Deep Learning for Automatic Detection and Segmentation from CT Angiography of Deep Inferior Epigastric Vascular Structures for Preoperative Planning of TRAM Flap Surgeries

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Background

Breast reconstruction helps to improve self-appearance and quality of life for breast cancer patients after mastectomy. Reconstruction can be either implant-based or autologous tissue-based, with the latter approach offering several advantages, including a more natural appearance and lifetime durability. Among the different types of tissue-based reconstruction, the free TRAM flap offers the best final cosmesis. However, careful preoperative mapping of the relevant vascular structures is needed because this type of reconstruction is accountable for approximately 30% of vascular complications [1].

Objective

To develop and validate a deep learning method that can automatically detect and segment the *vascular structures (focusing on* the deep inferior epigastric arteries (DIEA) and dominant subcutaneous branches or perforators) to potentially aid preoperative planning of TRAM flap surgeries.

Methods

100 CTA
(manually contoured)

68 CTA for training
nnU-Net +
17 CTA for internal
validation

15 CTA reserved for independent testing
of five different nnU-Net models
(2D, 3D low resolution, 3D full
resolution, 3D cascade, ensemble)

Results

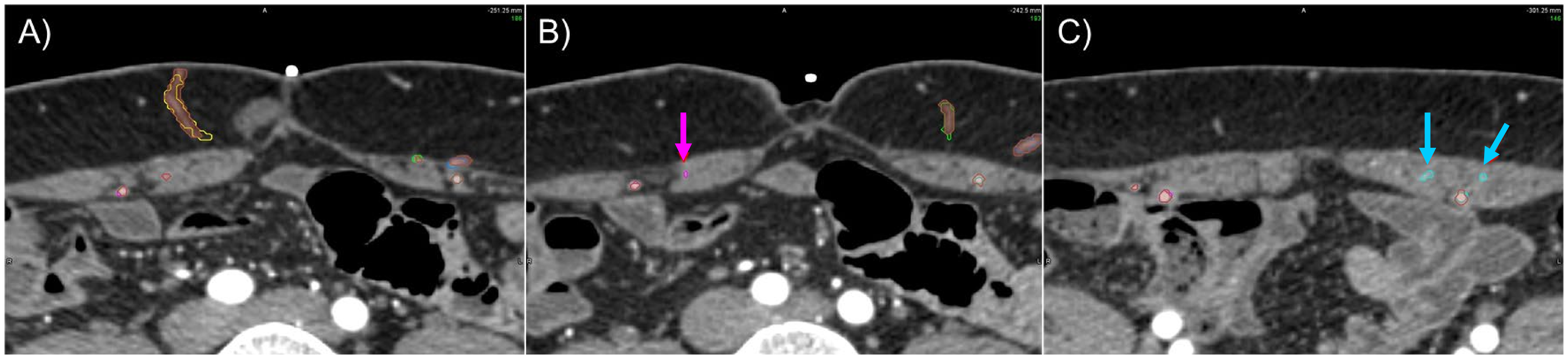

Figure 1. Comparison of manual contours vs. nnU-Net generated contours (**brown**, filled) on best performing case.
(A) Trained model accurately segmented both left and right DIEA and their associated perforators.
(B) Trained model accurately segmented the left DIEA and associated perforators but was unable to detect the branching of the right DIEA (**pink** arrow).
(C) Trained model accurately segmented the right DIEA and its branches but was unable to detect the branching of the left DIEA (**blue** arrows).

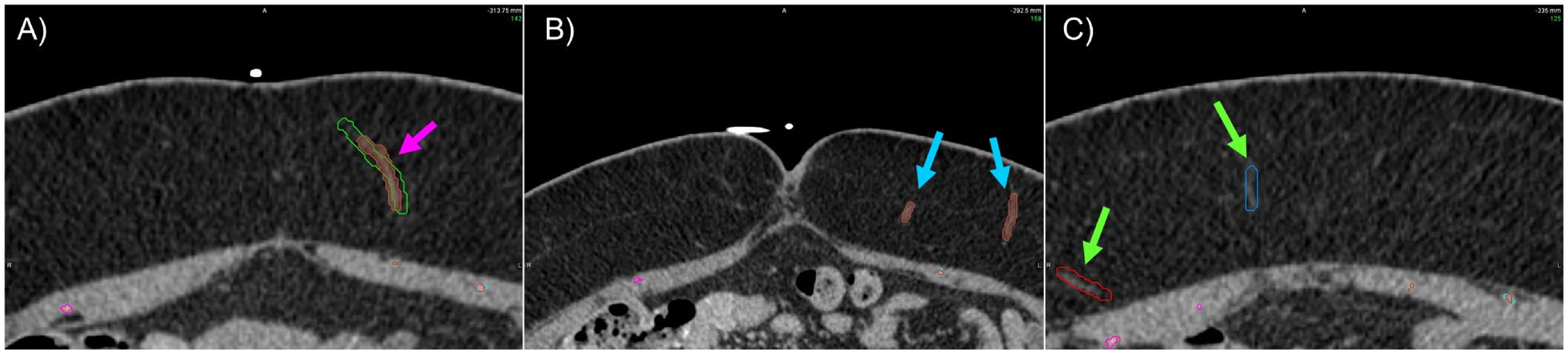

Figure 2. Comparison of manual contours vs. nnU-Net generated contours (**brown**, filled) on worst performing case.
(A) Trained model accurately segmented left DIEA and associated perforator (**pink** arrow).
(B) Trained model incorrectly segmented left perforators that were not found in ground truth (**blue** arrows).
(C) Trained model was unable to detect right perforators (**green** arrows).

Table 1. Summary Statistics of Dice Measurements. 3D cascade had the greatest mean Dice value (72.31%±8.28%).

	N	Mean	Std Dev	Median	Min	Max
3D Cascade Dice	15	0.7231	0.0828	0.715	0.563	0.904
Ensemble Dice	15	0.7228	0.082	0.7089	0.56	0.906
3D Full Resolution Dice	15	0.7196	0.0816	0.7022	0.553	0.906
2D Dice	15	0.7033	0.0863	0.6893	0.557	0.909
3D Low Resolution Dice	15	0.3788	0.0772	0.3682	0.242	0.486

Table 2. Pairwise Comparisons Using a Linear Mixed Model with Patient ID as Random Effect. P-values were adjusted by Tukey HSD method.

Similar performances between 2D, 3D full resolution, 3D cascade, and ensemble (p <.0001). 3D low resolution performed significantly worse than the other four methods.

Method A	Method B	Difference	Lower 95%	Upper 95%	P-value
2D Dice	3D Cascade Dice	-0.0198	-0.0530	0.0133	0.45
2D Dice	3D Full Resolution Dice	-0.0163	-0.0494	0.0168	0.64
2D Dice	Ensemble Dice	-0.0196	-0.0527	0.0135	0.46
3D Cascade Dice	3D Full Resolution Dice	0.0035	-0.0296	0.0366	1.00
3D Cascade Dice	Ensemble Dice	0.0003	-0.0328	0.0334	1.00
3D Full Resolution Dice	Ensemble Dice	-0.0032	-0.0364	0.0299	1.00
2D Dice	3D Low Resolution Dice	0.3244	0.2913	0.3576	<.0001
3D Cascade Dice	3D Low Resolution Dice	0.3443	0.3112	0.3774	<.0001
3D Full Resolution Dice	3D Low Resolution Dice	0.3408	0.3076	0.3739	<.0001
3D Low Resolution Dice	Ensemble Dice	-0.3440	-0.3771	-0.3109	<.0001

Conclusions

In this pilot project, our preliminary data suggests that the model can accurately identify the DIEA vessels. Additional work on a larger sample size is needed to verify that this algorithm can automate the detection of the vessels of interest and their associated perforators as well as the mapping of the location of these vessels.

References

1. Ribuffo D, Atzeni M, Corrias F, et al. Preoperative Angio-CT Preliminary Study of the TRAM Flap After Selective Vascular Delay. Ann Plast Surg 2007; 59: 611-616.
2. Isensee F, Jaeger PF, Kohl SAA, Petersen J, Maier-Hein KH. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nat Methods. 2021;18(2):203-211.