Using AI Models to Estimate Breast Tumor Bed Volumes to Aid in Radiotherapy Treatment Planning

1 Introduction

Breast cancer is initiated in the cells of the breast. It starts when the cells of the breast begin multiplying uncontrollably to form a tumor that can be felt as a lump or seen on an imaging test, such as a mammogram. While it is relatively common in women, men develop breast cancer too, although it occurs much less in men than in women. Breast cancer remains one of the most common cancers worldwide.

Ductal Carcinoma In Situ (DCIS) is a non-invasive type of breast cancer, in which abnormal cells are located in the lining of the breast ducts but do not extend beyond the walls of the ducts. This is the earliest form of breast cancer and the treatment has a high success rate if caught in this stage. On the contrary, Invasive breast cancer develops when cells from lobules or ducts break out into the surrounding breast tissues. It has the possibility of metastasizing by spreading through the lymphatic system or bloodstream to other parts of the body. Thus, early detection and treatment would be very important for a better outcome. In the United States alone, breast cancer is the second leading cause of cancer-related deaths among women. Approximately one in eight women will develop invasive breast cancer over their lifetime [1].

Estimation of the volume of the breast tumor bed after surgery is significant in postoperative radiotherapy, more so in Accelerated Partial Breast Irradiation (APBI). This is done by the help of surgical clips placed during the excision of the tumor by the surgeon. These clips are placed directly in or around the tumor site to mark the location. The accurate definition of the tumor bed determines directly the efficacy of the treatment, the control of the disease by delivering adequate radiation to the highest-risk area, and the reduction of possible side effects by minimizing irradiation to healthy tissue surrounding it [2]. Post-operative radiotherapy (RT) reduces locoregional recurrence rates and mortality rates in most patients with non-metastatic [3]. It targets residual cancer cells precisely and sterilizes lymph nodes that are susceptible to cancer cells spread.

The issue arises in the volume estimation which is done by locating the surgical clips in the scans, manually analyzing imaging results and measuring distance between clips. This manual process leads to intra-variance and inter-variance. This difference in tumor bed delineation can result in inconsistent treatment volumes which can potentially affect radiation targeting accuracy. Underestimation results in missing parts of the tumor bed which increases the risk of cancer recurrence. On the other end of the spectrum, overestimation exposes healthy tissue to unnecessary radiation leading to increased risk of side effects such as damage to lungs or heart.

Another challenge in the localization of the tumor bed after surgery is anatomical changes post operation, such as tissue deformation and seroma formation. These alterations commonly obscure the original bed of the tumor. In addition, technical variation such as superficial or full-thickness closure can also make it harder to clearly define the tumor bed. It then becomes challenging for radiation oncologists to precisely define their treatment target. The presence of surgical clips is helpful; however, they are not always found and may not necessarily define the tumor bed accurately due to displacement during healing [4].

Auto-segmentation methods are being proposed as a solution to these problems. Previously, computer vision and machine learning techniques were used for auto segmentation. These worked well for certain patients and datasets but failed to generalize and depended on careful manual selection of parameters based on information about the image properties. Currently deep learning based auto segmentation methods are being used such as Convolution Neural Networks and more specifically U-nets and V-nets. The challenge faced by such methods is that their performance relies heavily on clear definitions of tumor beds, which is often not achievable in radiotherapy due to the complexity of tumor shapes and imaging artifacts. The concept of a ground truth in RT fields is disputable because RT is both a science and an art entailing clinical input and creativity [5]. Hence they are currently not suitable for being a substitute to manual contouring and estimation by experienced radiation oncologists but may become a useful tool. This paper aims to conduct a comprehensive review of existing literature on tumor bed volume estimation in breast cancer and use of AI based models for such estimation.

2 Key Words

Breast Cancer, Deep Learning, Tumor Bed Estimation, Radiotherapy Treatment Planning

3 Number of Papers

This paper cites a total of 16 sources listed in the Reference section at the end.

4 Literature Survey

Deep learning methods have shown substantial promise in enhancing the accuracy and efficiency of tumor bed volume estimation in breast cancer radiotherapy planning. Surgical clips are used to mark the tumor bed, thus the target area for radiation therapy is delineated. Manual contouring by using surgical clips as reference markers has been reported to increase consistency in contouring. Even though the surgical clips provide useful marking points, several issues such as clip migration and differences in placement techniques still exist that may lead to inconsistencies in locating the tumor bed[6]. One of the main problems in radiotherapy treatment planning is accurate manual contouring of the tumor bed, as it is prone to significant inter- and intra-observer variability resulting in non-reproducible outcomes [7]. Intra-variance refers to variance in estimates made by the same person under different conditions and inter-variance refers to variance in estimates made by different people under the same conditions.

If the contour of the tumor bed is incorrect, then it will be either treated insufficiently, thus leaving room for cancer recurrence or treated too much leading to unnecessarily irradiation of healthy tissues and increase in their related side effects. In addition, surgery results in multiple anatomical changes that deform tissues and result in seroma formation, which is an accumulation of serous fluids. Thus, these alterations have made accurately identifying the tumor bed more difficult. Greater precision in tumor bed volume estimation has been demonstrated by recent developments in artificial intelligence.

Among various deep learning architectures, U-Net and its based 3D U-Net have been identified as the prominent models in medical image segmentation, including the delineation of tumor volumes. U-Net's encoder-decoder architecture captures very fine spatial information from an image and traces even the most complex anatomical shapes with remarkable precision. The 3D U-Net enabled the segmentation of volumetric data, making it crucial for medical imaging. Building on this foundation, integration of semi-supervised learning into the modified U-Net framework enhanced the postoperative localization of breast tumor beds through application of nonrigid registration and a volume penalty that accounted for tumor resection. This approach not only improved the registration accuracy but was also found to be better than the conventional techniques facilitating effective radiotherapy planning [8].

Additionally, saliency mapping was introduced within a 3D U-Net model where the saliency information from visible markers was used to prioritize high-relevance regions, leveraging spatial cues from markers to enhance segmentation accuracy in tumor beds during postoperative breast irradiation [9]. Another enhancement introduced preoperative tumor contour data, i.e., prior information, into the 3D U-Net framework to address challenges like low soft-tissue contrast and surgical changes in postoperative imaging, achieving improved segmentation accuracy as compared to the conventional gray-level thresholding methods [10].

Auto-segmentation of Clinical Target Volumes (CTV) for breast cancer radiotherapy has seen significant progress in recent years including the introduction of the novel DS-Conv model that incorporated dilated convolutions and residual connections to capture complex features in medical imaging. It has shown high accuracy, outperforming previous techniques like Depthwise Disout Convolutional Neural Network (DD-CNN) and Distributed Deep Neural Networks (DD-NN). It also achieved contouring in fraction of a time as compared to manual contouring. Further, to overcome the time-consuming nature of manual contouring and reduce the inter-observer variability, an automated deep neural network was developed for the segmentation of clinical target volumes (CTV) from CT images. This model operates in three distinct stages: labeling CT slices to identify the presence of CTV, cropping unnecessary regions, and applying a dynamically strided convolution technique (DS-Conv) for enhanced precision in critical breast regions. [11].

Advances in Deep Learning (DL), Radiomics, and Radiogenomics have been very popular, especially through the use of Convolutional Neural Networks (CNNs), for the detection of benign lesions in breast cancer in digital breast tomosynthesis. A systematic review of 30 studies highlights the fact that CNNs are useful in enhancing diagnostic accuracy and improving the localization of lesions in breast imaging and therefore promising for the resolution of the issues in breast cancer detection [12]. Radiomics extracts the quantitative imaging features, and radiogenomics bridges the imaging data with genetic information for a more personalized approach toward treatment insights. However, annotated datasets are still in short supply, and model interpretability is a concern, and more interdisciplinary work is needed to further enhance breast cancer detection and treatment [12].

The potential of CNNs and U-nets, among other methods, to automate the segmentation process and reduce radiation oncologists' reliance on human contouring has been studied [13]. A two-stage CNN successfully approximated contours with a Dice Similarity Coefficient (DSC) of 0.94. The technique indicates that completely automating the OAR segmentation task by DL may be possible, as mean values above 0.80 were observed for DL results, which will be of good clinical feasibility. DL will never substitute the physician; however, it can greatly assist improve efficiency and reduce the variability of different physicians in the clinic.

Other advanced developments are three-stage deep neural networks, which can achieve a high accuracy for automated CTV segmentation, particularly in critical regions of the breast, with significant potential to enhance the accuracy of the segmentation [14]. Radiomics and DL are distinct concepts, with contrasting strengths and weaknesses, though DL is highly effective for the detection of breast cancer than the traditional approaches. These technologies should also continue to be collaboratively worked upon in clinical practices with further exploration and consideration for the future fields, such as radiogenomics, that can potentially unravel novel dimensions of precision oncology [15].

As Table 1 summarizes the datasets, DSC scores, advantages, and limitations, it emphasizes the strengths as well as the needs for improvement of various approaches. Figure 1 gives a graphical comparison of DSC scores and helps discern each model's relative effectiveness in segmenting tumor volumes. While Table 1 summarizes key findings from recent studies to illustrate progress in this area, Figure 1 highlights DD-ResNet and Two-Stage CNN have surpassed the rest of the models by sufficient amount, hence showcasing improved accuracy and speed of manual planning efforts within radiotherapy. Overall, the use of AI models in estimating tumor bed volume for breast cancer has decreased observer variability, expedited result delivery, and enhanced consistency in radiotherapy planning.

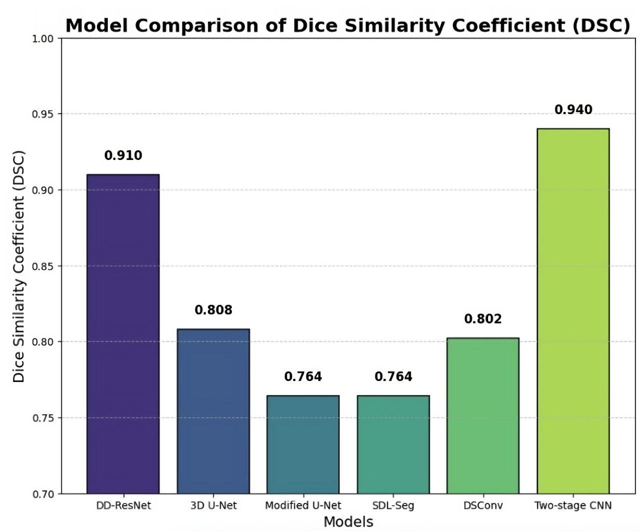

Figure 1: Model-wise Comparison of DSC

Table 1: Comparative Study of the Deep Learning Models Used for Breast Tumor Volume Estimation

Reference	Model	Dataset	Advantages	Limitations	Key Takeaways
[16]	Deep Dilated Residual Network (DD-ResNet)	800 patients	DSC for CTV segmentation was 0.91, Hausdorff Distance reduced, time per patient was 15s.	Requires large dataset; critical dependence on diverse patient anatomies.	High accuracy and speed, suitable for radiotherapy planning; needs validation on diverse cohorts.
[10]	3D U-Net	110 pairs of CT images	Preoperative contours lead to higher accuracy (DSC 0.808 vs 0.734).	Small dataset size; reliance on CT imaging.	Improves segmentation accuracy; larger multimodal datasets needed.
[8, 9]	Modified U-Net	30 CT scans pre- and post-surgery [9]	Real-time processing (<1s), target registration error <6.5mm.	Small dataset limits generalizability; extended training time.	Combines deep learning and non-rigid registration, enhancing alignment accuracy.
		145 prone CT images [8]	Mean Dice coefficient 76.4%; low computation time (11s).	Relies on quality of saliency maps and post-op CTs.	Outperforms U-Net, integrates saliency maps to improve accuracy and cost.
[11]	DSConv	455 cases, 50,425 slices	DSC 0.802 (right), 0.801 (left); DSConv pipeline outperforms others.	Requires large dataset for evaluation.	Better than end-to-end methods; effective for large-scale datasets.
[14]	Three-stage DNN	160 CT scans post-BCS	High DSC values: 0.94–0.96 across critical breast regions.	Needs interdisciplinary collaboration for further improvement.	Enhances segmentation accuracy, especially in critical regions.
[12, 15]	CNN, Radiomics, and Radiogenomics	N/A	Improves diagnosis accuracy, lesion localization, connects imaging with genetics.	Limited labeled datasets; interpretability challenges.	Enhances diagnostics and personalized treatment; more data needed.
[13]	Two-stage CNN	111 patients	DSC 0.94 for contouring, promising for automation of OAR segmentation.	Needs more annotated datasets and collaboration.	High accuracy, feasible for automation, reduces variability for doctors.

5 Proposed Algorithm

Radiation oncology approaches the brink of significant advancements in current clinical practices as artificial intelligence matures. Our study provides strong evidence for general improvements in all axes of delineation process through the design of aggressive AI-enabled procedures. Our proposed approach provides leverage on the deep learning techniques through the use of preoperative scans with manual contours, as well as the postoperative scans with surgical clips acting as critical markers for estimating breast tumor beds. This may present a promising solution to the challenges experienced with manual delineation. This work should be the baseline for any further development that integrates technology with practical application of clinical science to take care of patients.

Our idea is to build a deep learning framework that learns from preoperative and postoperative patient scans by using surgical clips as spatial markers. Deep learning would assist us in the analysis of complex 3D anatomical structures via Convolutional Neural Networks (CNN). These networks automatically learn features from images; in our case, these images would be patient scans. CNNs would study radiological images in layers. Each layer would capture different details ranging from very simple edges and textures up to more intricate anatomical patterns. This layering would be very useful, specifically for tumor bed delineation. It would allow for the simultaneous analysis of a series of different scan slices with knowledge not only of the local tissue details but also their pattern in the breast. Combining different pieces of information that include preoperative positions of a tumor, tissue changes after surgery, and clips during surgery makes it possible to obtain approximate estimations of the tumor bed. We shall use widely accepted metrics for evaluating delineations based on our study, such as the Dice similarity coefficient and the Hausdorff distance, to determine how closely our automated delineation matches expert-drawn contours.

The standardization of the tumor bed delineation process with the help of AI could thus create reproducible methodologies in ensuring treatments. Moreover, standardization is also crucial to ensure consistency in the strategies of treatment planning while maintaining accurate efforts in terms of radiotherapy delivery. These technological advancements will not replace the clinical education but rather complement it, thus letting the oncologist focus more time on the treatment plan and patient's care. Such advancements in systems, under close guidance from clinical oversight, present a major step forward toward perfecting the workflows in radiation oncology for breast tumor patients.

6 Conclusion

This work brings out the significant potential of deep learning techniques in radiation oncology, especially in breast tumor bed delineation. Through an extensive comparison of various deep learning models, our study shows how DD-ResNet and Two-Stage CNN have brought out the improvement in tumor localization and segmentation accuracy with one of the highest DSC scores. However, there are still challenges like dataset limitations, model generalization, and the need for interdisciplinary collaboration, which requires further research and refinement. AI-driven models using preoperative and postoperative imaging data show considerable promise in improving the precision and efficiency of tumor bed estimation, a critical step in radiotherapy planning. The work strongly highlights the use of merging technological advancement with clinical expertise in optimizing patient care by not letting the AI tool substitute but provide additional assistance to the oncologists. As such, overall, the present study will be a founding step in transforming the work-flows associated with radiotherapy for breast cancer, opening pathways for standardized, reproducible, and accurate treatments.

References

[1] American Cancer Society, Breast Cancer Facts & Figures 2022-2024. Atlanta: American Cancer Society, Inc., 2022. [Online]. Available: https://www.cancer.org/content/dam/cancer-org/research/cancer-facts-and-statistics/breast-cancer-facts-and-figures/2022-2024-breast-cancer-fact-figures-acs.pdf.

[2] Yang TJ, Tao R, Elkhuizen PH, van Vliet-Vroegindeweij C, Li G, Powell SN. Tumor bed delineation for external beam accelerated partial breast irradiation: a systematic review. Radiother Oncol. 2013 Aug;108(2):181-9. doi: 10.1016/j.radonc.2013.05.028. Epub 2013 Jun 24. PMID: 23806188.

[3] Marta GN, Coles C, Kaidar-Person O, Meattini I, Hijal T, Zissiadis Y, Pignol JP, Ramiah D, Ho AY, Cheng SH, Sancho G, Offersen BV, Poortmans P. The use of moderately hypofractionated post-operative radiation therapy for breast cancer in clinical practice: A critical review.

Crit Rev Oncol Hematol. 2020 Dec;156:103090. doi: 10.1016/j.critrevonc.2020.103090. Epub 2020 Aug 26. PMID: 33091800; PMCID: PMC7448956.

[4] Garreffa E, Hughes-Davies L, Russell S, Lightowlers S, Agrawal A. Definition of Tumor Bed Boost in Oncoplastic Breast Surgery: An Understanding and Approach. Clin Breast Cancer. 2020 Aug;20(4):e510-e515. doi: 10.1016/j.clbc.2020.03.003. Epub 2020 Mar 20. PMID: 32284305.

[5] Bridge P, Bridge R. Artificial intelligence in radiotherapy: A philosophical perspective. J Med Imaging Radiat Sci. 2019;50(4 Suppl 2):S27-S31. doi: 10.1016/j.jmir.2019.09.003.

[6] SShukla U, Langner UW, Linshaw D, Tan S, Huber KE, Miller CJ, Yu E, Leonard KL, Sueyoshi M, Diamond B, Edmonson D, Wazer DE, Gass J, Hepel JT. Comparison of Tumor Bed Delineation Using a Novel Radiopaque Filament Marker Versus Surgical Clips for Targeting Breast Cancer Radiotherapy. Am J Clin Oncol. 2023 Oct 1;46(10):427-432. doi: 10.1097/COC.0000000000001028. Epub 2023 Jul 13. PMID: 37440682.

[7] Zheng D, He X, Jing J. Overview of Artificial Intelligence in Breast Cancer Medical Imaging. J Clin Med. 2023 Jan 4;12(2):419. doi: 10.3390/jcm12020419. PMID: 36675348; PMCID: PMC9864608.

[8] Kazemimoghadam M, Chi W, Rahimi A, Kim N, Alluri P, Nwachukwu C, Lu W, Gu X. Saliency-guided deep learning network for automatic tumor bed volume delineation in post-operative breast irradiation. Phys Med Biol. 2021 Aug 27;66(17):10.1088/1361-6560/ac176d. doi: 10.1088/1361-6560/ac176d. PMID: 34298539; PMCID: PMC8639319.

[9] Wodzinski M, Ciepiela I, Kuszewski T, Kedzierawski P, Skalski A. Semi-Supervised Deep Learning-Based Image Registration Method with Volume Penalty for Real-Time Breast Tumor Bed Localization. Sensors (Basel). 2021 Jun 14;21(12):4085. doi: 10.3390/s21124085. PMID: 34198497; PMCID: PMC8231789.

[10] Xie X, Song Y, Ye F, Wang S, Yan H, Zhao X, Dai J. Prior information guided auto-segmentation of clinical target volume of tumor bed in postoperative breast cancer radiotherapy. Radiat Oncol. 2023;18:170. doi: 10.1186/s13014-023-02355-9.

[11] Qi X, Hu J, Zhang L, Bai S, Yi Z. Automated Segmentation of the Clinical Target Volume in the Planning CT for Breast Cancer Using Deep Neural Networks. IEEE Trans Cybern. 2022 May;52(5):3446-3456. doi: 10.1109/TCYB.2020.3012186. Epub 2022 May 19. PMID: 32833659.

[12] Hussain S, Lafarga-Osuna Y, Ali M, Naseem U, Ahmed M, Tamez-Peña JG. Deep learning, radiomics and radiogenomics applications in the digital breast tomosynthesis: a systematic review. BMC Bioinformatics. 2023;24:401. doi: 10.1186/s12859-023-05515-6.

[13] Chung SY, Chang JS, Choi MS, Chang Y, Choi BS, Chun J, Keum KC, Kim JS, Kim YB. Clinical feasibility of deep learning-based auto-segmentation of target volumes and organs-at-risk in breast cancer patients after breast-conserving surgery. Radiat Oncol. 2021 Feb 25;16(1):44. doi: 10.1186/s13014-021-01771-z. PMID: 33632248; PMCID: PMC7905884.

[14] Liu Z, Liu F, Chen W, Tao Y, Liu X, Zhang F, Shen J, Guan H, Zhen H, Wang S, Chen Q, Chen Y, Hou X. Automatic Segmentation of Clinical Target Volume and Organs-at-Risk for Breast Conservative Radiotherapy Using a Convolutional Neural Network. Cancer Manag Res. 2021 Nov 2;13:8209-8217. doi: 10.2147/CMAR.S330249. PMID: 34754241; PMCID: PMC8572021.

[15] Wei P. Radiomics, deep learning and early diagnosis in oncology. Emerg Top Life Sci. 2021 Dec 21;5(6):829-835. doi: 10.1042/ETLS20210218. PMID: 34874454; PMCID: PMC8786297.

[16] Men K, Zhang T, Chen X, Chen B, Tang Y, Wang S, Li Y, Dai J. Fully automatic and robust segmentation of the clinical target volume for radiotherapy of breast cancer using big data and deep learning. Phys Med. 2018 Jun;50:13-19. doi: 10.1016/j.ejmp.2018.05.006. Epub 2018 May 19. PMID: 29891089. https://pubmed.ncbi.nlm.nih.gov/29891089/.