# Multitask radiological modality invariant landmark localization using deep reinforcement learning

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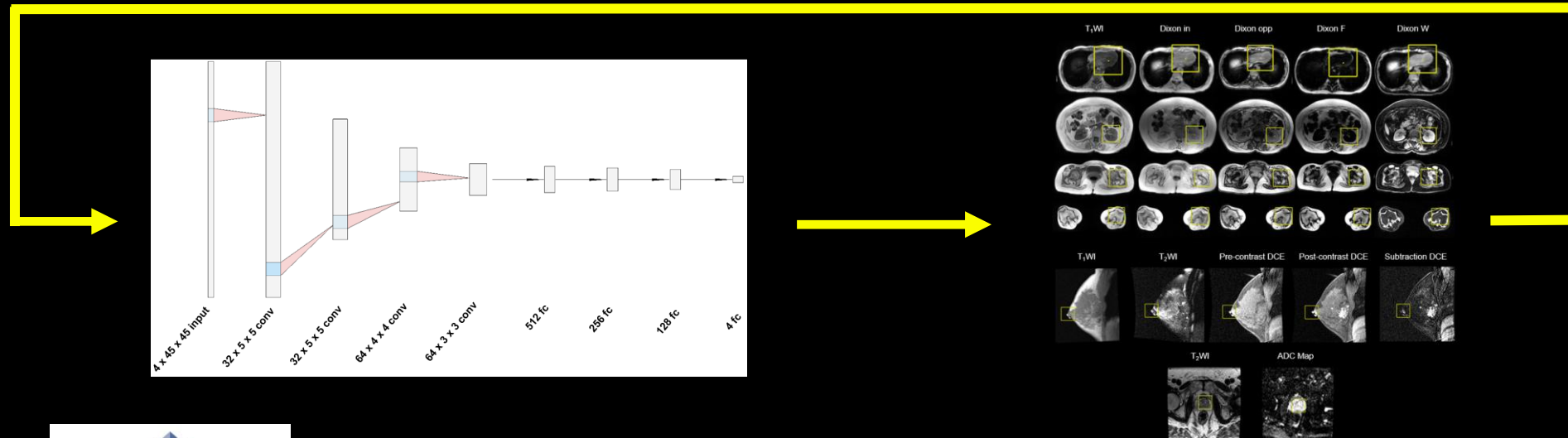
# Motivation

- Automatic anatomical localization is an integral part of an AI radiology framework.

- Anatomical localization has diverse applicability across multiple applications such as image segmentation, registration, and classification.

- Deep reinforcement learning (RL) has emerged as the best technique for landmark localization in recent years.

- Currently, the models developed using deep RL for landmark localization have been limited to a single application.
  - Example: Landmark localization within a predefined anatomical environment (e.g. brain MRI) acquired using specific imaging parameters (e.g. T1-weighted MRI).

# Multitask Modality Invariant Deep RL model

- We extend deep RL techniques and developed a **multitask deep RL model (MIDRL)** with single and multiple agents.

- MIRDL: A single model for simultaneous localization of a diverse set of landmarks across:

  - Different regions in the body (e.g. heart, breast, prostate, etc.)

  - Different imaging parameters (e.g. T1-weighted imaging, Dynamic contrast enhanced imaging, Diffusion Weighted Imaging)

  - Different imaging orientations (e.g. Axial, Sagittal, Coronal)
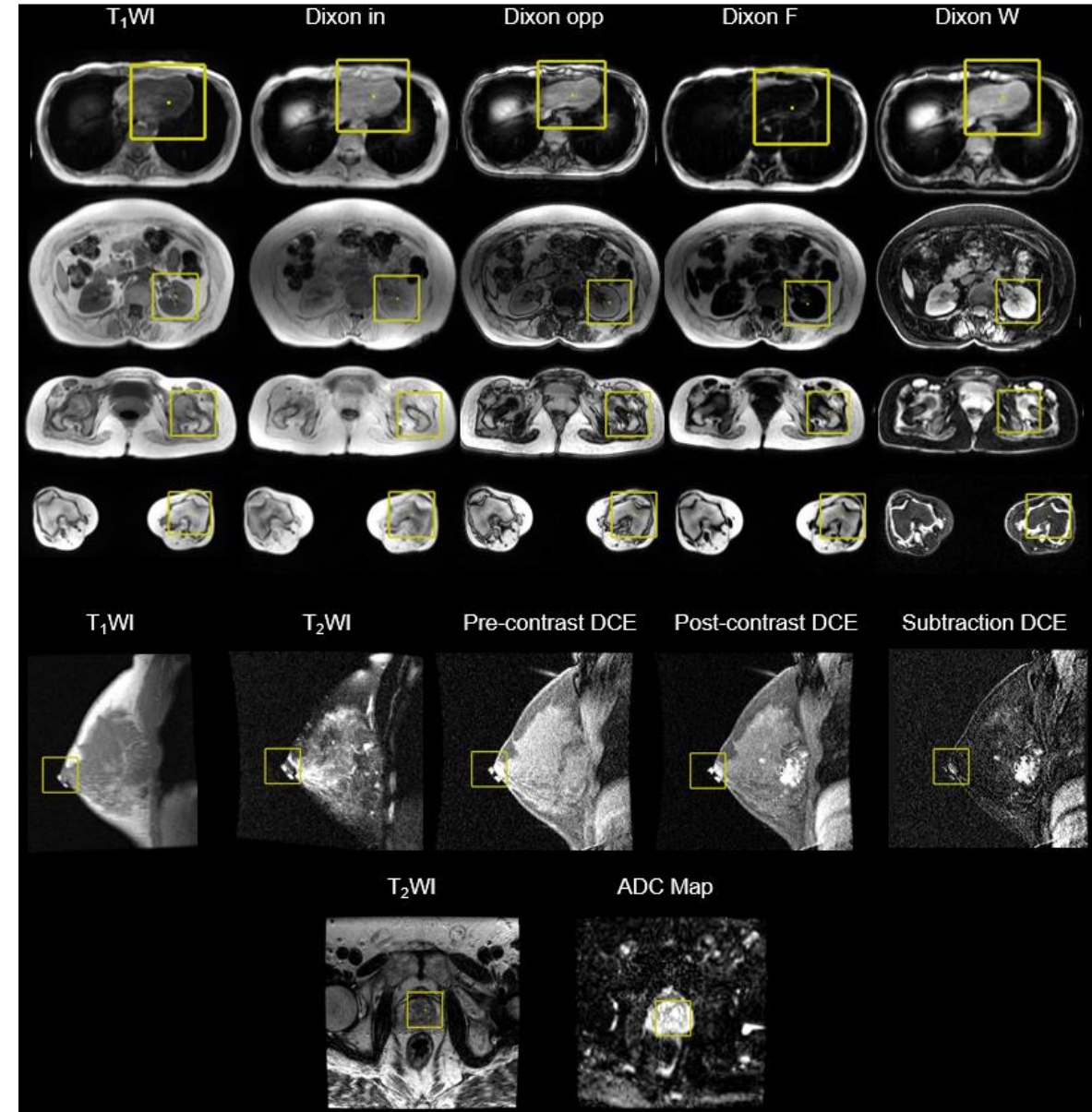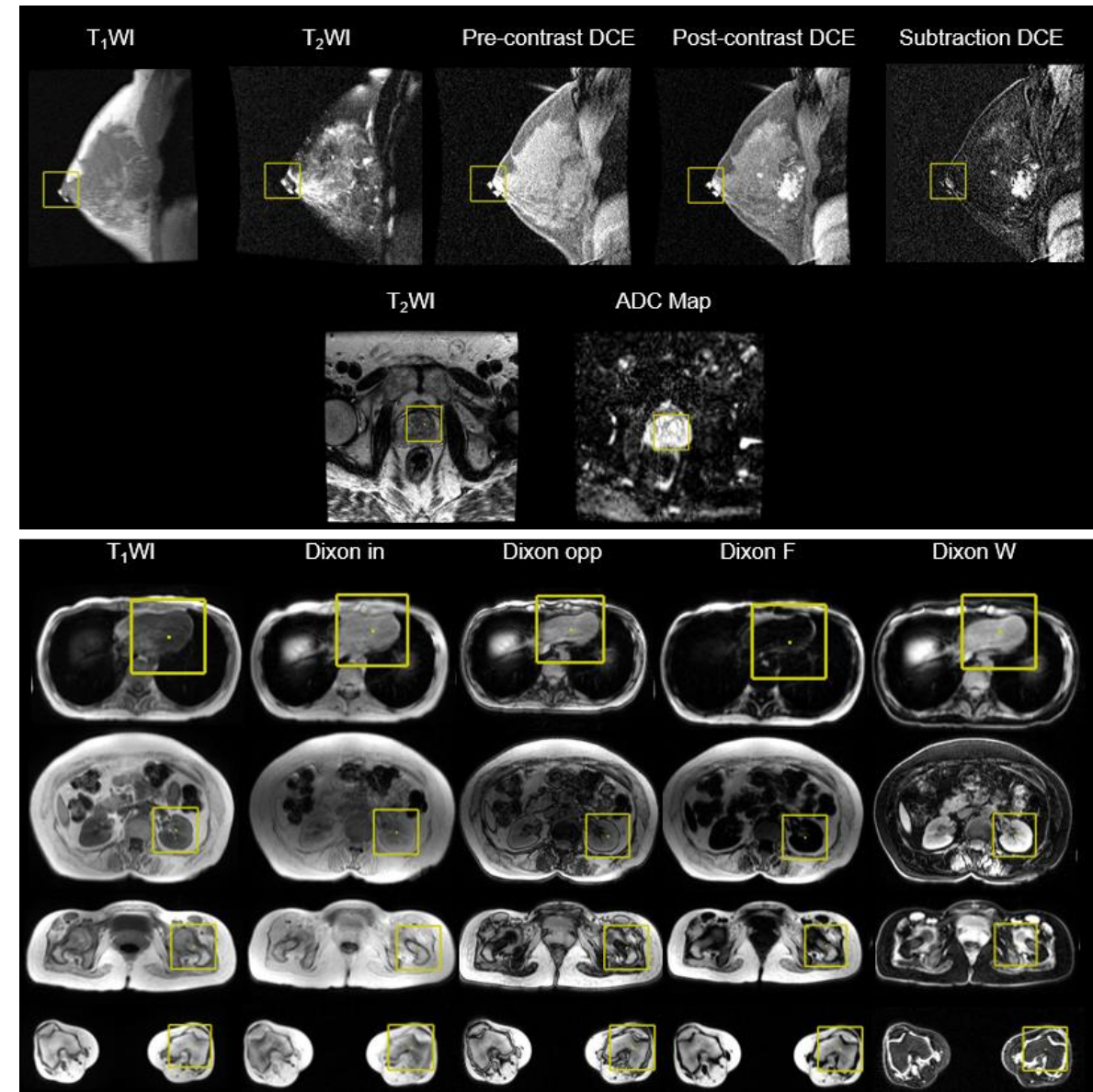
# Reinforcement Learning (RL) Framework



- Environment: Radiological image
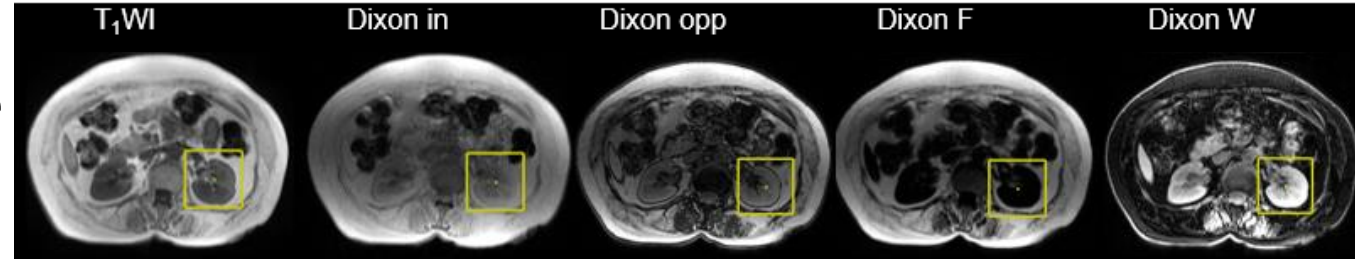
- State: Sequence of areas within the image (bounding box)

- Actions: move bounding box in one direction ($\pm x$ or $\pm y$ or $\pm z$)

- Reward: change in Euclidean distance to landmark
  - Positive if moved closer to landmark, negative if moved away
  - Clipped between -1 and 1
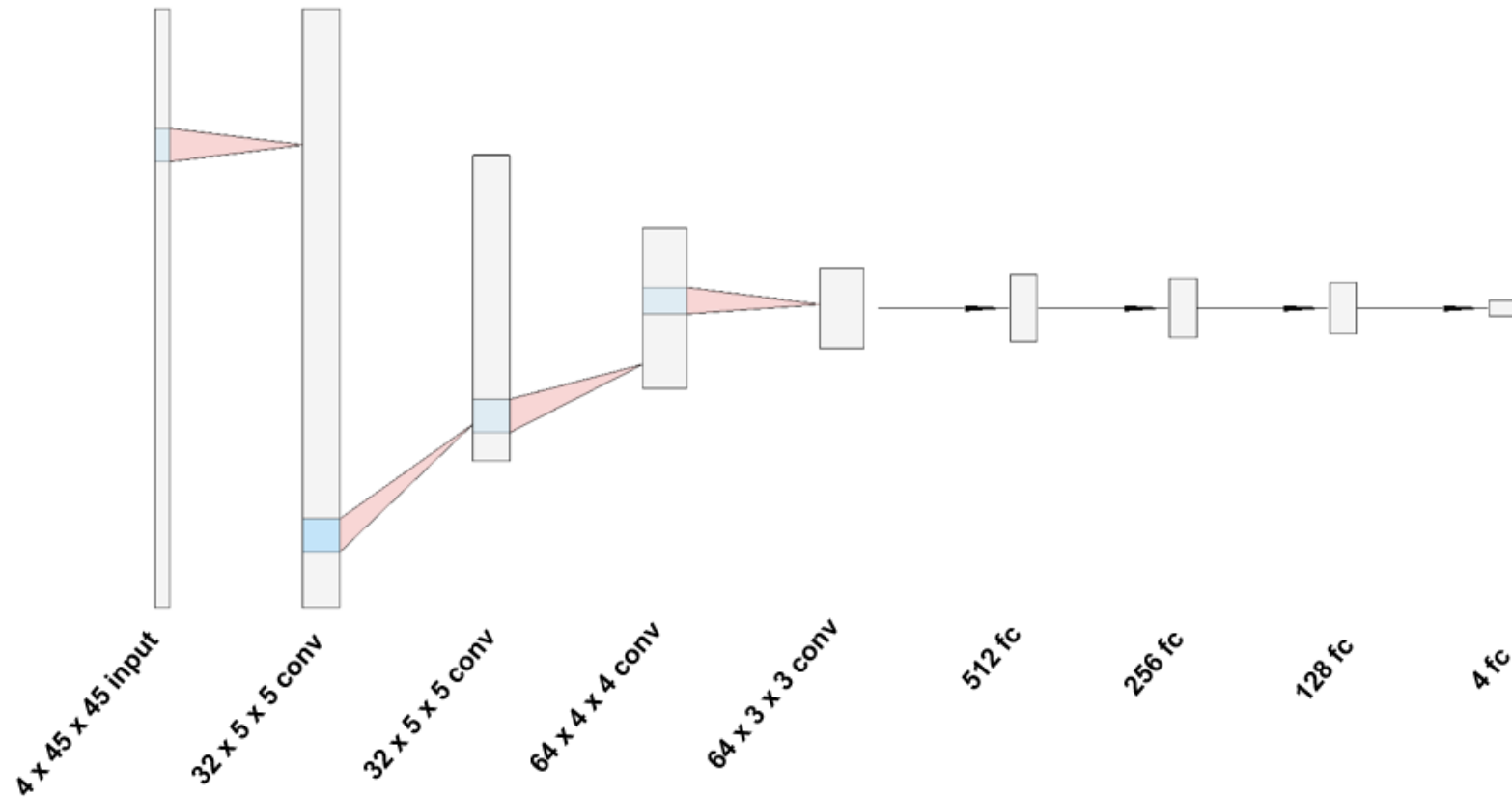
- Q-learning with experience replay

# Reinforcement Learning Models

- 2D MIDRL model
  - Single agent
  - Evaluated on individual 2D slices

- 3D MIDRL model
  - Multi-agent (4 agents)
  - Each agent locates its assigned landmark
  - Evaluated on 3D whole body volumes

# 2D DQN (single agent)



4 x 45 x 45 input · 32 x 5 x 5 conv · 32 x 5 x 5 conv · 64 x 4 x 4 conv · 64 x 3 x 3 conv · 512 fc · 256 fc · 128 fc · 4 fc

- Input: bounding box regions from last 4 time steps
- Output: Q-value for each action (x++, x--, y++, y--)

# 3D DQN

- Input (for each agent): bounding box regions from last 4 time steps
- Output (for each agent): Q-value for each action (x++, x--, y++, y--, z++, z--)
- 3D DQN: analogous to 2D
  - Convolutional layers are shared among all agents
  - Each agent has its own separate final fully connected layers
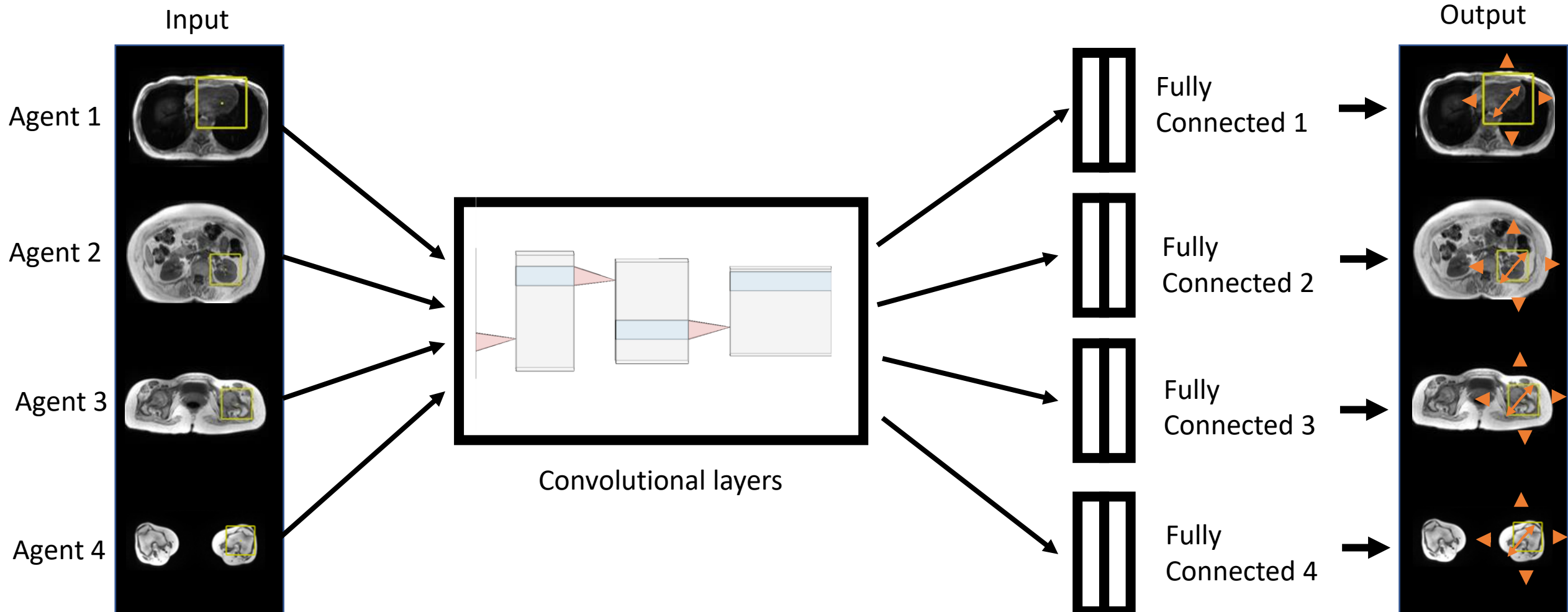
# Multiparametric MRI (mpMRI)
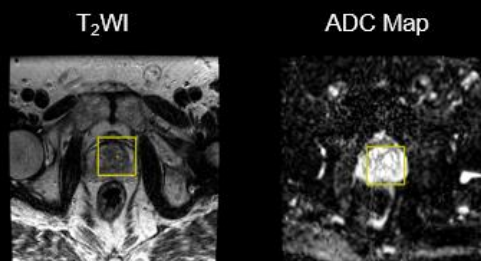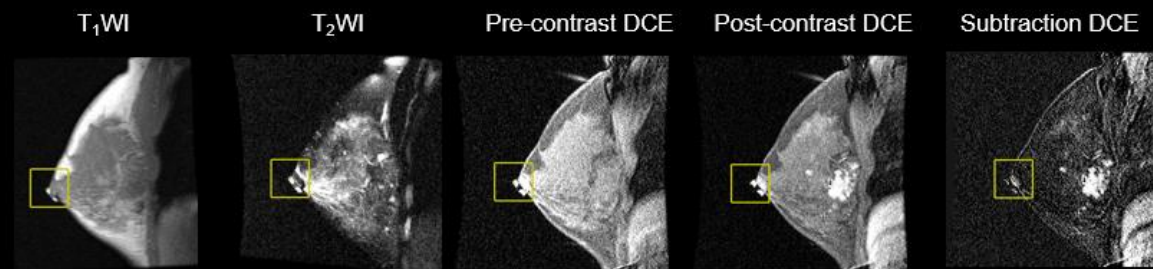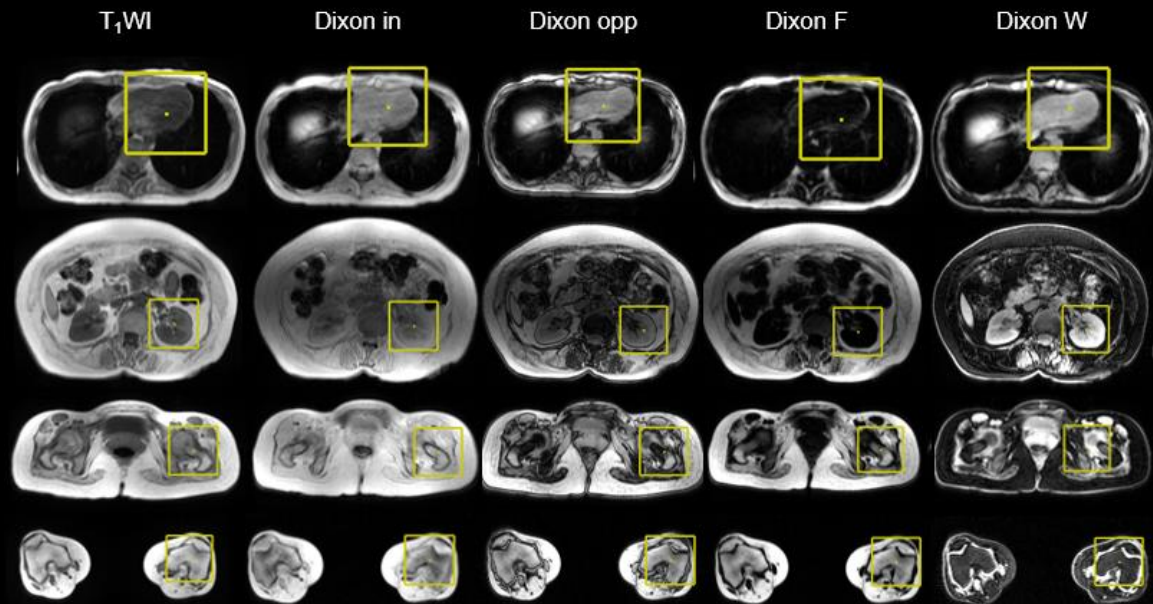
# Clinical Dataset

- 25 whole body mpMRI (2D and 3D)

- 24 breast mpMRI (2D)

- 8 prostate mpMRI (2D)

| Imaging Parameter | Heart | Kidney | Trochanter (pelvis) | Knee | Nipple | Prostate |
|---|---|---|---|---|---|---|
| T1WI | ✔ | ✔ | ✔ | ✔ | ✔ | |
| T2WI | ✔ | ✔ | ✔ | ✔ | ✔ | ✔ |
| Dixon in | ✔ | ✔ | ✔ | ✔ | | |
| Dixon opp | ✔ | ✔ | ✔ | ✔ | | |
| Dixon fat | ✔ | ✔ | ✔ | ✔ | | |
| Dixon water | ✔ | ✔ | ✔ | ✔ | | |
| Post DCE | | | | | ✔ | |
| Pre DCE | | | | | ✔ | |
| Sub DCE | | | | | ✔ | |
| ADC | | | | | | ✔ |

# 2D MIDRL model locating landmarks

Target bounding box: red

Agent's bounding box: yellow

Multi-scale search

Nipple

Prostate

Heart

Kidney

Trochanter

Knee

# 3D MIDRL model locating landmarks

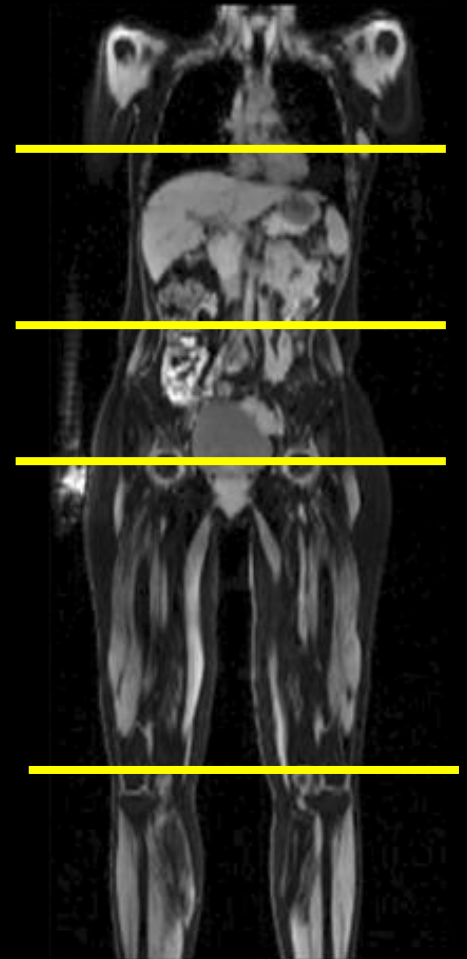Target bounding box: red

Agent's bounding box: yellow

Multi-scale search



Kidney                    Trochanter                    Heart                    Knee

# Results

## 2D Single Agent IoU

| | **Heart** | **Kidney** | **Trochanter** | **Knee** | **Breast** | **Prostate** |
|---|---|---|---|---|---|---|
| T1WI | $0.75 \pm 0.20$ | $0.70 \pm 0.35$ | $0.74 \pm 0.23$ | $0.88 \pm 0.06$ | $0.78 \pm 0.16$ | |
| T2WI | $0.58 \pm 0.21$ | $0.59 \pm 0.20$ | $0.29 \pm 0.36$ | $0.68 \pm 0.11$ | $0.51 \pm 0.29$ | $0.48 \pm 0.42$ |
| Dixon in | $0.79 \pm 0.12$ | $0.62 \pm 0.25$ | $0.85 \pm 0.06$ | $0.88 \pm 0.05$ | | |
| Dixon opp | $0.77 \pm 0.27$ | $0.74 \pm 0.17$ | $0.83 \pm 0.09$ | $0.87 \pm 0.08$ | | |
| Dixon F | $0.78 \pm 0.11$ | $0.69 \pm 0.33$ | $0.78 \pm 0.14$ | $0.87 \pm 0.03$ | | |
| Dixon W | $0.82 \pm 0.14$ | $0.70 \pm 0.35$ | $0.75 \pm 0.18$ | $0.91 \pm 0.03$ | | |
| Post DCE | | | | | $0.20 \pm 0.32$ | |
| Pre DCE | | | | | $0.50 \pm 0.42$ | |
| Sub DCE | | | | | $0.12 \pm 0.24$ | |
| ADC | | | | | | $0.34 \pm 0.36$ |
| All parameters | $0.76 \pm 0.19$ | $0.68 \pm 0.28$ | $0.73 \pm 0.25$ | $0.86 \pm 0.09$ | $0.47 \pm 0.37$ | $0.41 \pm 0.36$ |

(mean ± std dev)

# Results

2D Single Agent Distance Errors (mm)

| | Heart | Kidney | Trochanter | Knee | Breast | Prostate |
|---|---|---|---|---|---|---|
| T1WI | $9.8 \pm 10.4$ | $23.1 \pm 46.2$ | $9.6 \pm 10.2$ | $3.5 \pm 2.4$ | $3.1 \pm 3.4$ | |
| T2WI | $22.3 \pm 17.7$ | $19.0 \pm 12.7$ | $68.2 \pm 51.8$ | $13.4 \pm 5.3$ | $9.5 \pm 7.4$ | $20.6 \pm 21.2$ |
| Dixon in | $7.0 \pm 4.3$ | $15.1 \pm 13.8$ | $5.5 \pm 2.2$ | $3.6 \pm 1.2$ | | |
| Dixon opp | $10.1 \pm 16.8$ | $11.6 \pm 12.1$ | $6.4 \pm 3.2$ | $3.8 \pm 2.7$ | | |
| Dixon F | $7.4 \pm 4.8$ | $17.7 \pm 30.0$ | $7.9 \pm 4.7$ | $3.8 \pm 0.7$ | | |
| Dixon W | $6.2 \pm 5.6$ | $15.6 \pm 24.6$ | $9.8 \pm 8.5$ | $2.3 \pm 0.7$ | | |
| Post DCE | | | | | $30.0 \pm 29.5$ | |
| Pre DCE | | | | | $3.3 \pm 2.8$ | |
| Sub DCE | | | | | $38.6 \pm 28.7$ | |
| ADC | | | | | | $16.7 \pm 24.8$ |
| All parameters | $10.0 \pm 11.5$ | $16.9 \pm 25.5$ | $15.7 \pm 27.5$ | $4.5 \pm 3.9$ | $16.9 \pm 22.9$ | $18.7 \pm 20.7$ |

(mean ± std dev)

# Results

## 3D Multi-Agent IoU

| | Heart | Kidney | Trochanter | Knee |
|---|---|---|---|---|
| T1WI | $0.62 \pm 0.21$ | $0.66 \pm 0.19$ | $0.78 \pm 0.10$ | $0.43 \pm 0.34$ |
| T2WI | $0.47 \pm 0.14$ | $0.44 \pm 0.32$ | $0.34 \pm 0.26$ | $0.35 \pm 0.37$ |
| Dixon in | $0.71 \pm 0.14$ | $0.54 \pm 0.23$ | $0.81 \pm 0.10$ | $0.45 \pm 0.39$ |
| Dixon opp | $0.62 \pm 0.19$ | $0.71 \pm 0.14$ | $0.74 \pm 0.13$ | $0.51 \pm 0.42$ |
| Dixon F | $0.48 \pm 0.29$ | $0.51 \pm 0.29$ | $0.85 \pm 0.10$ | $0.69 \pm 0.29$ |
| Dixon W | $0.65 \pm 0.13$ | $0.75 \pm 0.14$ | $0.60 \pm 0.25$ | $0.49 \pm 0.41$ |
| All parameters | $0.60 \pm 0.20$ | $0.61 \pm 0.24$ | $0.70 \pm 0.23$ | $0.49 \pm 0.37$ |

(mean ± std dev)

# Results

## 3D Multi-Agent Distance Errors (mm)

| | Heart | Kidney | Trochanter | Knee |
|---|---|---|---|---|
| T1WI | 12.6 ± 9.4 | 10.2 ± 6.5 | 6.4 ± 2.7 | 22.9 ± 20.4 |
| T2WI | 18.0 ± 7.6 | 29.3 ± 33.2 | 27.6 ± 17.1 | 91.7 ± 126.2 |
| Dixon in | 8.1 ± 4.7 | 18.3 ± 21.8 | 5.5 ± 2.6 | 51.6 ± 64.0 |
| Dixon opp | 11.4 ± 6.5 | 8.5 ± 4.5 | 7.0 ± 3.2 | 57.4 ± 78.5 |
| Dixon F | 21.7 ± 17.9 | 39.2 ± 72.0 | 4.2 ± 2.4 | 32.3 ± 75.9 |
| Dixon W | 10.1 ± 4.8 | 6.9 ± 4.0 | 15.9 ± 14.5 | 68.7 ± 92.6 |
| All parameters | 13.5 ± 10.3 | 18.3 ± 34.1 | 10.4 ± 11.4 | 52.5 ± 78.4 |

(mean ± std dev)

# Conclusion

- One model for locating multiple landmarks in many different imaging environments
- More computationally efficient than one model per environment

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