

Conclusion:

This study explored the use of eight PCS calculated by a commercial software, applied to real clinical data to characterise plan quality and complexity at one radiotherapy centre. By assessing whether new treatment plans align with the measured PCS, this framework could streamline PSQA, improving efficiency.

Keywords: Plan complexity metrics, PSQA, plan quality

References:

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Poster Discussion

Deep Learning-Based Dose Prediction for Head and Neck Tumors: Influence of Loss Function and Model Architecture

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Purpose/Objective:

In recent years, deep learning-based approaches for dose prediction in head and neck cancer treatments have made significant progress. However, the effects of key factors, such as the choice of loss function and model architecture, on the accuracy of dose predictions—evaluated using clinically relevant dosimetric parameters—remain underexplored. This study aims to examine how these factors influence the performance of deep learning dose prediction models, focusing on clinically relevant dosimetric parameters (e.g., V95% and mean dose).

Material/Methods:

This study analyzed 104 patients treated for oropharyngeal and hypopharyngeal cancer at Leiden University Medical Center between 2017 and 2024. All patients received a prescribed dose of 54.25 Gy to the elective lymph nodes and 70 Gy to the primary tumor. The dataset was divided into a training set of 69 patients and a test set of 35 patients. To investigate the impact of loss functions, we evaluated two approaches: Mean Absolute Error (MAE) loss and a combination of MAE and a DVH-based loss^[1]. For model architecture, we explored four state-of-the-art networks, including UNet-based and Transformer-based architectures: DoseNet, HDUNet, C3D (cascade structure), and DOSE-PYFER (cascade structure)^[2,3,4]. The model inputs included CT images, PTV masks, and OAR masks.

Results:

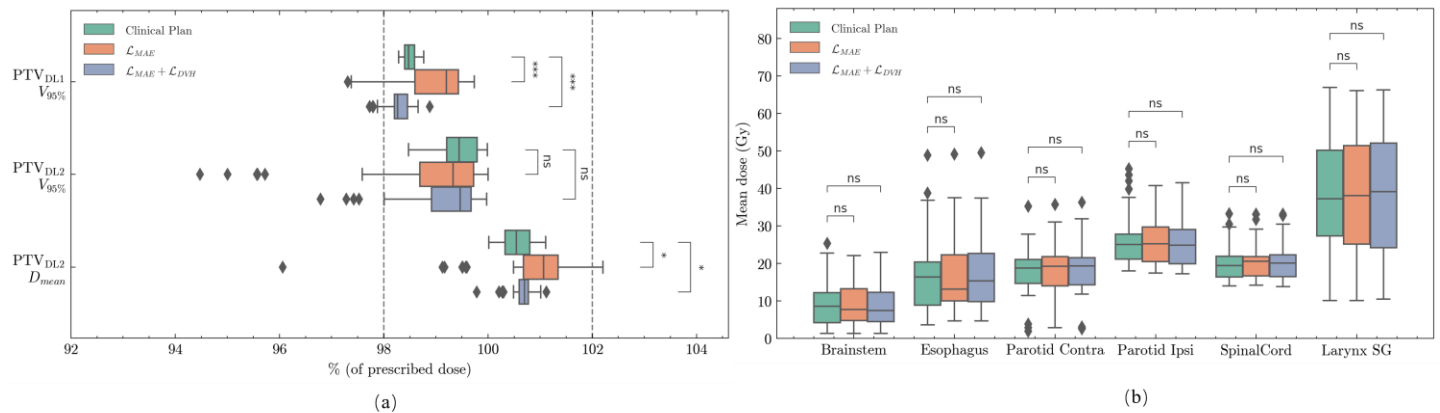


Figure 1 (a) Boxplots with dosimetric parameters comparison for targets. (b) Boxplots with dosimetric parameters comparison for OAR. DL1 = dose level 1 (5425 cGy), DL2 = dose level 2 (7000 cGy). Ipsi = ipsilateral, Contra = contralateral, SG = supraglottis. Statistical significance was tested using a two-tailed Wilcoxon signed-rank test. ***: $0.0001 < p \leq 0.001$, *: $0.01 < p \leq 0.05$, ns = not significant.

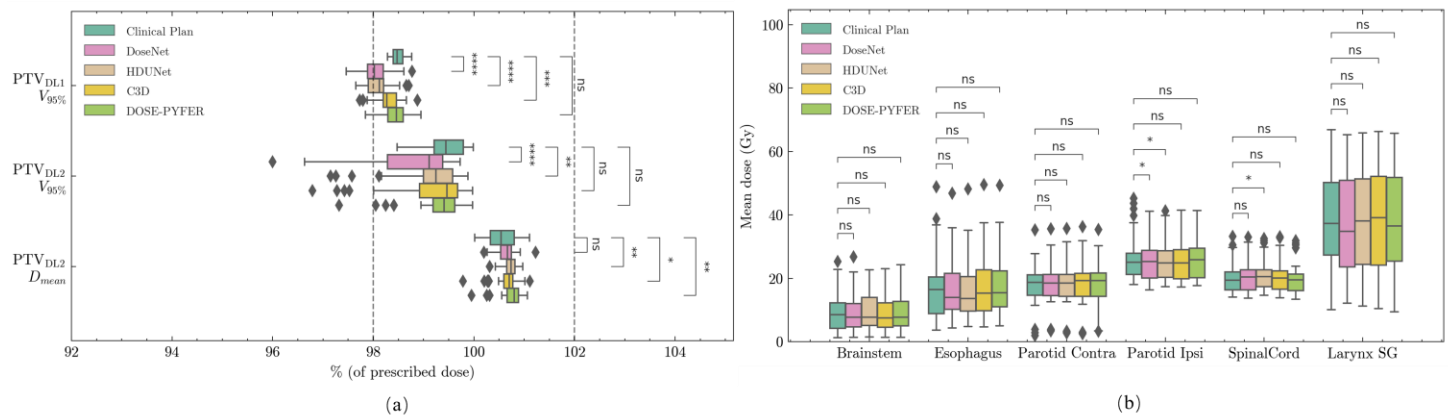


Figure 2 (a) Boxplots with dosimetric parameters comparison for targets. (b) Boxplots with dosimetric parameters comparison for OAR. DL1 = dose level 1 (5425 cGy), DL2 = dose level 2 (7000 cGy). Ipsi = ipsilateral, Contra = contralateral, SG = supraglottis. Statistical significance was tested using a two-tailed Wilcoxon signed-rank test. ****: $p \leq 0.0001$, ***: $0.0001 < p \leq 0.001$, **: $0.001 < p \leq 0.01$, *: $0.01 < p \leq 0.05$, ns = not significant.

The results demonstrated significant differences between the predicted dose using MAE loss and MAE+DVH loss in terms of $PTV_{DL1} V95\%$ and $PTV_{DL2} D_{mean}$ when compared to clinical plans. However, no significant differences were observed for OAR mean dose ($p > 0.05$). Predictions using MAE+DVH loss exhibited reduced variance compared to those using MAE loss alone.

For most networks, no significant differences were found in OAR mean dose ($p > 0.05$). For $PTV_{DL1} V95\%$ and $PTV_{DL2} V95\%$, DOSE-PYFER demonstrated no significant differences from clinical plans. However, more than 25% of predictions from DoseNet and HDUNet failed to meet the clinical constraint for $PTV_{DL1} V95\%$ ($\geq 98\%$).

Conclusion:

Based on targets and OAR dosimetric parameters, we recommend using a combined MAE and DVH-based loss function for dose prediction tasks. Advanced cascaded architectures, such as C3D and DOSE-PYFER, demonstrated superior performance and are therefore preferred. These findings indicate that, with the appropriate configuration, deep learning-based dose prediction methods can effectively align with clinical dose distributions across clinically relevant dosimetric parameters.

Keywords: Deep learning, Dosimetric parameters

References:

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Proffered Paper

Quantitative scores of cardiac calcifications detected on planning CT predict long-term cardiotoxicity after radiotherapy for breast cancer

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Purpose/Objective:

Breast cancer (BC) patients undergoing radiotherapy (RT) may experience long-term cardiotoxicity. In modern series, delivering low heart dose, non-dosimetry predictors are emerging: among them, cardiac calcifications (CAC). The purpose was to test if CAC scores at planning CT are associated with long-term cardiac events.

Material/Methods:

Planning CT and dosimetry/clinical information of 1172 consecutive patients treated at our hospital (2009-2017) with tangential field 3DCRT whole breast irradiation (40Gy/15fr) were available (right:569, left:603). Cardiac events were prospectively registered by the curing radiation oncologist. Heart was automatically segmented using a previously validated AI-based tool (MIM_Protegé) and the mean heart dose (MHD) was assessed. Patients with pacemaker/electrodes were identified based on heart density histograms and automatic high-density material detection in the superior vena cava, using TotalSegmentator^{Ref-1}; these patients were excluded because of their potentially altered baseline cardiac functionality. CAC were identified by a home-made Python script based on the search of 'calcified lesion' as >130HU pixels and area>1mm² or ≥4 adjacent pixels. Agatston score (AS)^{Ref-2}, CAC_volume and HU score (Max_HU) were assessed. Their association with the risk of cardiac events was tested by logistic regression, including the potential effect of MHD and available clinical parameters (including age, chemo/monoclonal/hormonal therapy, diabetes, smoking and hypertension). The resulting multivariable model was internally validated through bootstrapping.

Results:

Table-1							
Variables	p-value	Odds	95% CI Odds	Model p-value	ROC p-value	AUC	95% CI AUC
Volume score							
Age	0.0343	1.0406	1.0030, 1.0797	<0.0001	<0.0001	0.77	0.744, 0.795
MHD>1Gy	0.0093	3.3086	1.3433, 8.1493				
CAC Score	<0.0001	1.0005	1.0012, 1.0023				
Agatson score							
Age	0.0337	1.0408	1.0031, 1.0800	<0.0001	<0.0001	0.771	0.745, 0.796
MHD>1Gy	0.0123	3.1338	1.2811, 7.6660				
CAC Score	<0.0001	1.0013	1.0008, 1.0019				
Maximum HU score							
Age	0.0117	1.0466	1.0102, 1.0844	<0.0001	<0.0001	0.755	0.729, 0.78
MHD>1Gy	0.0142	2.9528	1.2424, 7.0180				
CAC Score	0.002	1.0026	1.0011, 1.0042				