence (AI) have emerged as key tools for automating and standardizing the analysis of medical images.

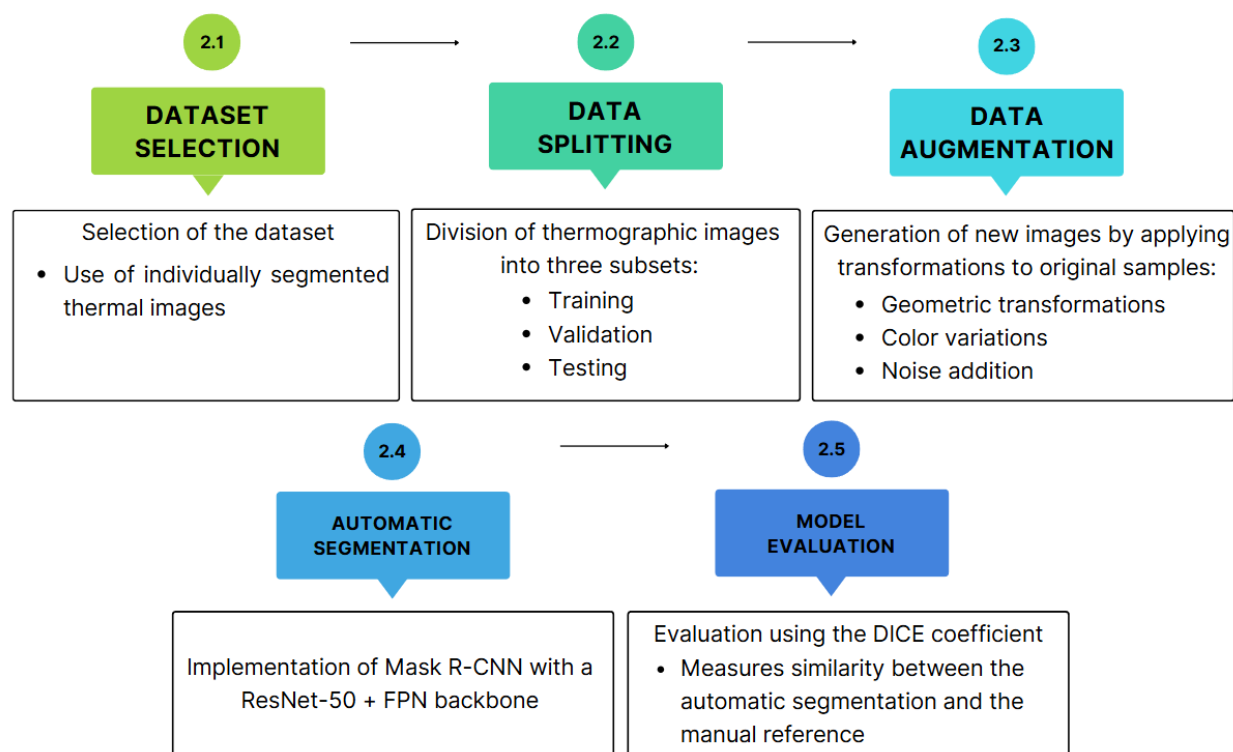


Fig. 1. General overview of the proposed methodology for automatic BR segmentation in breast thermograms

In particular, the automatic segmentation of the BR in thermograms has become increasingly relevant in the context of early breast cancer risks, as it enables precise delineation of the RoI and reduces the influence of adjacent areas that could introduce noise or bias in the thermal analysis.

Image segmentation in breast thermography requires accurate isolation of the BR to prevent other regions from affecting the temperature analysis. Automatic segmentation helps reduce inter-observer variability, standardize image preprocessing, and optimize the performance of computer-aided diagnosis systems [10].

In recent years, several deep learning (DL)-based approaches have been developed to address segmentation, aiming to reduce the subjectivity in interpreting thermal patterns relevant to the detection of breast cancer-related anomalies. Ghayoumi Zadeh et al. [4] proposed a hybrid model combining an unsupervised deep autoencoder with user-assisted segmentation, achieving an accuracy

of 94.87 % in early detection by minimizing errors arising from thermal similarity between the BR and surrounding regions.

Similarly, Civilibal et al. [2] implemented a Mask R-CNN architecture trained with manual masks to automatically segment the BR, achieving an *F1-score* of 97.1% and a *mAP* of 86.8% ($\text{IoU} \geq 0.5$). These studies demonstrate that accurate BR segmentation contributes to the standardization of thermal analysis and enhances the quality of preprocessing in diagnostic support systems. Convolutional neural networks (CNNs) also have shown outstanding performance in classification and medical image segmentation. Among the most advanced architectures is Mask R-CNN, which is well known for its ability to perform instance segmentation, enabling the precise identification of specific regions within an image, even in complex clinical scenarios [6].

This work proposes an automated system based on the Mask R-CNN architecture to accurately

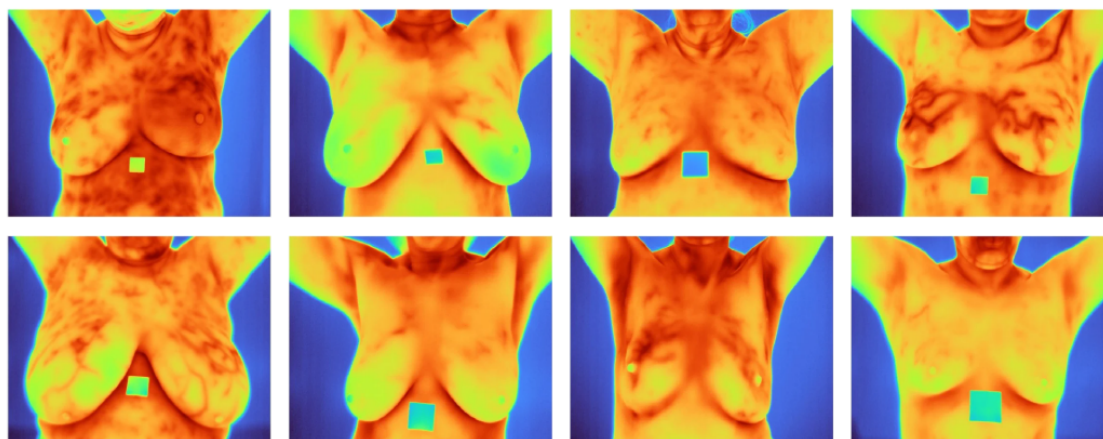


Fig. 2. Examples of breast thermograms from the DMR database [13]

segment the BR in infrared thermograms, aiming to isolate it from the background and other irrelevant structures that may introduce noise into thermal analysis. As a result, the model achieves precise automatic segmentation of the BR, reaching a DICE coefficient of $90.98\% \pm 3\%$, an IoU of $82.7\% \pm 5\%$, an F1-score of $91.0\% \pm 3\%$, and an overall accuracy of $98.2\% \pm 1\%$.

The proposed approach aims to contribute to the development of objective and reproducible tools for the analysis of breast thermograms, facilitating their integration into diagnostic support systems as part of complementary monitoring strategies.

2 Methodology

The methodology followed in this study was structured into five main stages, ranging from dataset selection to model evaluation. Each phase was designed to ensure the quality of training, the validity of the results, and the reproducibility of the automatic segmentation process. The overall workflow is summarized in Fig. 1.

2.1 Dataset

For this study, an exploratory review was conducted to identify a reference thermographic database used in breast cancer research. As a result, the Dataset for Mastology Research (DMR), a public database

developed by the Federal Fluminense University in Brazil, was selected. This database has been widely referenced in the scientific literature in this field. This dataset includes thermal images (539×682 pixels) corresponding to patients classified as healthy or with a positive breast cancer diagnosis confirmed by biopsy. The images were acquired using a FLIR SC620 infrared camera, which has a thermal sensitivity of 0.04°C (Fig. 2) [13].

The DMR consists of thermograms from 157 women, distributed into two groups: 82 healthy patients and 76 with a confirmed breast cancer diagnosis. The age of the participants goes from 27 to 94 years, providing a diverse dataset in terms of physiological characteristics and thermal patterns.

Although multiple anatomical views are available for each subject, only the frontal view was selected for this study, as it offers the highest anatomical symmetry between the breasts and is the most commonly used in related research.

2.2 Manual Segmentation of Rols

In image processing, a binary mask is an image that represents the ideal segmentation of the Rol (reference) and is used as a reference to compare the results obtained by an automatic method. This mask uses only two possible values: one (1), representing the pixels that belong to a specific

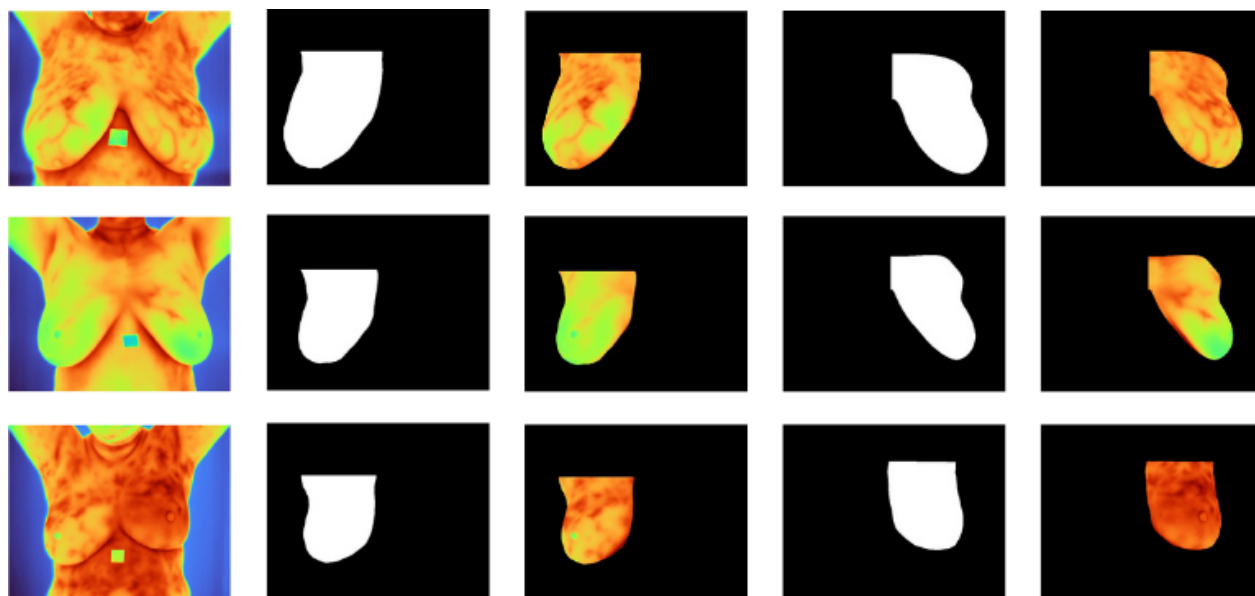


Fig. 3. Individual binary masks of the BR from thermograms

Roi, and zero (0), indicating pixels that should be ignored or excluded from the analysis [9].

For this study, segmentation masks previously generated in [11] were used to isolate breast regions in each thermogram, eliminating the background and other irrelevant areas. The upper boundary of the breast region was defined at the axillary level. Although the axillary region is known to reflect changes associated with breast cancer, it was not included in this study, since the data set lacked specific annotations for that area.

Given that temperature distribution may vary between breasts of the same patient, individual masks were generated for each side (Fig. 3). A total of 314 binarized masks were obtained and used as ground truth for training and validating the proposed automatic segmentation model.

2.3 Data Augmentation and Splitting

One of the main challenges in training deep neural networks is the limited availability of annotated data, particularly in the medical domain. To increase the diversity of conditions and enhance the model's generalization capability, data augmentation techniques were applied to the

original images and their corresponding masks. Ten transformations were applied: horizontal flip, vertical flip, random rotation ($\pm 15^\circ$), brightness adjustment, contrast adjustment, Gaussian noise addition, fuzzy scaling, shear transformation, grayscale conversion, and color inversion (Fig. 4).

These operations were selected to simulate variability in thermal conditions, acquisition artifacts, and differences in patient positioning or anatomy. To train and evaluate the segmentation model, the dataset was partitioned into training, validation, and testing subsets, keeping a 60-20-20 proportion. Augmentation was performed only on the training set to enrich the input variety without compromising the integrity of the evaluation process.

Altering the validation or test sets could introduce bias and lead to overly optimistic performance metrics, as the model would be indirectly exposed to those variations during training. By keeping these subsets unchanged, a more objective and representative evaluation of the performance of the model is ensured. As a result, the training set, which initially consisted of 186 individual masks, expanded to 1860 samples after data augmentation. The validation and test sets consist of 62 and 66 individual masks, respectively.

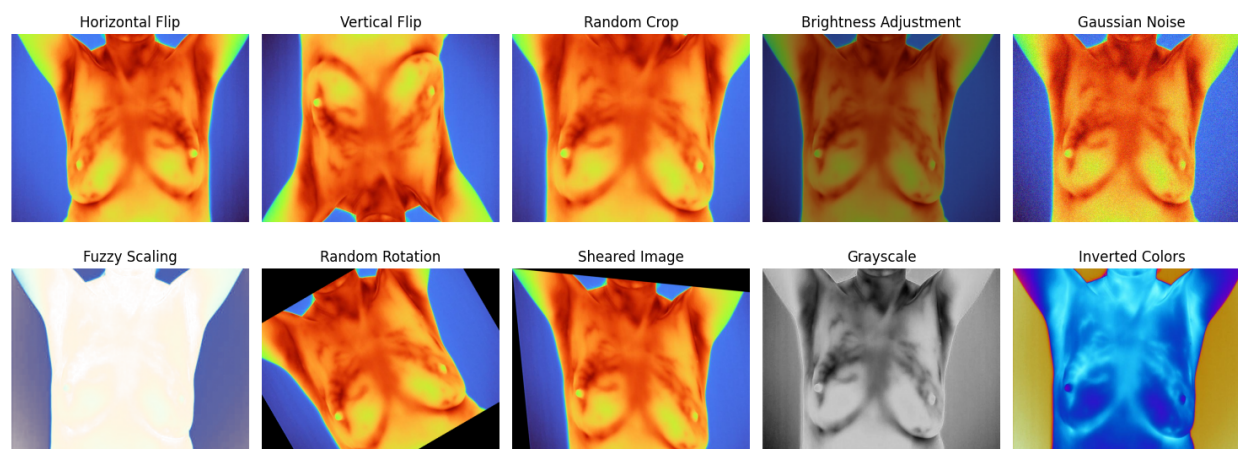


Fig. 4. Examples of data augmentation techniques applied to training thermograms

As a result, the training set, which initially consisted of 188 individual masks, expanded to 1880 samples after data augmentation. The validation and test sets consist of 64 individual masks each.

The training set is used to optimize the model's weights and minimize prediction error. The validation set assesses performance on unseen data and fine-tuned hyperparameters in parallel with the training process. After each update, the model is evaluated on the validation set for further adjustments. Finally, the test set is reserved for the final evaluation to verify that the model did not overfit and could generalize effectively. This partitioning avoids patient overlap, ensuring each subject appears in only one subset. This criterion is crucial in medical studies to avoid artificially raising the model's performance estimates.

2.4 Automatic Segmentation Using Mask R-CNN

To address the automatic segmentation of breast thermograms, the *Mask R-CNN* architecture was employed. Mask R-CNN was proposed by He et al. [6] as a direct extension of the Faster R-CNN model by incorporating a third branch that enables the prediction of a binary pixel-level mask for each detected object, in parallel with object classification and bounding box regression. Unlike earlier models that required multiple stages or sequential procedures, Mask R-CNN introduces a

flexible and straightforward approach that maintains high accuracy while minimizing the increase in inference time. One of its major innovations is the *RoIAlign* module, designed to correct the loss of spatial precision caused by the RoIPool module in Faster R-CNN. RoIAlign avoids coordinate quantization during the extraction of RoIs and instead uses bilinear interpolation to preserve precise alignment between original image pixels and the feature maps—an essential aspect for pixel-level segmentation tasks.

The backbone of the Mask R-CNN architecture (Fig. 6) consists of a ResNet-50 as a feature extractor and a Feature Pyramid Network (FPN) for multi-scale detection. Thus, the model can represent large, medium, and small objects simultaneously, which is particularly useful when ROI sizes vary significantly, as in the case of thermograms. The Region Proposal Network (RPN) examines the feature maps generated by the backbone and proposes candidate RoIs that may contain objects. It generates anchors of various scales (32, 64, 128, 256, 512 pixels) and aspect ratios (0.5, 1, 2) by sliding windows over the activation maps. Each anchor is scored based on the likelihood of containing an object. To ensure better alignment with the feature map resolution, the RoIAlign module interpolates each region of interest (RoI) to a fixed resolution of 7×7 pixels, avoiding the spatial quantization introduced by RoIPool.

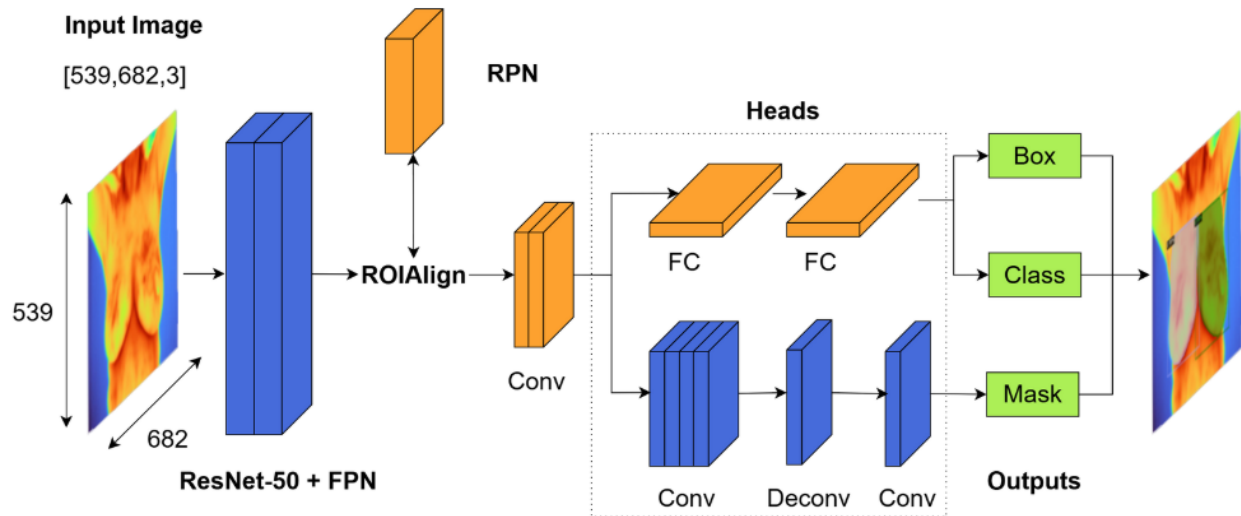


Fig. 5. Structure of the Mask R-CNN model used for segmentation of the BR in thermal images

Then, Mask R-CNN directs each RoI to two independent branches. The first branch predicts the object class and refines the bounding box coordinates.

In parallel, the second branch handles instance segmentation using a small convolutional subnetwork, generating a mask that aligns with the segmented object.

2.5 Model Evaluation

To assess the automatic segmentation results, it is necessary to compare their similarity with the groundtruth masks. For an objective and quantitative estimation, the following metrics were considered [14].

2.5.1 Intersection over Union (IoU).

The IoU or Jaccard Index is a similarity metric that quantifies the degree of overlap between the predicted mask (A) and the ground truth mask (B). It is defined as the number of pixels in the intersection of both masks divided by the number of pixels in their union:

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

Its value ranges from 0 to 1, where 0 indicates no overlap and 1 indicates perfect overlap. Higher IoU values represent greater similarity between the predicted and ground truth masks.

2.5.2 DICE Coefficient

The DICE coefficient is a similarity metric that quantifies the agreement between the predicted and reference masks. Additionally, it provides a measure of the reproducibility of the segmentation process. DICE values range from 0 to 1, where 1 indicates perfect segmentation. It is defined in Eq. 2, where $|A|$ represents the predicted segmentation and $|B|$ the corresponding manual reference:

$$\text{DICE} = \frac{2 \cdot |A \cap B|}{|A| + |B|}. \quad (2)$$

2.5.3 F1-Score

The F1-score evaluates the balance between false positives and false negatives, that is, between precision and recall. It is calculated as:

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \quad (3)$$

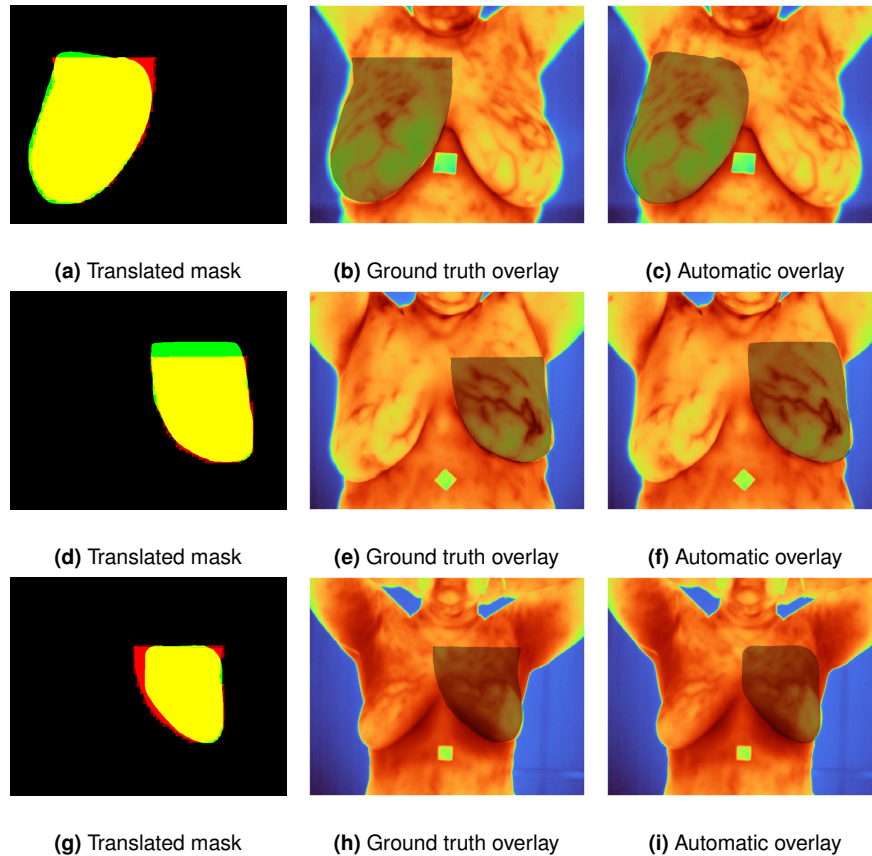


Fig. 6. Visual comparison of three representative cases of automatic segmentation. Each row corresponds to one case, showing: (a, d, g) translated binary mask, (b, e, h) ground truth overlaid on the thermogram, and (c, f, i) automatic prediction overlaid

where:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}. \quad (4)$$

- TP (True Positives): pixels correctly classified as positive.
- FP (False Positives): pixels incorrectly classified as positive.
- FN (False Negatives): pixels that should be positive but were classified as negative.

2.5.4 Accuracy

Accuracy measures the overall proportion of correctly classified pixels (both positive and

negative) with respect to the total number of pixels in the image:

$$\text{Acc} = \frac{TP + TN}{TP + FP + FN + TN}, \quad (5)$$

where:

- TN (True Negatives): pixels correctly classified as negative.

The combined use of these metrics provides a comprehensive evaluation of the performance of the model, considering not only the spatial overlap between masks but also its ability to minimize classification errors.

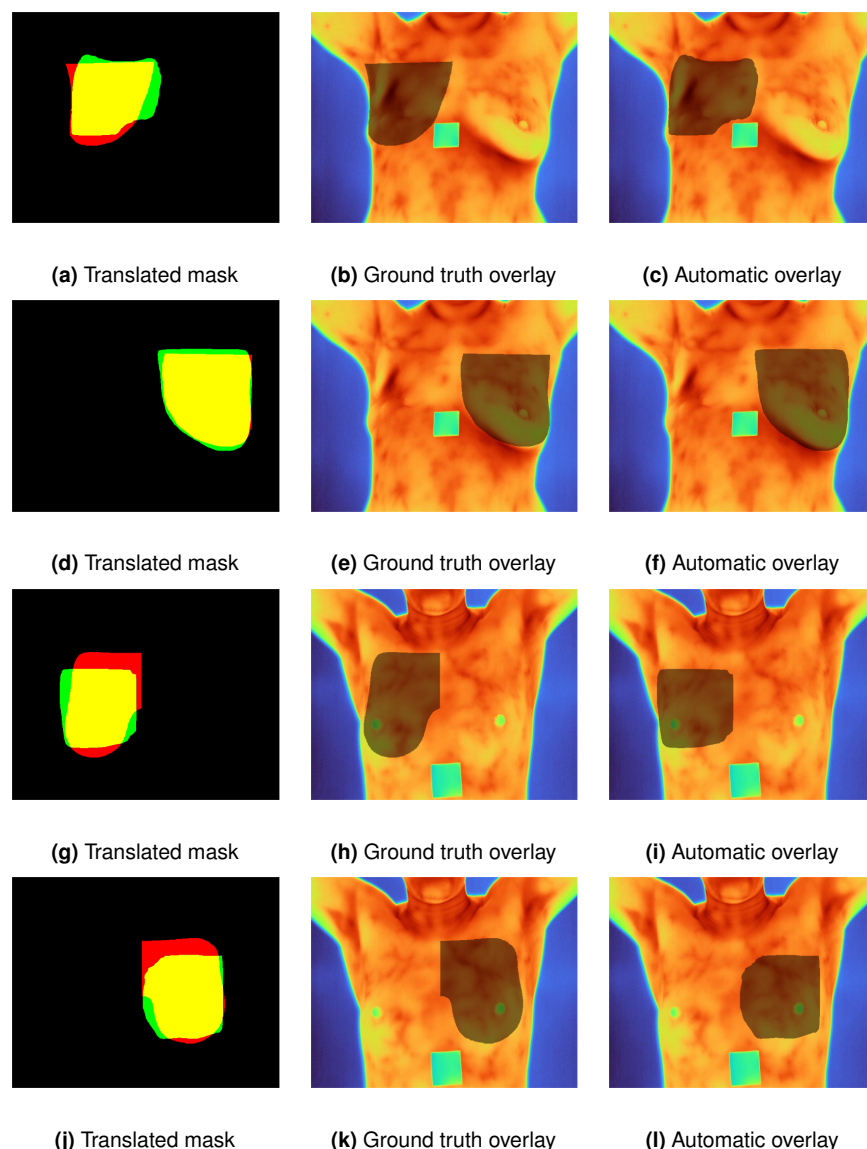


Fig. 7. Visual comparison of three representative cases with lower segmentation performance. Each row corresponds to one case, showing: (a, d, g, j) translated mask, (b, e, h, k) ground truth overlay, and (c, f, i, l) automatic overlay

3 Experimental Results

The model was trained using the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 2.5×10^{-4} , a momentum of 0.9, and a weight decay of 1×10^{-4} . A batch size of two images was used, and training was carried out for 500 iterations. The masks were generated at a resolution of

28×28 pixels and resized during inference to fit the corresponding RoI. During inference, a confidence threshold of 0.8 was applied to filter predictions. Predicted masks with fewer than 100 pixels in total were discarded, meaning that entire small regions were excluded, not subregions within larger masks.

This helped eliminate low-confidence, low-relevance false positives before metric

evaluation. This configuration was selected considering the computational limitations of the CPU-based execution environment.

The performance of the proposed Mask R-CNN model was quantitatively assessed on a test set composed of 66 infrared breast thermograms. Evaluation was carried out at the pixel level using the performance metrics described in Section 2.5. Figure 6 presents three representative cases of automatic breast region segmentation, each showing the translated binary mask, the ground truth overlay, and the predicted overlay on the original thermogram. A high spatial agreement is observed between the predicted and manual masks, even in cases with subtle thermal contrast. The corresponding evaluation metrics are summarized in Table 1, confirming the strong and consistent performance of the model across different image conditions.

Figure 6 presents a visual case corresponding to the first among the three cases shown, illustrating the meaning of the DICE coefficient value obtained for an individual image ($DICE = 95.48\%$). The yellow-highlighted regions indicate the overlap between the automatic and manual segmentations. This visualization provides an intuitive understanding of the high spatial agreement achieved by the model for this particular case.

The overall results indicated a high spatial agreement between the automatic segmentations and their corresponding annotated ground truths. An average $DICE = 90.98\% \pm 3\%$ and $IoU = 82.70\% \pm 5\%$ demonstrate that the model is capable of accurately delineating the BR, even in thermograms with subtle contrast between the BR and surrounding areas. The $F1\text{-score} = 91.00\% \pm 3\%$ confirms balanced performance between precision and recall, while the $accuracy = 98.20\% \pm 1\%$ reflects strong overall classification at the pixel level.

The overall results indicated a high spatial agreement between the automatic and manual segmentations. To further analyze the model's limitations, Figure 7 presents four cases from two different subjects with lower segmentation performance, illustrating common challenges encountered.

In the first case (Figure 7a), the subject presented marked breast asymmetry, with a significantly reduced volume in the right breast. The model was able to partially identify the region corresponding to the existing tissue on that side. In contrast, the contralateral breast, with a considerably larger volume (Figure 7d–f), was segmented with greater accuracy, demonstrating the ability of the method to adapt to different tissue volumes within the same subject.

This scenario highlights both the challenge of segmenting altered anatomical structures and the robustness of the model under variable clinical conditions. In the second subject (Figure 7g–i), characterized by a notably reduced amount of breast tissue, the model was still able to delineate part of the breast region in two independent cases. Despite the atypical presentation, the method demonstrated its ability to detect subtle structures even under non-standard conditions. These cases demonstrate that the segmentation method can maintain adequate performance even in less favorable or unexpected clinical scenarios.

Overall, the results demonstrate that the proposed approach can produce precise, reproducible, and anatomically consistent segmentation of the BR in thermal images. These findings support its applicability as a preprocessing module in computer-aided diagnostic systems for breast thermography.

4 Discussion

Before comparing the proposed approach with previous studies, it is important to note that direct comparisons are limited by differences in objectives, segmentation targets, experimental protocols, reported metrics, and dataset composition. Table 2 summarizes the most relevant works using the DMR-IR/Brazilian Thermal Imaging Database or including it as part of their experimental data.

Table 2 compares related works reported in the literature on breast thermogram segmentation using the DMR-IR and mixed datasets. Most of them evaluate either conventional ROI extraction strategies or deep learning architectures such as U-Net and Mask R-CNN. Alvarez-Padilla et al. proposed the anatomy-guided multiscale U-Net,

Table 1. Evaluation metrics for the three segmentation cases shown in Fig. 6

Metric	Case 1	Case 2	Case 3
DICE	95.48%	92.90%	95.21%
IoU	91.35%	86.74%	90.85%
F1-score	95.48%	92.90%	95.21%
Accuracy	97.94%	98.47%	98.99%

Table 2. Comparison with previous studies related to breast thermogram segmentation. All reported metrics are expressed as percentages

Study	Task	Method	Dataset	Reported metrics
Civilibal et al. [2]	Segmentation	Mask R-CNN	DMR-IR	Mean Overlap: 86.80%
Venkatachalam et al. [15]	Inflamed ROI segmentation	ROI segmentation method	DMR-IR	Accuracy: 91.50% Dice: 85.70%
Venkatachalam et al. [16]	Breast boundary segmentation	DM-HTRAT	DMR-IR	Accuracy: 96.50% Dice: 96.40%
Rosli et al. [12]	Breast-region segmentation	U-Net variants	DMR-IR	Dice: 96.30% IoU: 92.92%
Alvarez-Padilla et al. [1]	Breast-region segmentation	Anatomy-guided multiscale U-Net	Mixed	Dice: 98.80% IoU: 95.80%
This work	Breast-region segmentation	Mask R-CNN	DMR-IR	Accuracy: 98.20% Dice: 90.98% IoU: 82.70% F1-score: 91.00%

which achieved a Dice score of 98.80% and an IoU of 95.80%. However, the use of mixed datasets and additional anatomical priors may have contributed to this performance. Similarly, U-Net-based approaches reported by Rosli et al. demonstrated strong segmentation capabilities, confirming the suitability of encoder-decoder architectures for thermographic breast analysis, reaching a Dice score of 96.30% and an IoU of 92.92%.

Finally, Civilibal et al. [2] employed Mask R-CNN to detect the breast region in thermograms within a bounding box, reporting an overlap score of 86.8% when evaluating segmentation quality.

In contrast, the proposed approach employs the Mask R-CNN framework without anatomical constraints or specialized preprocessing pipelines. Despite its simplicity, it achieves strong results with a Dice coefficient of 90.98% and an IoU of 82.70%. While these values are lower than some optimized segmentation models, the method effectively extracts regions and benefits from the generalization of instance segmentation architectures. Although accuracy and F1-score are important metrics, they are not frequently reported; in this study, we achieved 98.20% accuracy and 91% F1-score, providing a more

balanced evaluation of segmentation. Overall, the comparison shows that the proposed approach achieves competitive performance in breast-region segmentation of thermograms.

5 Conclusions

The implementation of the Mask R-CNN model for automatic breast-region segmentation in thermograms has demonstrated robust performance, achieving a Dice coefficient of $90.98\% \pm 3\%$, an IoU of $82.70\% \pm 5\%$, an F1-score of $91.00\% \pm 3\%$, and an accuracy of $98.20\% \pm 1\%$.

These metrics reflect a high degree of spatial overlap and accurate pixel classification, supporting the effectiveness of the model for breast thermogram segmentation.

The network was able to successfully distinguish the breast region from adjacent areas, despite the thermal similarity characteristic of this type of imaging.

This discrimination capacity is reinforced by the application of data augmentation techniques, which increased the diversity of the training set and allowed the model to generalize to anatomical, thermal, and positional variations.

In addition, the comparison with other models evaluated under the same dataset and execution conditions showed that the proposed Mask R-CNN-based approach achieved a high and competitive performance.

The presented methodology constitutes an automated, reproducible, and high-throughput solution for breast-region segmentation in thermograms, contributing to future computer-aided diagnostic systems aimed at the analysis of thermal abnormalities associated with breast cancer.

Overall, the proposed methodology provides a methodologically consistent and competitive approach for breast-region segmentation in DMR-IR thermograms, supporting its potential integration into future computer-aided diagnostic workflows.

As future work, deeper backbone variants or emerging architectures such as Transformers will be explored. In addition, segmentation will be extended to specific clinical subregions of interest to enable a more detailed thermal characterization of breast abnormalities.

References

1. **Alvarez-Padilla, F. J., Argudin-Ferran, M. V., Flores, J. L., Alvarez-Padilla, J. R. (2026).** Anatomy-guided breast segmentation in thermograms using a multiscale UNet hybrid framework. *BMC Medical Imaging*, Vol. 26, No. 35. DOI: 10.1186/s12880-025-02100-6.
2. **Civilibal, S., Cevik, K. K., Bozkurt, A. (2023).** A deep learning approach for automatic detection, segmentation and classification of breast lesions from thermal images. *Expert Systems with Applications*, Vol. 212, pp. 118774. DOI: 10.1016/j.eswa.2022.118774.
3. **Cook, K. M., Figg, W. D. (2010).** Angiogenesis inhibitors: Current strategies and future prospects. *CA: A Cancer Journal for Clinicians*, Vol. 60, No. 4, pp. 222–243. DOI: 10.3322/caac.20075.
4. **Ghayoumi Zadeh, H., Fayazi, A., Binazir, B., Yargholi, M. (2021).** Breast cancer diagnosis based on feature extraction using dynamic models of thermal imaging and deep autoencoder neural networks. *Journal of Testing and Evaluation*, Vol. 49, No. 3, pp. 1516–1532. DOI: 10.1520/JTE20200044.
5. **Gonzalez-Hernandez, J.-L., Recinella, A. N., Kandlikar, S. G., Dabydeen, D., Medeiros, L., Phatak, P. (2019).** Technology, application and potential of dynamic breast thermography for the detection of breast cancer. *International Journal of Heat and Mass Transfer*, Vol. 131, pp. 558–573. DOI: 10.1016/j.ijheatmasstransfer.2018.11.089.
6. **He, K., Gkioxari, G., Dollár, P., Girshick, R. (2017).** Mask r-cnn. 2017 IEEE International Conference on Computer Vision (ICCV), IEEE, pp. 2980–2988. DOI: 10.1109/ICCV.2017.322.
7. **Kiymet, S., Aslankaya, M. Y., Taskiran, M., Bolat, B. (2019).** Breast cancer detection from thermography based on deep neural networks. 2019 Innovations in Intelligent Systems and Applications Conference (ASYU),

IEEE, pp. 1–5. DOI: 10.1109/ASYU48272.2019.8946367.

8. **Lahiri, B. B., Bagavathiappan, S., Jayakumar, T., Philip, J. (2012).** Medical applications of infrared thermography: A review. *Infrared Physics & Technology*, Vol. 55, No. 4, pp. 221–235. DOI: 10.1016/j.infrared.2012.03.007.
9. **MathWorks (2025).** Specify roi as binary mask.
10. **Rogowska, J. (2009).** Overview and fundamentals of medical image segmentation. In **Bankman, I. N.**, editor, *Handbook of Medical Image Processing and Analysis*. Academic Press, Burlington, 2 edition, pp. 73–90.
11. **Romero-Carmona, A. P., Rangel-Magdaleno, J. J., Renero-Carrillo, F. J., Ramirez-Cortes, J. M., Peregrina-Barreto, H. (2025).** Lightweight statistical and texture feature approach for breast thermogram analysis. *Journal of Imaging*, Vol. 11, No. 10, pp. 358. DOI: 10.3390/jimaging11100358.
12. **Rosli, R. S., Habaebi, M. H., Islam, M. R., Al Hussaini, M. A. S. (2025).** Analysis of breast region segmentation in thermal images using U-Net deep neural network variants. *Frontiers in Bioinformatics*, Vol. 5, pp. 1609004. DOI: 10.3389/fbinf.2025.1609004.
13. **Sequeiros, G. O. (2013).** Desenvolvimento de um Banco de Dados Acessíveis Via Web com Recuperação Baseado no Conteúdo. Master's thesis, Instituto de Computação, Universidade Federal Fluminense.
14. **Survarachakan, S., Prasad, P. J. R., Naseem, R., Pérez de Frutos, J., Kumar, R. P., Langø, T., Alaya Cheikh, F., Elle, O. J., Lindseth, F. (2022).** Deep learning for image-based liver analysis—a comprehensive review focusing on malignant lesions. *Artificial Intelligence in Medicine*, Vol. 130, pp. 102331. DOI: 10.1016/j.artmed.2022.102331.
15. **Venkatachalam, N., Shanmugam, L., Heltin, G. C., Govindarajan, G., Sasipriya, P. (2021).** Enhanced segmentation of inflamed ROI to improve the accuracy of identifying benign and malignant cases in breast thermogram. *Journal of Oncology*, Vol. 2021, pp. 5566853. DOI: 10.1155/2021/5566853.
16. **Venkatachalam, N., Shanmugam, L., Heltin Genitha, C., Kumar, S. (2024).** Automated breast boundary segmentation to improve the accuracy of identifying abnormalities in breast thermograms. *IETE Journal of Research*, Vol. 70, No. 2, pp. 1462–1471. DOI: 10.1080/03772063.2023.2194277.
17. **World Health Organization (2026).** Breast cancer. Available at: <https://www.who.int/news-room/fact-sheets/detail/breast-cancer>.

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* Corresponding author is H. Peregrina-Barreto.