AUTOMATIC SEGMENTATION OF HEAD AND NECK CANCER FROM CT IMAGES USING CT 3D CONVOLUTION NEURAL NETWORK

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Abstract no:

INTRODUCTION

➢Accurate tumor segmentation is essential for effective radiotherapy planning, ensuring precise radiation delivery while minimizing harm to surrounding healthy tissues. However, manual segmentation by radiation oncologists is time-consuming, subjective, and prone to inter-observer variability and can introduce inconsistencies in treatment planning that may affect patient outcomes.

➢While PET/CT enhance segmentation accuracy, their high costs and limited accessibility restrict their use in many clinical settings. Since CT remains the most widely available imaging modality; developing a reliable AI-driven segmentation approach is highly beneficial.

➢Deep learning, particularly UNet-based architectures, has shown significant promise in medical image analysis by enabling automated, high-precision tumor delineation, improving segmentation accuracy, consistency, and reduce the time required for manual annotations.

AIM

➢ To develop a fully automated CT-based segmentation model using the self-configurable 3D nnU-Net framework, improving segmentation accuracy, reproducibility, and accessibility while reducing dependency on PET/CT imaging.

KEY FINDINGS

➢Public Dataset (n = 136): The model achieved a DSC of 0.76 and an HD95 of 12.67 mm, demonstrating high segmentation accuracy and precise boundary detection on the public dataset.

➢Private Dataset (n = 30): The model showed lower performance with a DSC of 0.63 and an HD95 of 20.05 mm, indicating potential challenges due to data quality or imaging differences in the private dataset.

➢Combined Datasets: When both datasets were merged, the model achieved an intermediate DSC of 0.72 and an HD95 of 15.74 mm, underscoring that effective preprocessing and training strategies can mitigate variability and enhance overall performance.

METHODS

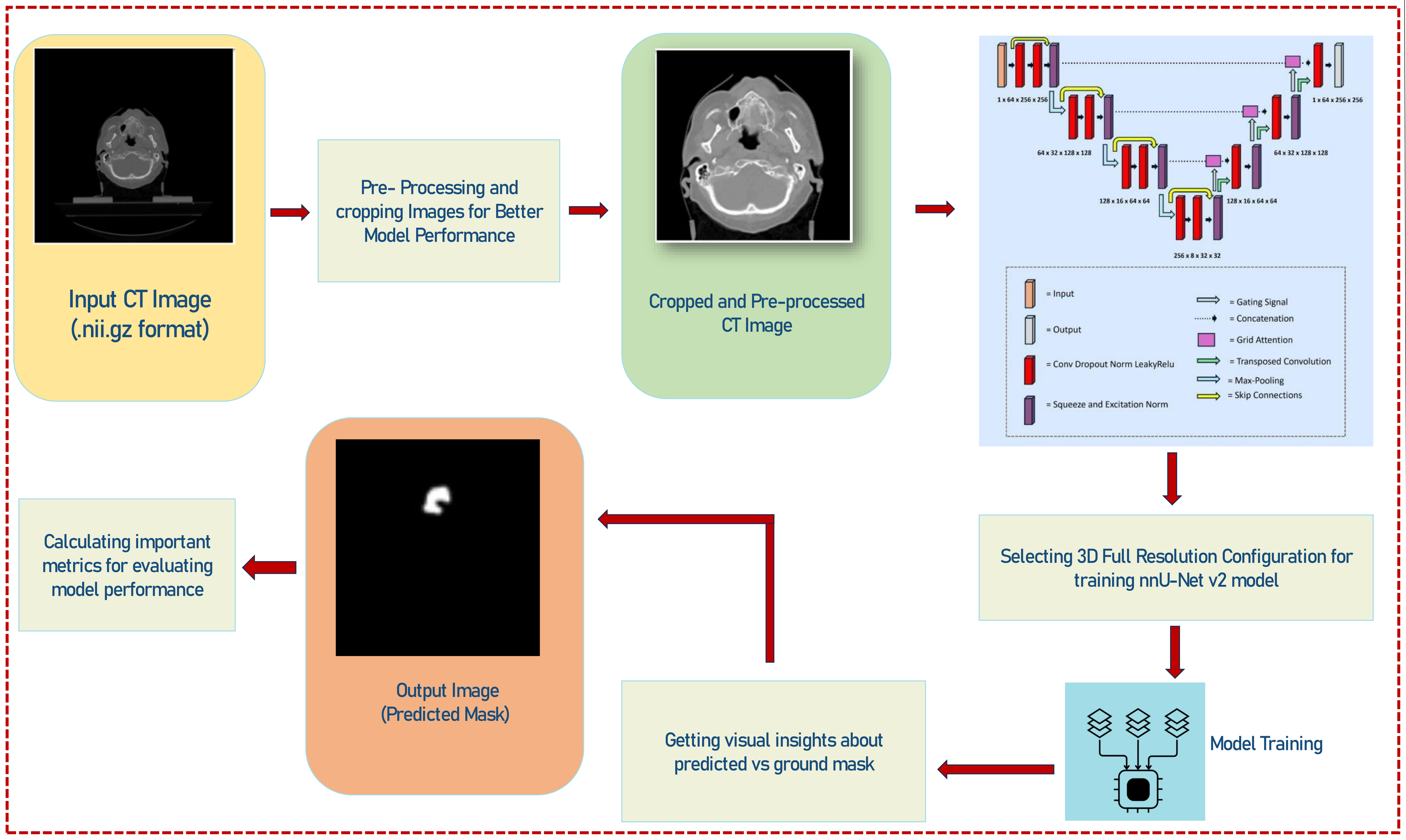
Patients treated for Head and Neck Cancer (N=167)

Inclusion criteria

1. Patients with diagnosed Head and Neck Cancer
2. Contrast-enhanced computed tomography of Head and Neck
3. No treatment before the CT scan
4. Treatment with Radiation and Chemoradiation only

Patients included in the study (N=166)
Public Dataset HN1 (n=136)
Private Dataset HNC (n=30)

DATA SPLIT (85:15)	
Training cohort (n=142) HN1 -122 samples (86%) HNC -20 samples (14%)	Testing cohort (n=24) HN1 -14 samples (58%) HNC -10 samples (42%)



RESULTS

Ablation Study

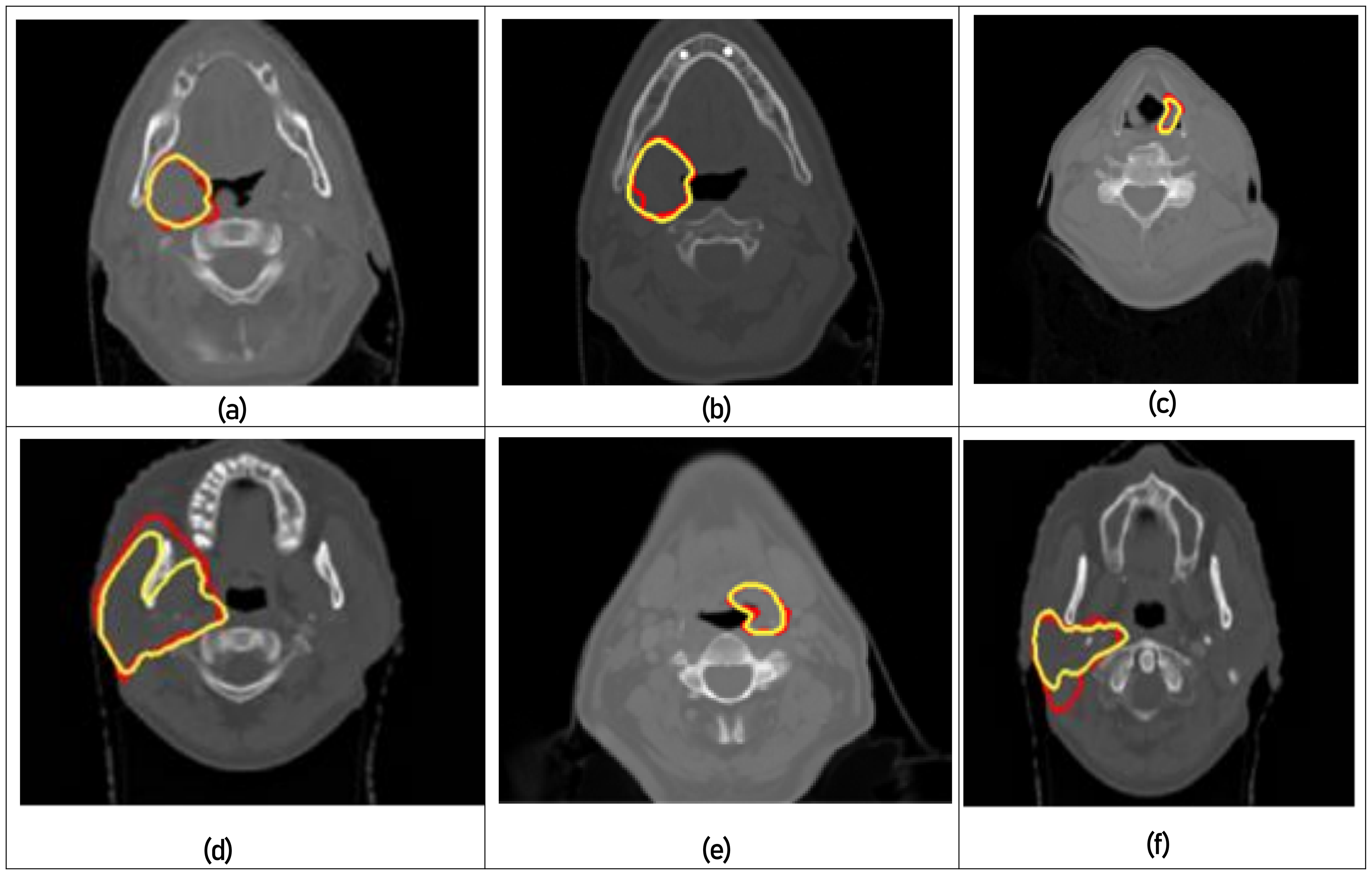
➢ Preprocessing applied: cropping to 256×256 and windowing (WL=40, WW=400).
➢ Compared nnU-Net configurations: 3D Full Resolution vs. Residual Encoder L.
➢ Selected 3D Full Resolution due to superior performance.

Configuration	Performance on Cropped and Preprocessed Data				
	Epochs	DSC	Precision	Recall	HD95 (in mm)
3D Full Resolution	500	0.59	0.60	0.58	16.08
	2000	0.66	0.63	0.70	16.56
3D Full Resolution + Residual Encoder L	500	0.63	0.58	0.69	16.80
	2000	0.65	0.62	0.68	15.13

Cross Validation & Optimization

➢ Optimization via SGD with Nesterov momentum.
➢ Loss function: Combination of Cross-Entropy and Dice Loss.
➢ Employed 3-fold cross validation to minimize test set bias.
➢ Experiments conducted on an NVIDIA DGX Station (Tesla V100, 32 GB), using CUDA Toolkit 11.8.0, Python 3.9, and PyTorch 1.11.

Datasets	Average Results of Three-Fold Cross Validation Across Combined and Individual Datasets			
	DSC	Precision	Recall	HD95 (in mm)
HN1	0.76	0.71	0.83	12.67
CMC	0.63	0.55	0.80	20.05
HN1 + CMC	0.72	0.65	0.82	15.74



The qualitative visualization of the segmentation results are illustrated in above figure, where the red boundary represents the ground truth, and the yellow boundary indicates the predicted mask. Images (a), (b), and (c) correspond to examples from the public HN1 dataset while (d), (e), and (f) are from the private HNC dataset

CONCLUSION

Enhances accessibility in resource-limited settings, making automated segmentation more feasible for clinical integration. Future work could explore integrating nnU-Net with MedSAM or fine-tuning nnU-Net with bounding box-based localization to further enhance segmentation performance. Additionally, expanding the dataset to include more diverse patient populations could improve the model's generalization.

REFERENCES

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