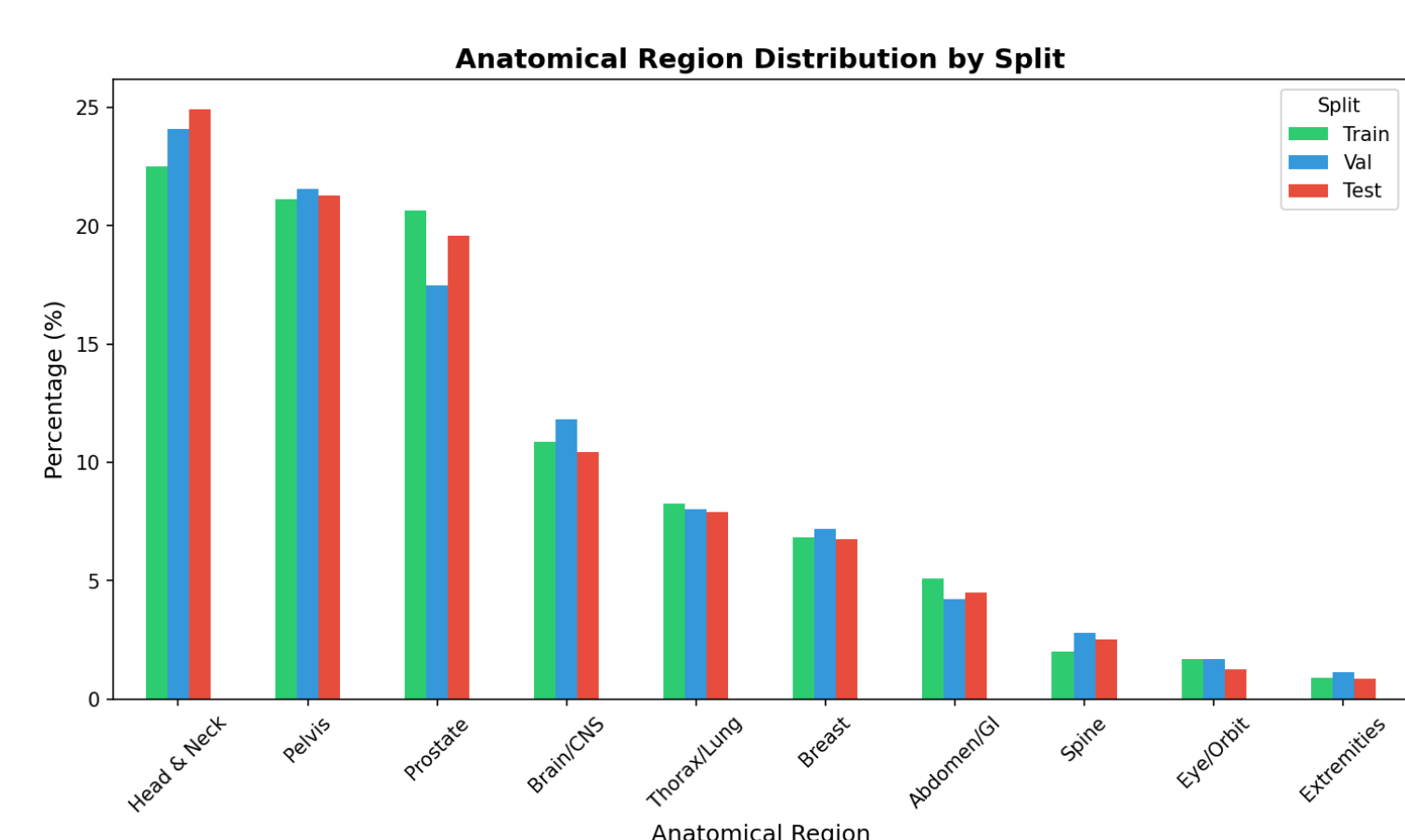


INTRODUCTION

- Develop a unified machine learning model which can predict the dose distribution for any disease site treated with VMAT
- To prediction a 3D dose distribution, the model uses minimal inputs
 - CT dataset
 - Structure contours
 - Treatment site
 - Isodose levels for SIB plans
- Rapidly outputting a clinically acceptable dose distribution deliverable via standard VMAT arcs, without requiring any beam geometry or optimization parameters, additional work is required

METHODS AND MATERIALS

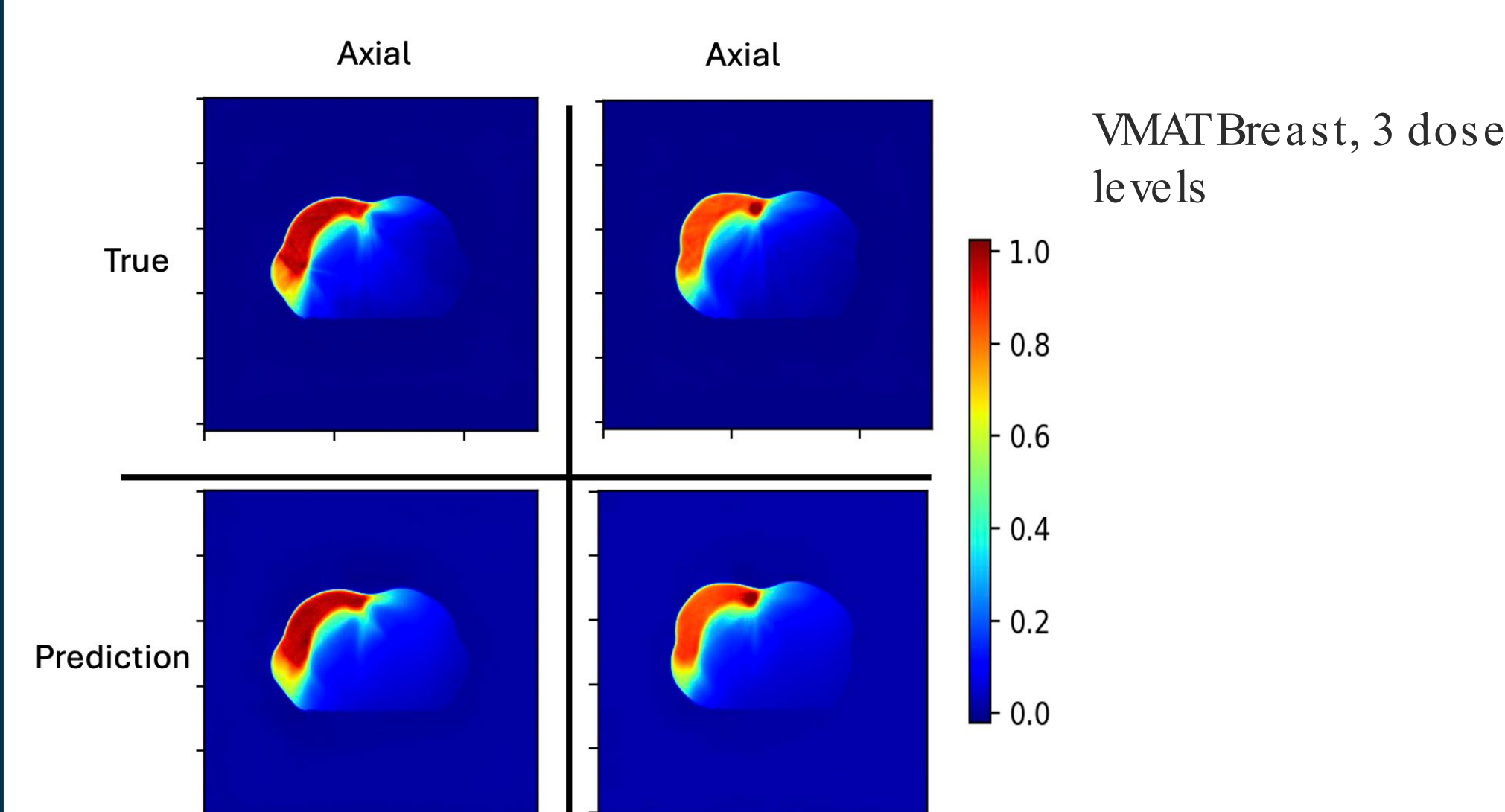
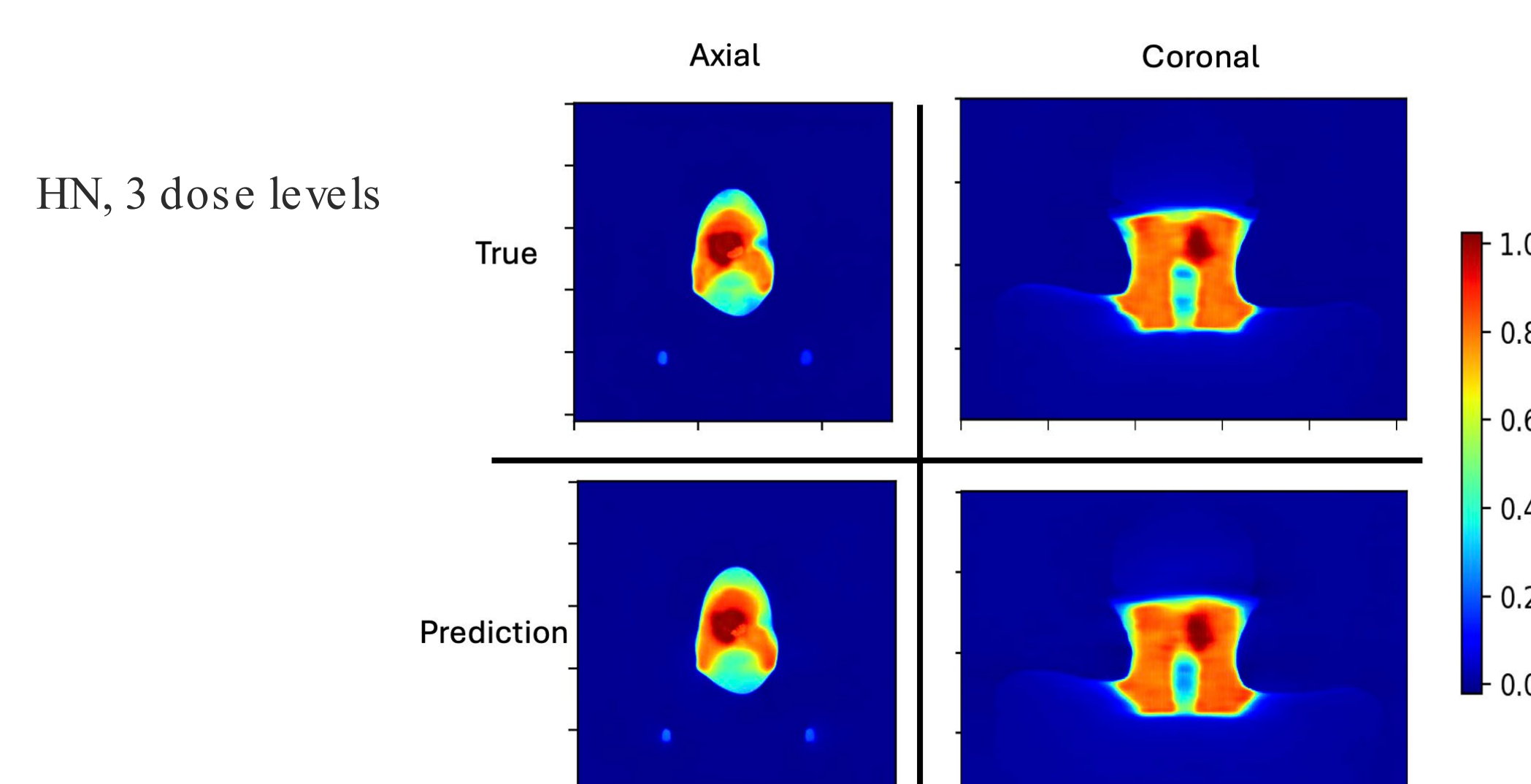
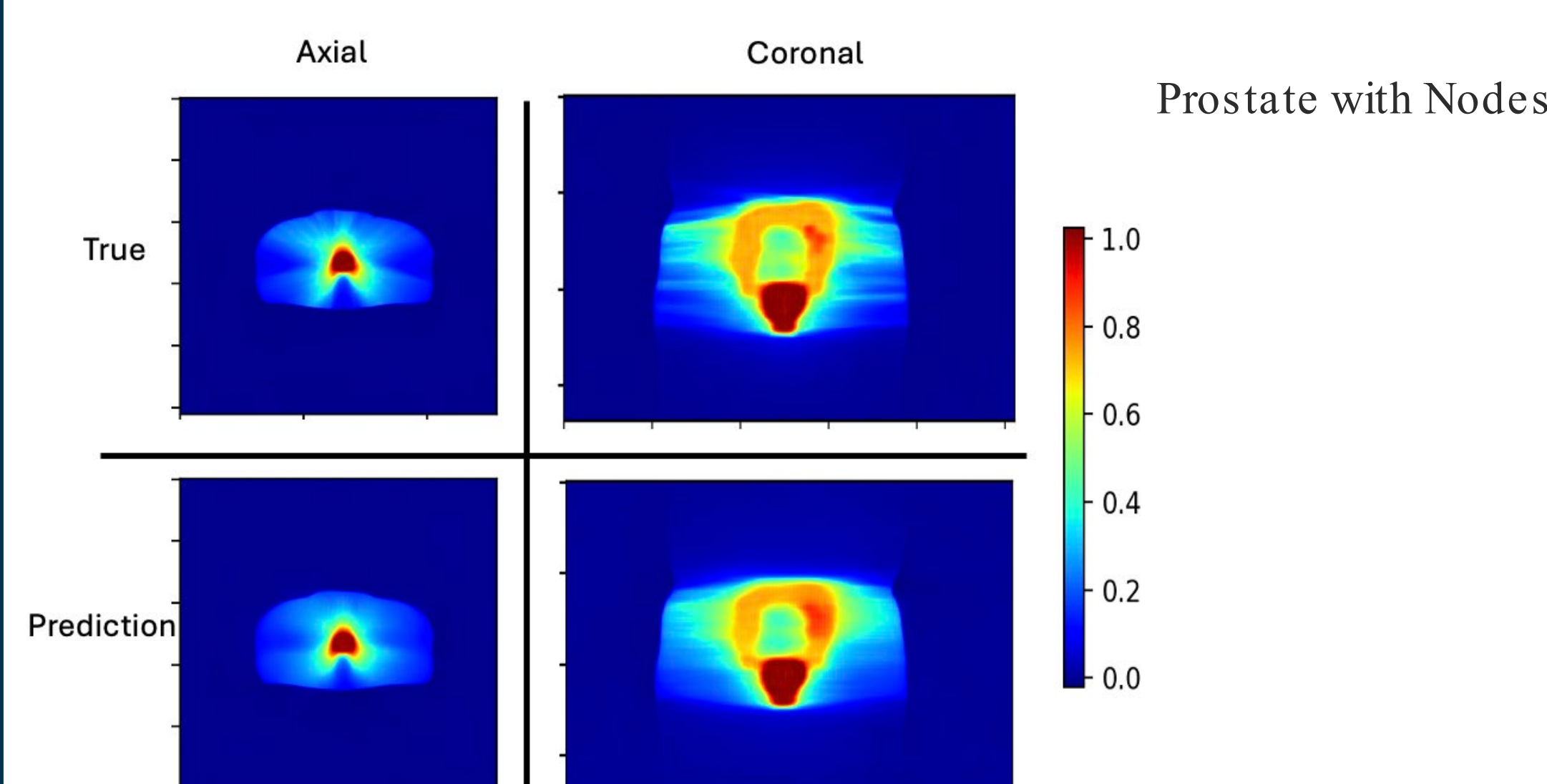
- An automated data exporting and housing infrastructure was developed to download a large dataset of our clinical treatment plans
- In a pilot study a subset of 4893 treatment plans was used to train and test a transformer model for preliminary dose prediction. All VMAT treatment plans in our clinical dataset were selected independent of treatment site
- Model inputs include 3D CT images encoded into latent space using a pretrained LTX-Video Variational Autoencoder (VAE), 3D binary masks for target volumes and organs-at-risk were similarly encoded
- Text embeddings of the treatment site and isodose levels were generated via using a Contrastive Language-Image Pre-training (CLIP) model
- Patients Excluded
 - Non-head-first supine
 - Non-coplanar arc plans
 - Multi-iso plans
 - Plans with avoidance sectors
- Number of Plans
 - Training: 3425
 - Validation: 734
 - Testing: 734



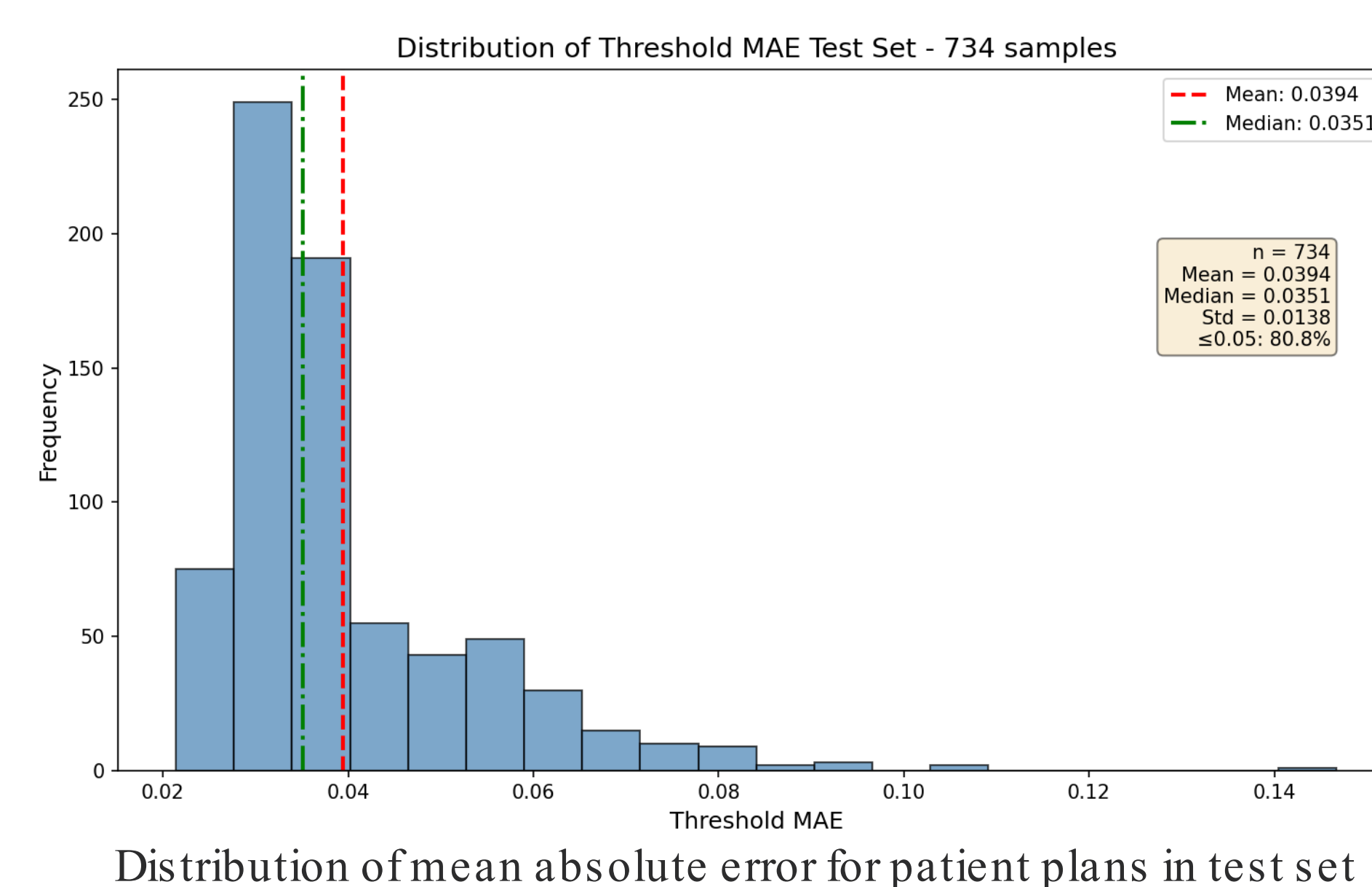
Split of treatment sites for training, validation and test sets

RESULTS

- Dose distribution scaled to have a range of 0-1
- Mean absolute error (in percent) was used to assess the difference between the clinical treatment dose distribution with the model predicted dose distribution, analyzing values greater than 10% of the maximum
- Sample predicted dose distribution with “true” clinical treatment dose distributions shown below



- The model was evaluated on a held-out test set of 734 treatment plans across all available treatment sites the overall mean of the mean absolute error was 3.9%

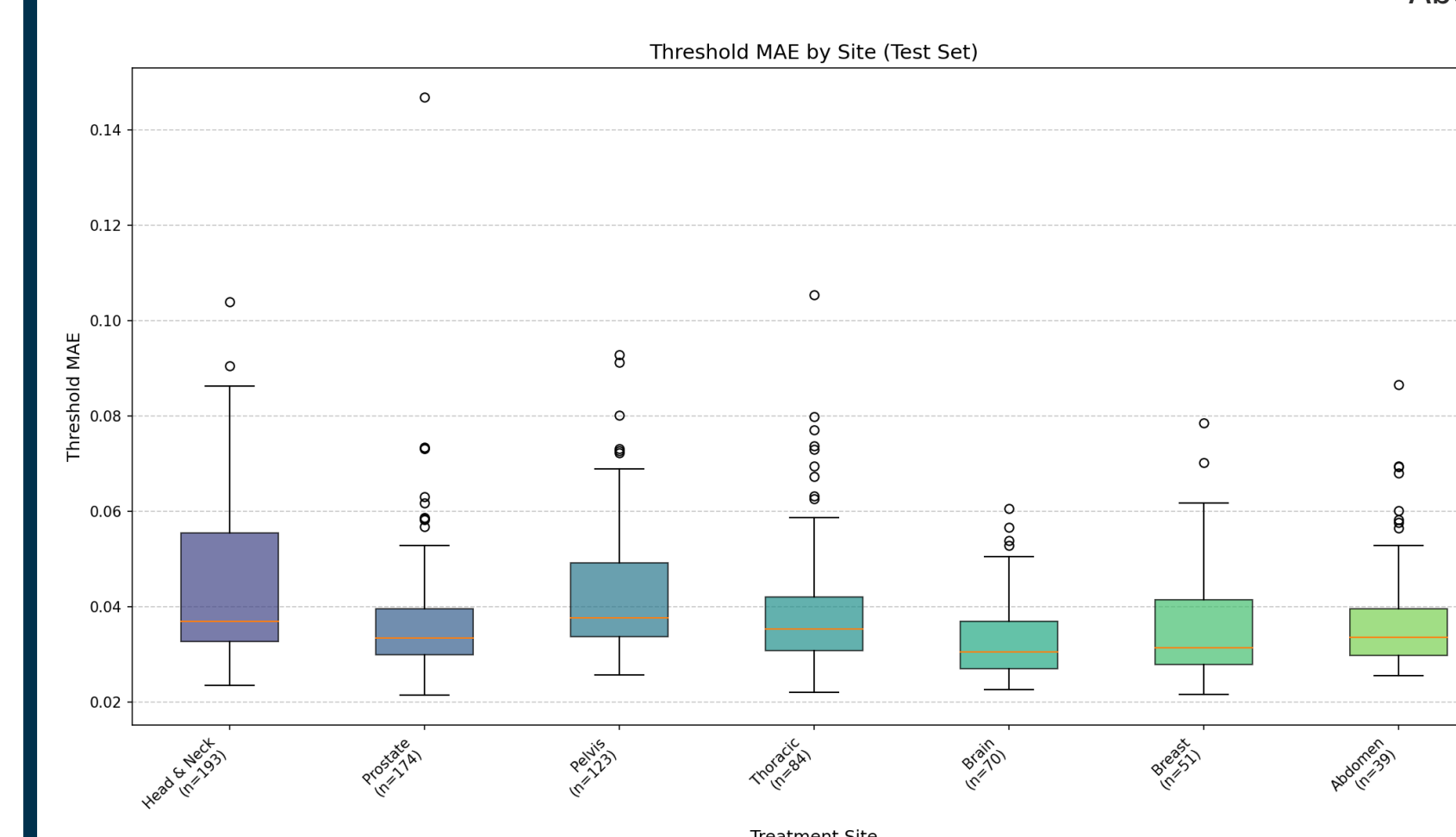


Distribution of mean absolute error for patient plans in test set

RESULTS

- Test set broken into treatment site, larger MAE for Head-and-Neck plans 4.3% (not significantly different). Larger deviations seen for non-standard planning techniques, e.g. normalization different from clinical standard

Site	Count	Mean_MAE(%)
Head & Neck	193	4.34
Prostate	174	3.65
Pelvis	123	4.23
Thoracic	84	3.95
Brain	70	3.34
Breast	51	3.61
Abdomen	39	3.94



Mean absolute error by treatment region

CONCLUSIONS

- Developed model makes dose predictions across multiple treatment sites
- This approach demonstrates that modern vision-language architectures can learn dose distribution patterns directly from treatment planning data, potentially enabling rapid dose estimation for more automated planning workflows

FUTURE STEPS

- Including additional data into the training, validation and testing of the model to reach over 10k plans.
- Adding additional inputs into the modeling such as OAR contour masks and additional beam parameters
- Quantify the performance of the model with additional metrics such as DVH values
- Evaluating generalizability and zero-shot/one-shot performance

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