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JOINT AAPM | COMP MEETING

Automated 3T DCE-MRI Breast Lesion Segmentation: A Two-Stage V-Net Deep Learning Approach for Enhanced Clinical Efficiency

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ABSTRACT

Background and Objectives

In medical imaging, the accurate segmentation of lesions is a fundamental step for monitoring tumour progression and extracting quantitative radiomic features for lesion characterization. Traditionally, this task has relied on manual input, which is notoriously time-consuming and heavily influenced by operator variability, often impacting the consistency of subsequent analyses. To address these challenges, this study developed an automated deep learning (DL) model based on the V-Net architecture specifically for malignant breast lesion segmentation on 3T DCE-MRI.

Methodological Framework

This retrospective study involved 131 women undergoing DCE-MRI prior to neoadjuvant chemotherapy between 2016 and 2021. A two-stage V-Net approach was implemented. In the first stage, an initial model was trained to generate a raw breast mask with ample borders, effectively restricting the search area for subsequent detection. In the second stage, the breast region was divided into smaller 3D patches to capture fine-grained features, where a second V-Net model identified the specific lesions. Fine-tuning was then applied to these patches to establish optimal binarization thresholds and minimize false positives. The Dice Similarity Coefficient (DSC) was used to evaluate the performance compared to two expert readers.

Key Results and Performance

The study evaluated various parameters, finding that utilizing 100% background patches combined with a 0.6 binarization threshold yielded the most accurate results. This configuration achieved a median Dice score of 0.77 for the training set and 0.71 for the test set when compared to manual segmentation. Notably, the automated system was approximately **five times faster** than manual processes, significantly enhancing workflow efficiency.

Clinical Significance

The proposed model successfully reduces human operator variability and provides a highly efficient alternative to manual methods. However, human supervision remains essential to address false positives and fine-tune results. While current outcomes are satisfactory, further improvements could be achieved through dataset augmentation, architectural modifications, and hardware upgrades.

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INTRODUCTION

The automation and standardization of medical image analysis have become increasingly important in the era of AI and big data. In breast cancer imaging, automated lesion segmentation can improve reproducibility, enable the creation of large labelled datasets, and support downstream applications such as radiomics and predictive modelling. This study investigates a deep learning-based approach for the automated segmentation of malignant breast lesions from 3T DCE-MR images, addressing the challenges posed by their irregular morphology and heterogeneous appearance.

METHODS AND MATERIALS

A retrospective cohort of 131 patients with malignant breast lesions undergoing neoadjuvant chemotherapy was analyzed using 3T DCE-MR images. Manual breast and lesion segmentations performed by an experienced radiologist on the second subtracted DCE image served as the ground truth. To address the challenges of segmenting small, heterogeneous lesions in high-resolution 3D images, we developed a two-stage deep learning pipeline based on the V-Net architecture. The first stage localises the breast to reduce the search space and computational burden, while the second stage performs high-resolution lesion segmentation within the breast region. This hierarchical strategy enables efficient processing while preserving lesion detail. The complete workflows are illustrated in Figures 1 and 2. The V-Net models were implemented in Python using the PyTorch framework and trained on an NVIDIA GeForce GTX 1650 GPU.

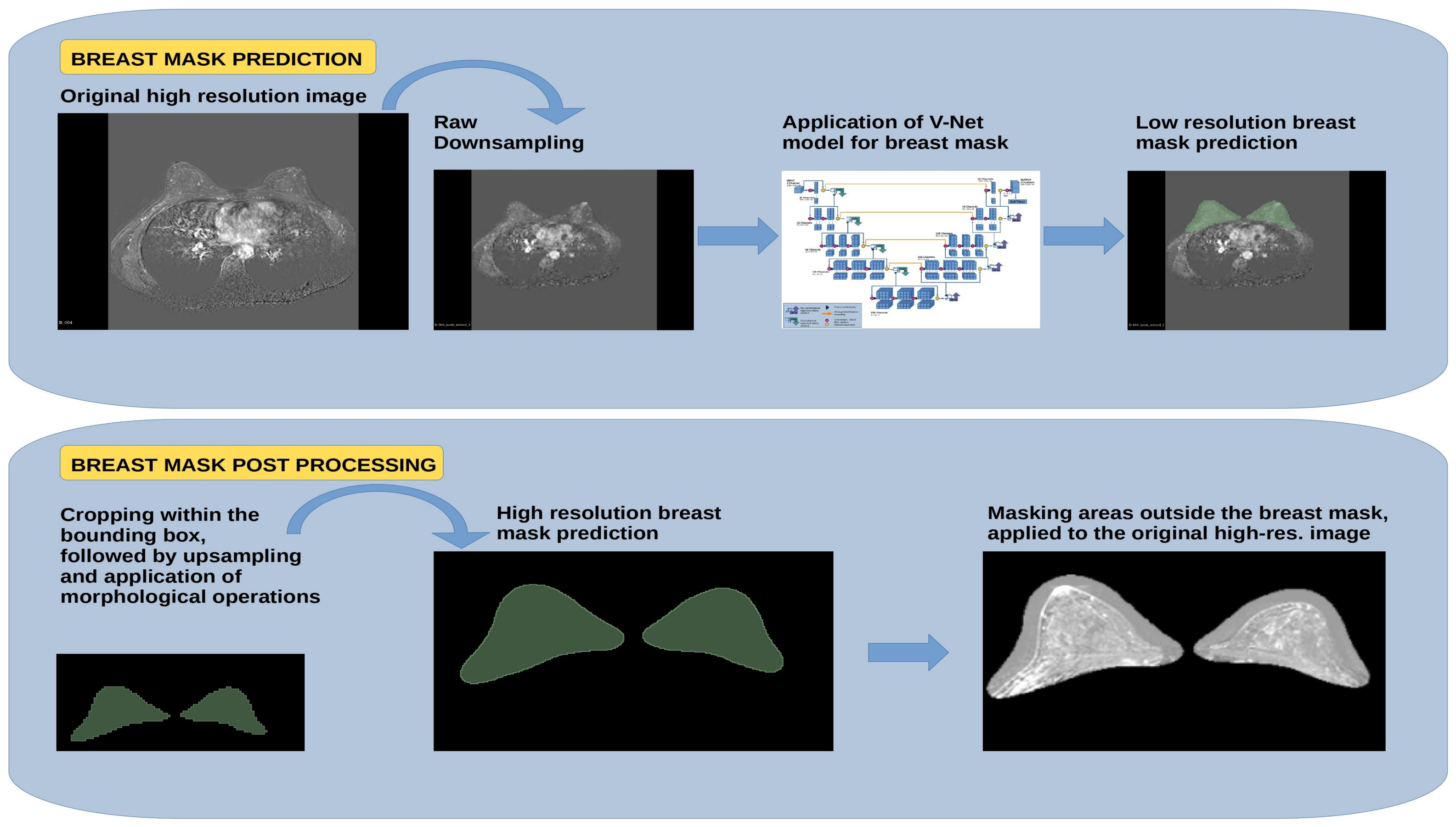

Figure 1. Breast segmentation. A V-Net was trained on the full 3D DCE-MR image using manually delineated breast masks. The resulting breast mask removes surrounding contrast-enhancing structures, reduces the image size, and defines the region of interest for the subsequent lesion segmentation stage.

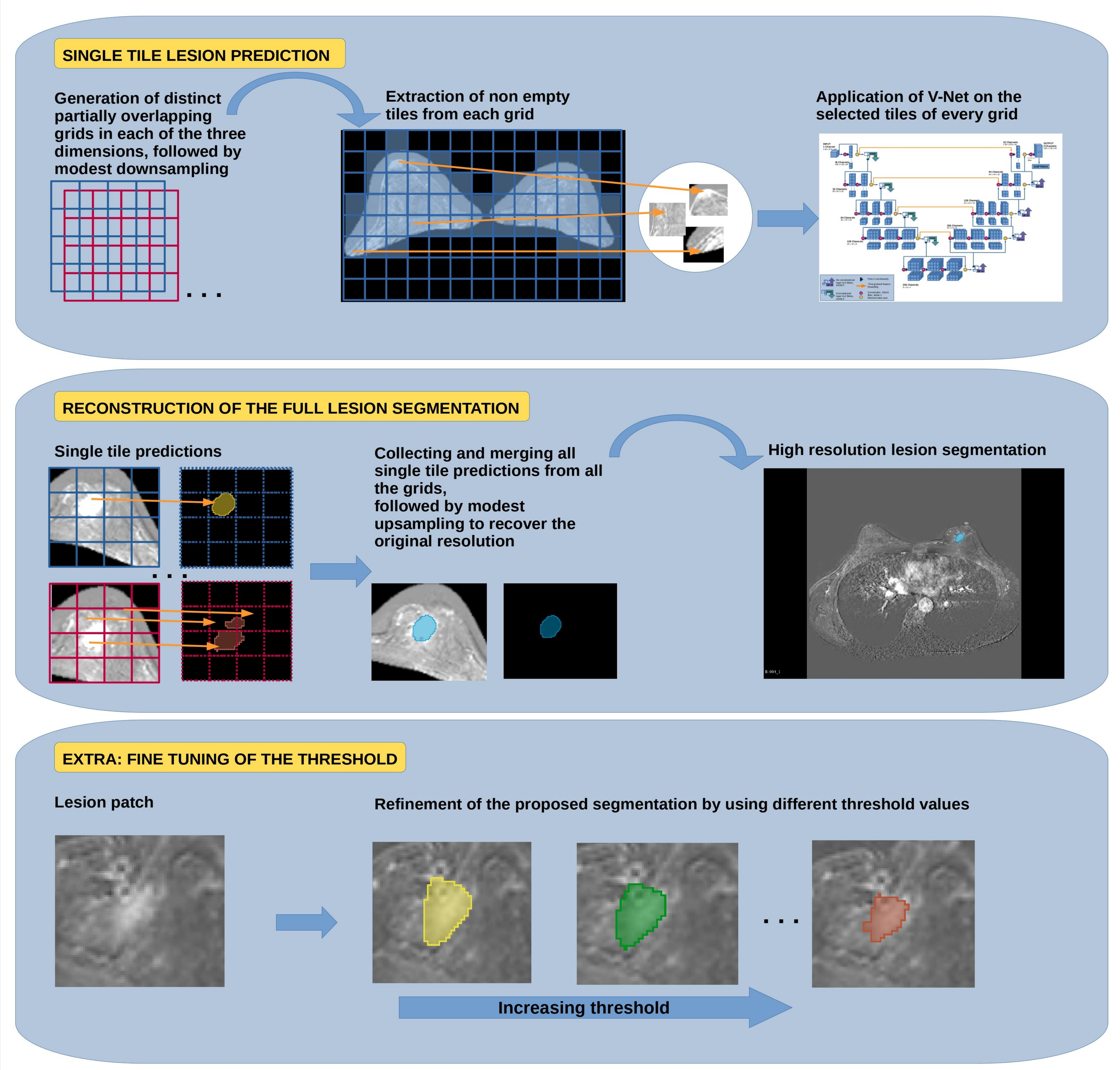

Figure 2. Lesion segmentation. The breast mask is used to define a bounding box, which is divided into partially overlapping high-resolution patches. A second V-Net performs lesion segmentation on each patch. Positive (lesion) and negative (background) patches are included during training to increase the effective dataset size and improve robustness. The final lesion mask is reconstructed by merging the patch predictions from all grids using a proper binarization threshold to further refine the segmentation.

RESULTS

Segmentation performance was evaluated by comparing the predicted breast and lesion masks with the radiologist's manual ground truth using the Sørensen–Dice coefficient (DSC) and Relative Size Difference (RSD). Breast segmentation results are reported in Table 1. For lesion segmentation, different training configurations were investigated by varying the proportion of background patches and the binarization threshold (Figure 3). The best-performing model used a threshold of 0.5 and all available background patches. The corresponding results are reported in Table 2.

Metric	Mean	2 SD
DSC	0.835	0.005
RSD	0.22	0.03
Accuracy	0.962	0.001
Specificity	0.965	0.002
Precision	0.77	0.01
Sensitivity	0.927	0.009

Table 1. results for raw breast segmentation (mean ± 2SD from several folds).

Metric	Median	IQR
DSC	0.71	0.52-0.82
RSD	0.003	-0.276-0.300
Accuracy	0.9998	0.9998-0.9999
Specificity	0.9999	0.9999-1.0000
Precision	0.74	0.64-0.85
Sensitivity	0.81	0.53-0.92

Table 2. results for lesion segmentation (from single train/test split).

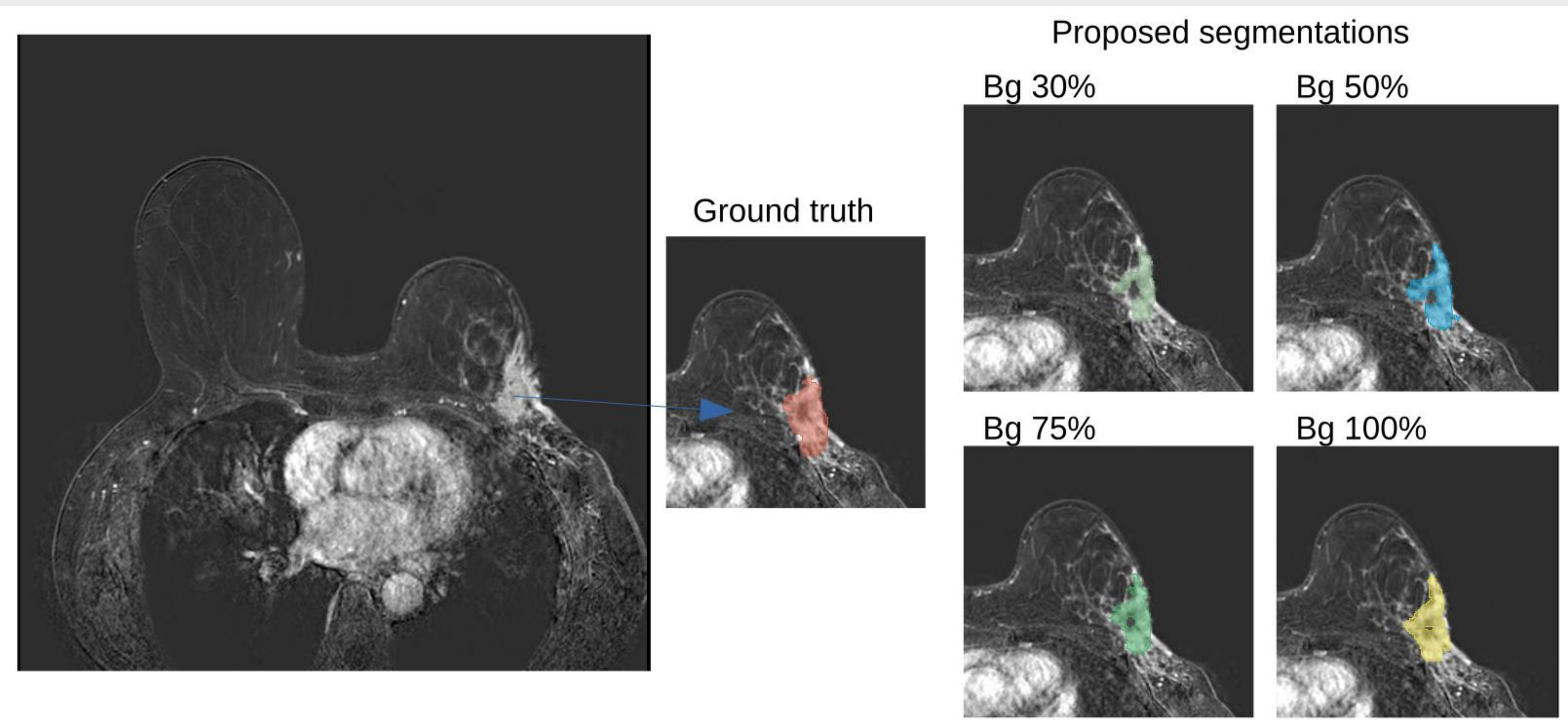

Figure 3. From left to right: Example DCE-MR slice, ground truth, and lesion segmentation results produced by models trained with different percentages of background patches.

DISCUSSION

Malignant lesion segmentation remains challenging due to the intrinsic variability of breast lesions in terms of size and composition. The proposed pipeline achieved satisfactory performance, reaching a median Dice score of 0.71 on the test set. Visual inspection highlighted occasional false-positive detections corresponding to active axillary lymph nodes, while some additional lesions detected by the model were confirmed upon review. The proposed approach also reduced segmentation time by at least a factor of five compared with manual delineation.

CONCLUSIONS

Despite the limited sample size, the proposed two-stage pipeline demonstrated reliable and efficient lesion segmentation, achieving satisfactory accuracy while substantially reducing segmentation time. These results support its potential as a backbone for future radiomics and predictive modelling studies. Future work will focus on multicentric validation and improving model robustness through architectural refinements and data augmentation to enhance generalization across different scanners and imaging protocols.