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Domain Knowledge Driven 3D Dose Prediction Using Moment-Based Loss Function

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PURPOSE

To introduce a novel moment-based loss function for predicting 3D dose distribution for the challenging conventional lung IMRT plans. The moment-based loss function is convex and differentiable and can easily incorporate clinical dose volume histogram (DVH) domain knowledge in any deep learning framework without computational overhead

MATERIAL & METHODS

We used a large dataset of 360 (240 for training, 50 for validation and 70 for testing) challenging conventional lung patients with 2Gy x 30 fractions to train the deep learning (DL) model using clinically treated plans at our institution.

We trained a UNet like CNN architecture using computed tomography (CT), planning target volume (PTV) and organ-at-risk contours (OAR) as input to infer corresponding voxel-wise 3D dose distribution. We evaluated three different loss functions: 1) Mean Absolute Error (MAE) Loss 2) MAE Loss + DVH Loss (*D. Nguyen et. Al*) 3) MAE Loss + Moments Loss.

Moment of a structure s is given by,

$$M_p(s) = \left(\frac{1}{|V(s)|}\sum_{j\in V(s)} d_j^p\right)^{\frac{1}{p}}$$

where, M_p is the p^{th} moment of the structure, $V(s)$ are the voxels belonging to the structure s and d is the dose

And the moment loss used in this study is given by,

$$Moment\ loss = w\sum_{s} \|M_p(s) - \overline{M_p}\,(s)\|_2^2$$

where, w is the weight for p^{th} moment of the structure $M_p(s)$ is the actual moment and $\overline{M_p}(s)$ is the predicted moment for structure s.

The quality of the predictions was compared using different DVH metrics as well as dose-score and DVH-score, recently introduced by the *AAPM knowledge-based planning grand challenge*.

RESULTS

Model with MAE + Moment loss function outperformed the MAE and MAE+DVH loss by 11.45% and 8.85% respectively. Dose score remains same for all the loss functions for a given model. (MAE+Moment) loss outperformed MAE loss with 32% and 20.84% improvement in homogeneity and conformity error respectively. (MAE+Moment) loss outperformed (MAE+DVH) loss with 7.23% and 7.58% improvement in homogeneity and conformity error, respectively. Model with MAE+Moment loss also converged twice as fast as MAE+DVH loss, with training time of ~7 hours compared to ~14 hours for MAE+DVH Loss.

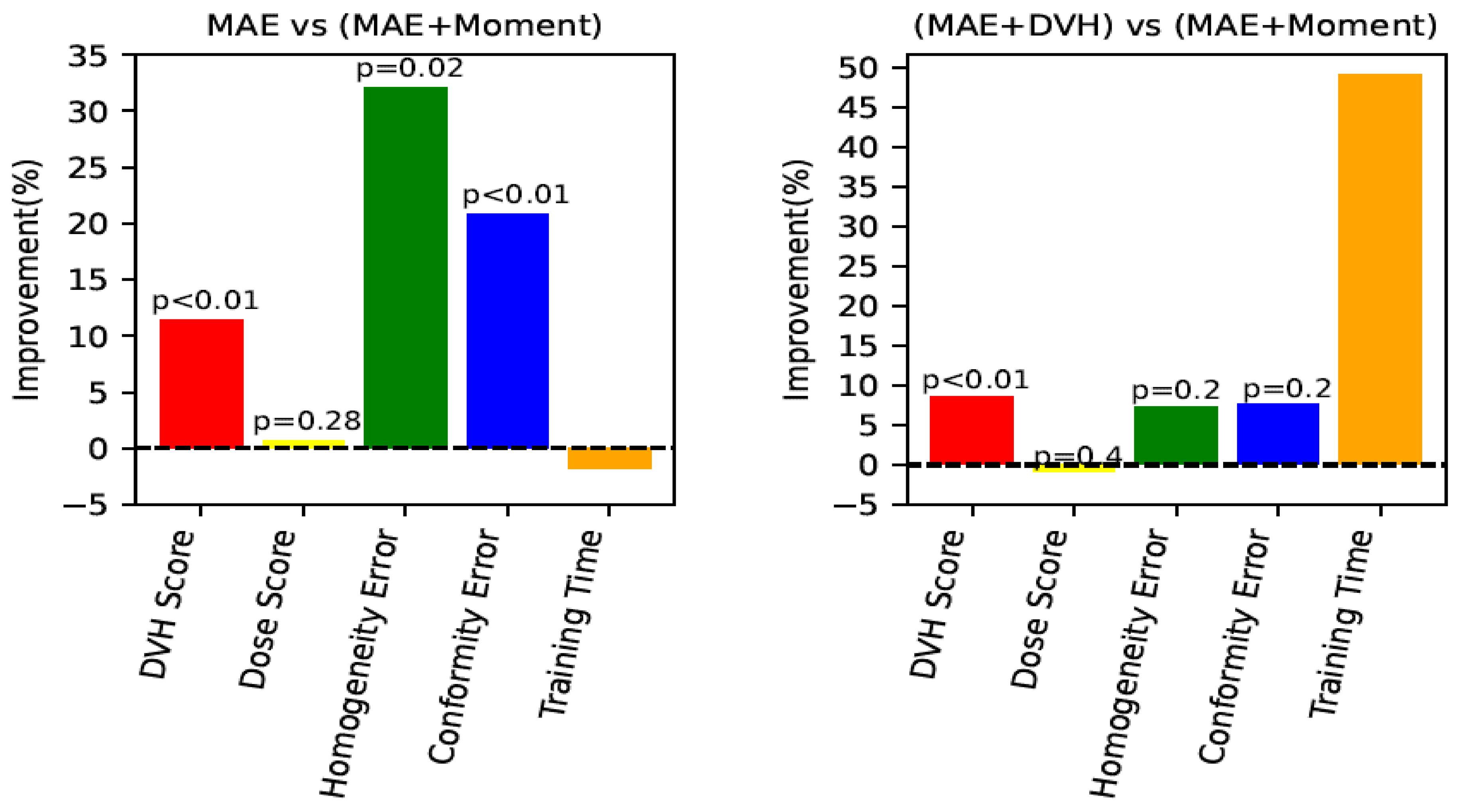

Figure 1 Comparison of different metrics for (a) MAE vs (MAE + Moment) and (b) (MAE+ DVH) vs (MAE + Moment) losses.

Figure 2 on the left shows the dose prediction error (in percentage of prescription) for different OARs and target volume. Critical OARs like cord, esophagus showed substantial improvement in max/ mean absolute dose error using MAE + Moment loss compared to other two. PTV D95 and D99 showed marginal improvement in the dose prediction quality compared to MAE loss. Figure 2 on right show the DVH comparison for different loss function with the same model. The DVH for the predicted dose using MAE + Moment loss (indicated in dot) is more like the actual dose compared to the DVH for MAE + DVH loss (indicated in dash)

RESULTS CONTINUED

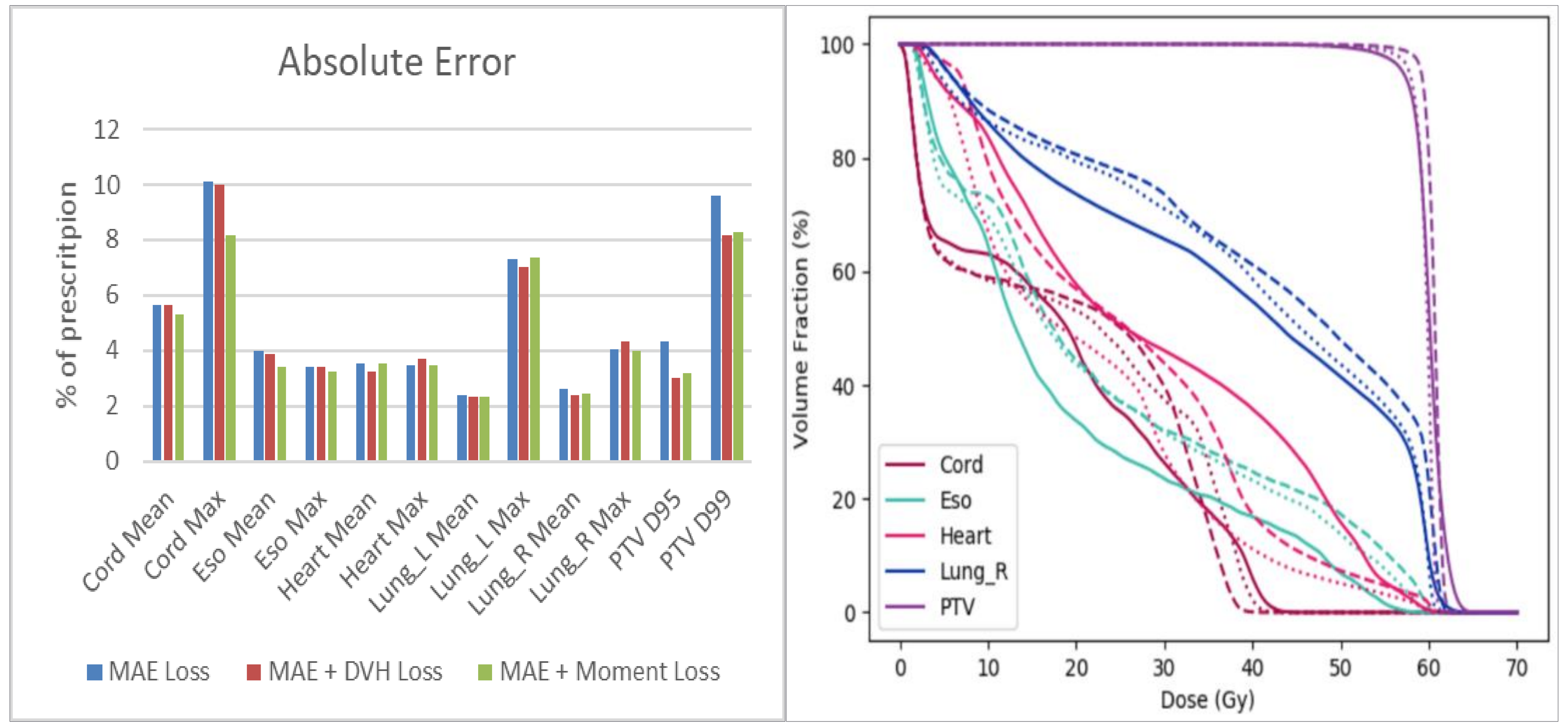

Figure 2 Left- Absolute error comparison for different loss type **Right-** DVH comparison for i) actual dose(solid) ii) predicted dose using MAE + DVH loss (dash) iii) predicted dose using MAE + Moment loss (Dot)

CONCLUSION

DVH metrics are widely accepted evaluation criteria in the clinic. However, incorporating them into the 3D dose prediction model is challenging due to their non-convexity and non-differentiability. Moments provide a mathematically rigorous and computationally efficient way to incorporate DVH information in any deep learning architecture.

REFERENCES

D. Nguyen et al. Incorporating human and learned domain knowledge into training deep neural networks: A differentiable dose-volume histogram and adversarial inspired framework for generating Pareto optimal dose distributions in radiation therapy, Medical Physics 47, 837–849 (2020)

ACKNOWLEDGEMENTS

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