AI-Based Real-Time 3D MRI Predictions from a Single kV Projection: A Transfer Learning Approach

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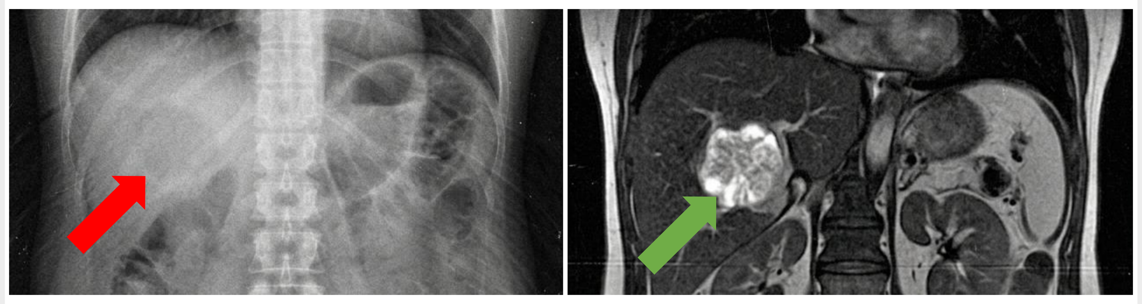
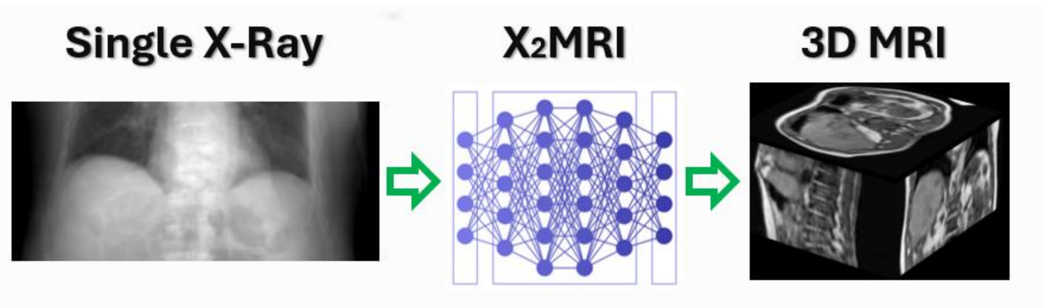
INTRODUCTION

Many tumors in the chest and abdomen exhibit complex 3D motion during treatment. Image guidance is key in Radiation Oncology!



~15,000 Standard LINACs worldwide | <200 MR-LINACs Worldwide

We aim to use Deep Learning to make high-quality image guidance more accessible to the world.

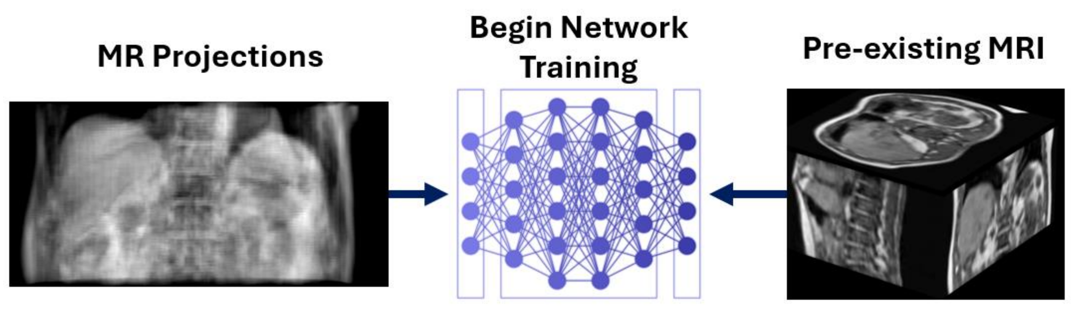


- Deep learning network called X2MRI
- Network predicts 3D MRI from a single standard 2D X-Ray projection
- Inference is in real time, so fluoroscopic X-Ray can become Dynamic, Time-Resolved 4D MRI

METHODS AND MATERIALS

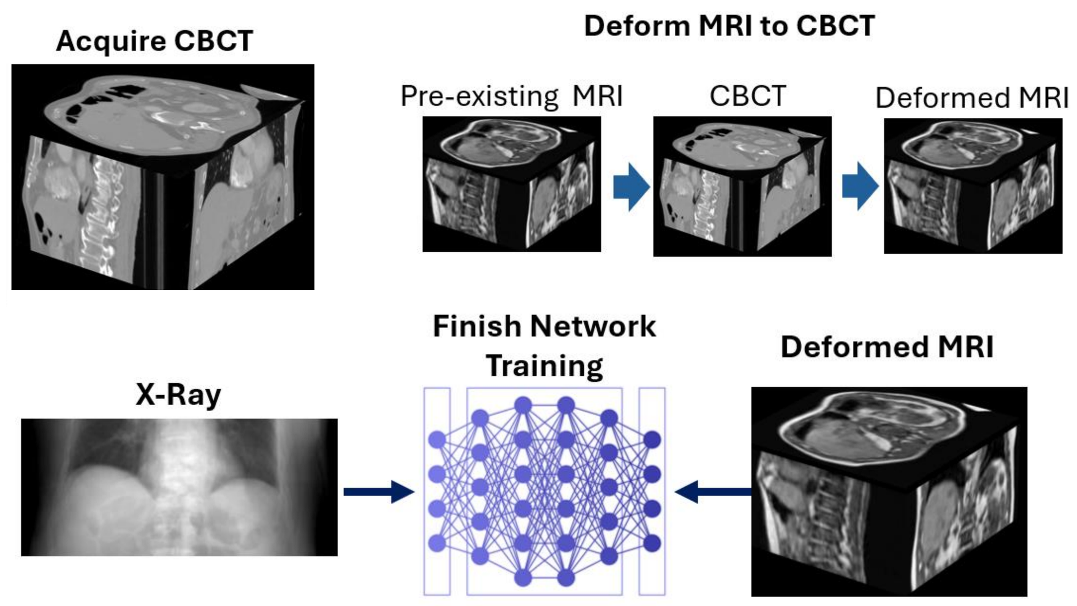
The network is patient-specific and will be trained on a patient's pre-existing MRI scans to provide the most accurate results for that patient.

Step 1: Train



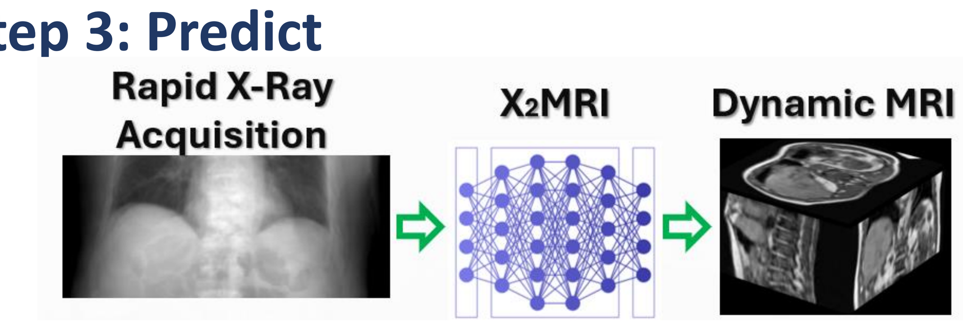
- Begin training on MR projections (math equivalent of DRR) derived from the pre-existing MRI scans. This teaches the network the basics of the 2D to 3D mapping.

Step 2: Transfer Learning



- The network sees the most up-to-date anatomy and learns X-Ray input before it begins inference
- Transfer Learning is done with only 2 datapoints: inhalation and exhalation breath-hold kV-MR pairs

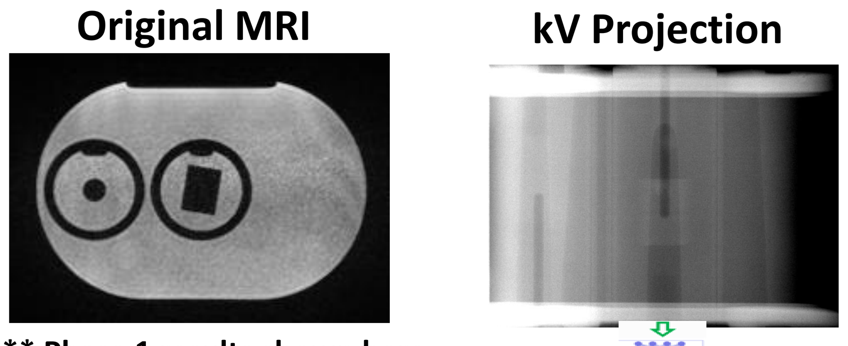
Step 3: Predict



- X2MRI predicts what new MRI volumes would look like from a new input X-Ray
- X2MRI enables high-resolution, 3D motion tracking from rapid X-Ray acquisition

RESULTS

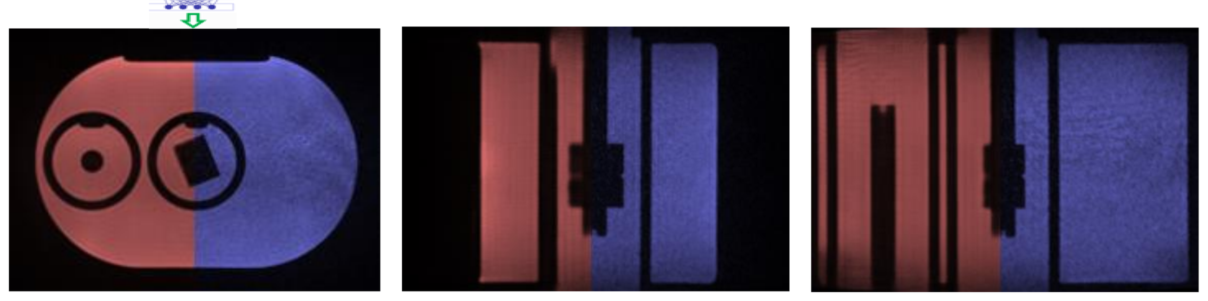
Phase 1: Motion Phantom Data**:



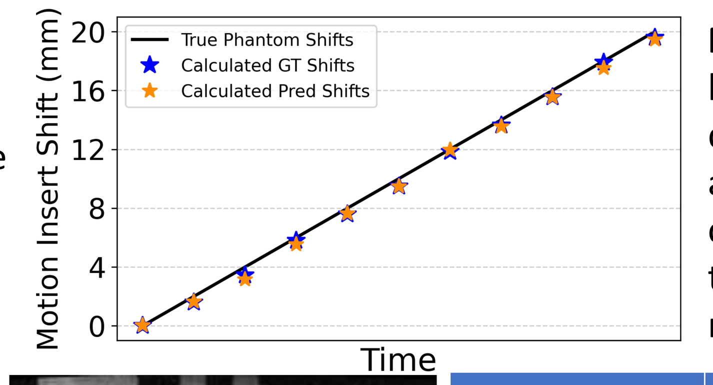
** Phase 1 results shown here were obtained with a slightly different workflow than outlined in the Methods. Longer Transfer Learning with more training data available was used compared to Phases 2 and 3, which used minimal transfer learning data.

Motion Phantom Figure: From the kV projection X2MRI predicted an MRI of the phantom. Axial (left), sagittal (middle), and coronal (right) slices of a fusion of the prediction (red) and ground truth (blue) are shown. Note that the cuboid rotated from MRI acquisition to kV acquisition and X2MRI accurately predicts the rotation.

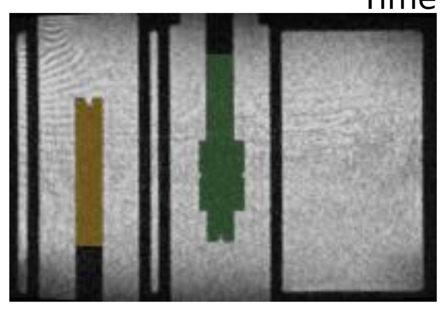
MR Prediction and Ground Truth Fusion



Motion Insert Positional Accuracy



Motion Accuracy Plot: X2MRI was given 11 kV images with the movable insert in a different position. Masks of the movable and static inserts were automatically contoured on the predicted and ground truth MRIs. The sup-inf shift accuracy of the motion insert is shown in the plot.

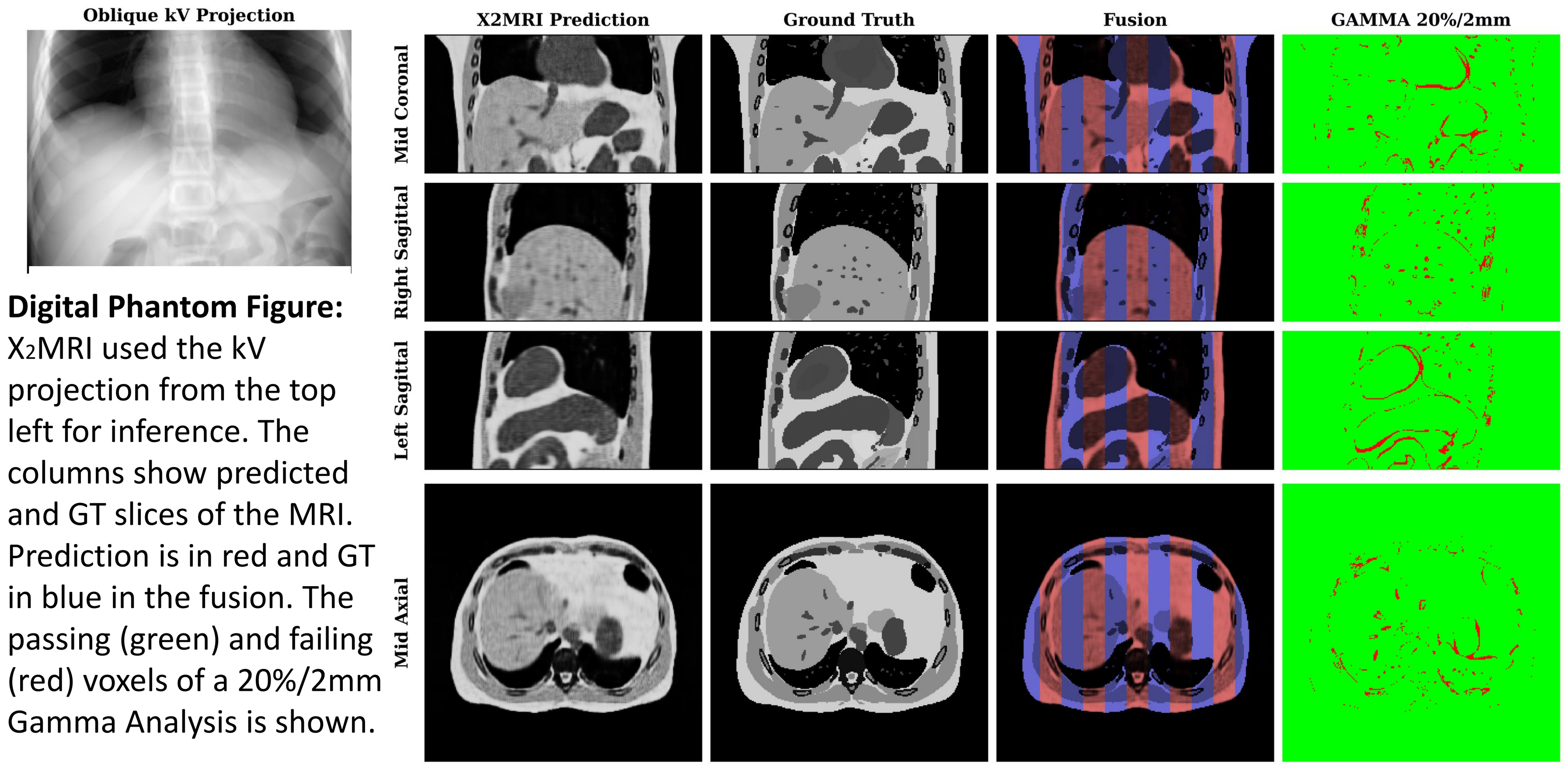


Insert Type	Dice Score (N=11)
Motion (Green)	0.971 [0.967, 0.977]
Static (Yellow)	0.985 [0.985, 0.988]

Table: The dice score (Median [Min, Max]) between predicted and ground truth masks.

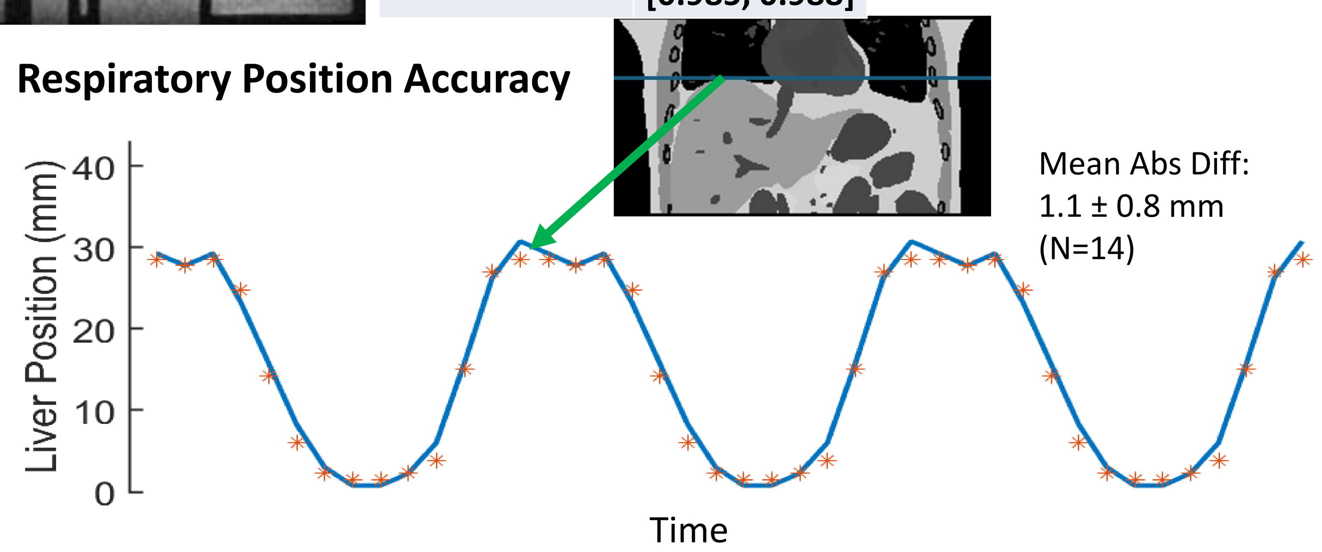
Phase 2: Digital Anthropomorphic Phantom Data:

Large to Small Stomach: AP Projection (180 Degrees) Inhalation Phase



Digital Phantom Figure: X2MRI used the kV projection from the top left for inference. The columns show predicted and GT slices of the MRI. Prediction is in red and GT in blue in the fusion. The passing (green) and failing (red) voxels of a 20%/2mm Gamma Analysis is shown.

Respiratory Position Accuracy



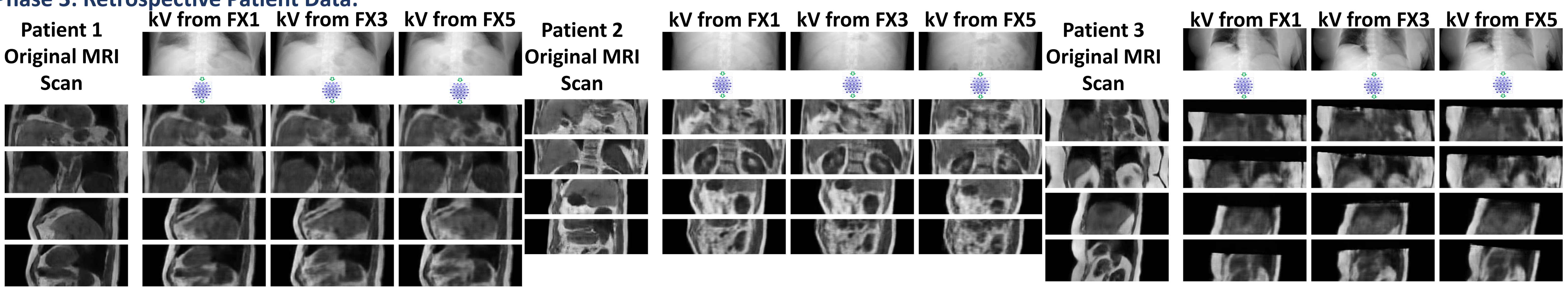
Respiratory Position Plot: We gave X2MRI 14 X-Rays all at a different respiratory phase and measured the positional accuracy of the predicted liver dome.

Inter-Fraction Anatomy Change Table: Between MRI acquisition and kV acquisition the stomach size changed. The accuracy of this change in size is shown in the table.

Inter-Fraction Anatomy Change Accuracy

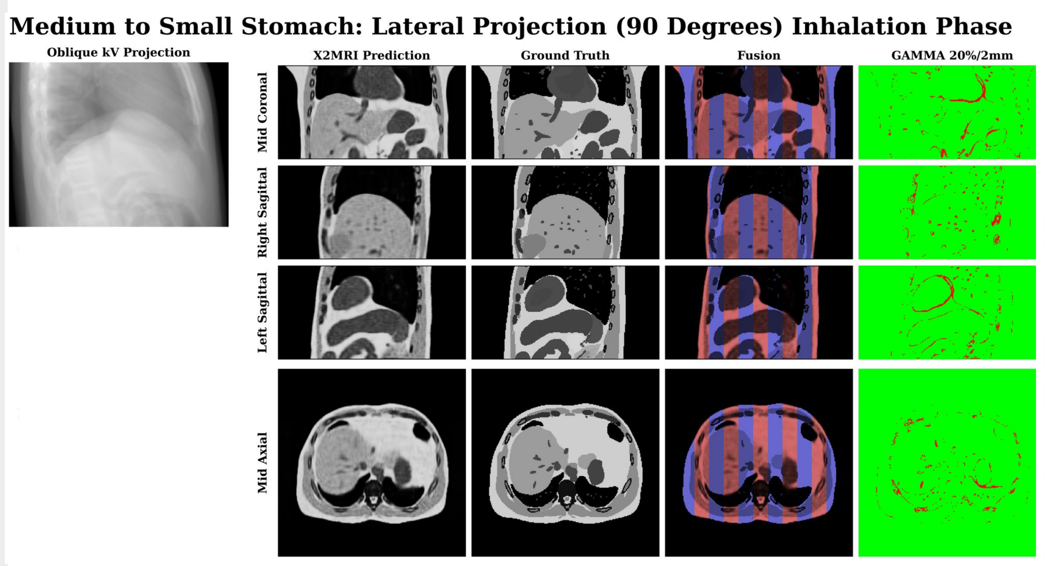
Stomach Size in MRI	True Stomach Size in kV	Predicted Stomach Size from kV
415 cc	510 cc	465 ± 3 cc
510 cc	313 cc	347 ± 4 cc
313 cc	510 cc	448 ± 1 cc

Phase 3: Retrospective Patient Data:



Retrospective Patient Figures: These results use data from an IRB-approved study. The leftmost column shows coronal and sagittal slices of an MRI scan of the patient taken during Simulation. The remaining three columns show an X-Ray extracted from the raw CBCT data and X2MRIs prediction shown below it. No ground truth MRI is available.

ONGOING WORK



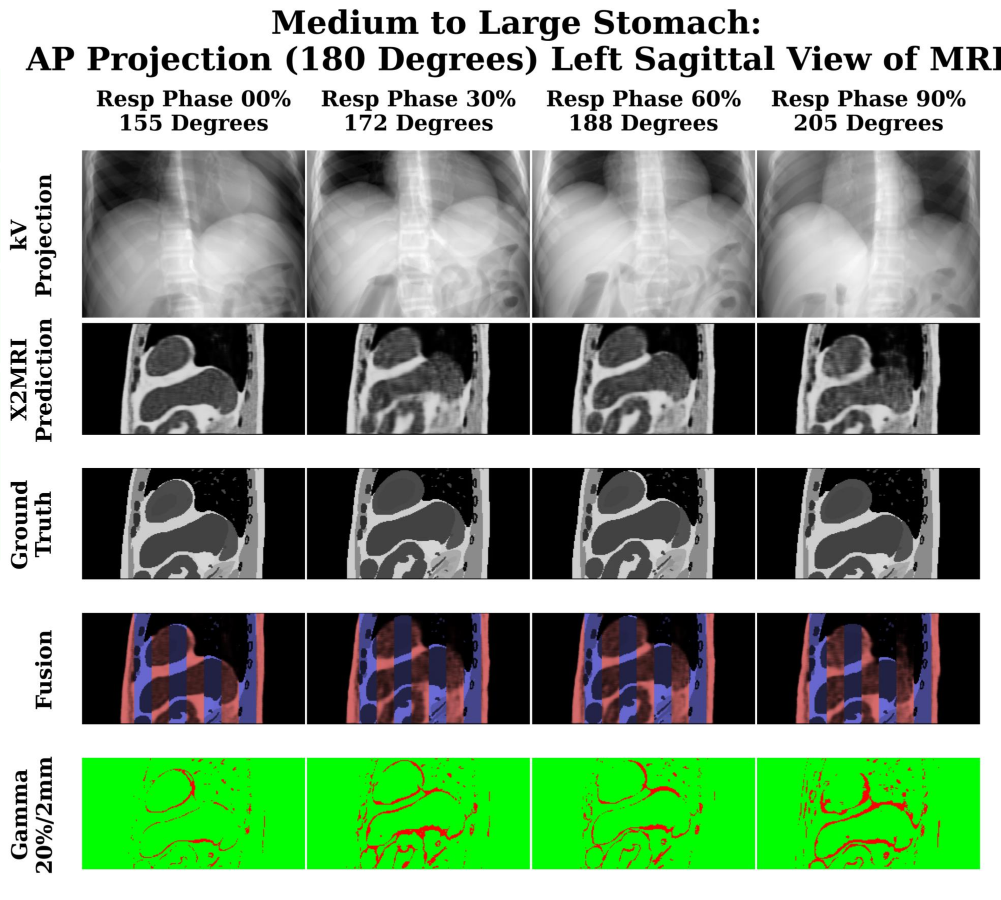


Figure on Left: The network can produce similar quality output if the projection angle is changed.
Figure on Right: A single network can accept projection angles from a span of 50 degrees paving the way for MRgRT on a conventional LINAC with on-board kV imaging and gantry rotation.

CONCLUSIONS

X2MRI shows strong promise for generating real-time 3D MRI volumes from 2D X-ray projections, demonstrating the high positional and shape accuracy required for real-time image guidance. In **Phase 1**, the network accurately predicted the size and shape of a motion insert. In **Phase 2**, it precisely localized the liver dome position using minimal data for transfer learning. While Phase 2 also successfully captured robust directional trends across six tested stomach sizes (3 shown here), it consistently underestimated the magnitude of those volume changes. All Phase 2 results were fully replicated across both male (shown) and female phantoms using lateral (see *Ongoing Work*) and oblique projection angles. Finally, **Phase 3** results show qualitatively reasonable MRI predictions using real patient X-Rays of six patients (three shown here).
Promising preliminary results for a network that accepts multiple projection angles are highlighted in *Ongoing Work*; future efforts will focus on refining output magnitude accuracy and expanding the range of acceptable projection angles.
Inference time is around 20 ms per MRI volume, so real-time image guidance is possible.

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