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# Neonatal Brain MRI Motion Correction using Adult MRI



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## Introduction

- Neonatal Brain MRIs are frequently corrupted with motion artifacts.
- Deep Learning (DL) models, UNets<sup>[1]</sup>, perform well in adult data; less effective for neonatal scans (domain shift)
- Scarcity of high-quality neonatal data is a major issue.
- **Goal: performed motion correction with DL on neonatal data** with simulated motion artifacts<sup>[4]</sup>.
- Compare model trained on adult data with model trained on neonatal data.

## Dataset

- 359 adult T1w brain MRI scans (CC-359<sup>[2]</sup>) and 359 neonatal T2w (DHCP<sup>[3]</sup>) scans.
- 60 neonatal T2w scans as the test set.

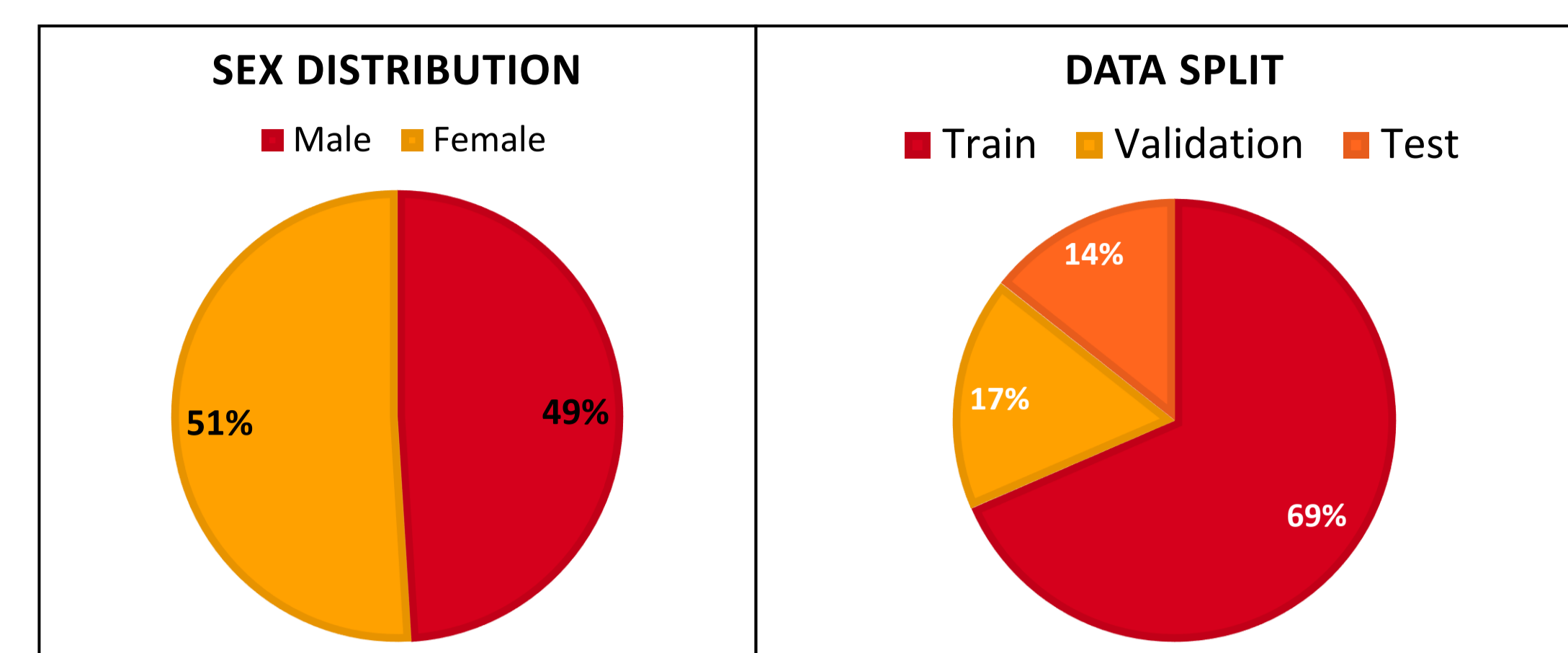


Fig. 1: Sex and Data splits for both adult and neonatal data

## Model

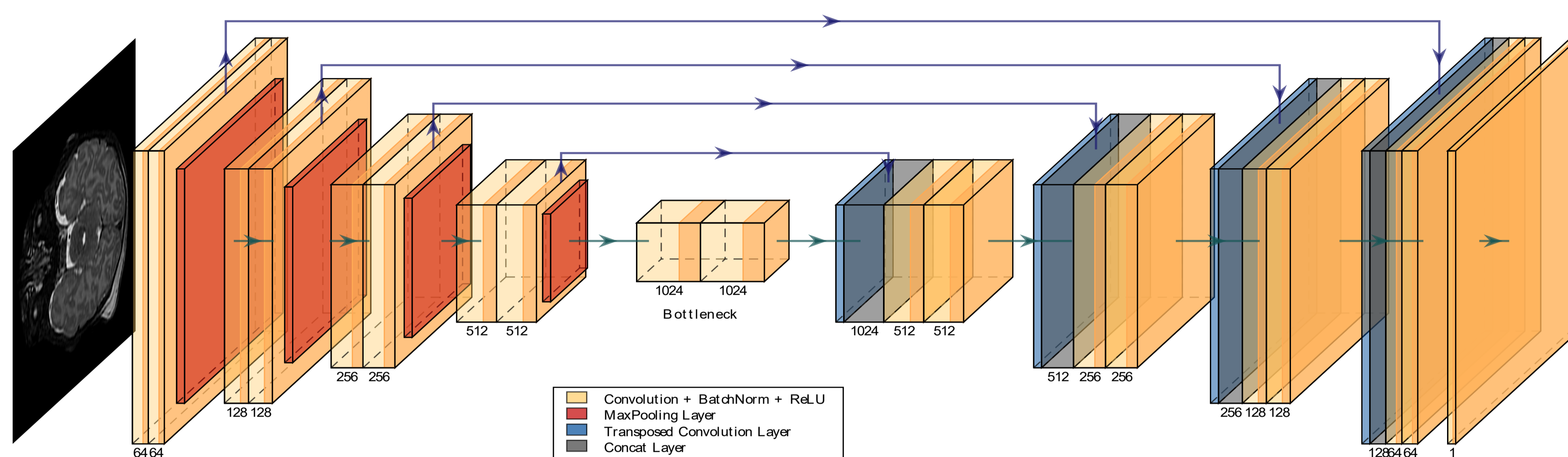


Fig. 2: Two instances of this UNet model (UNet Adult on adult data and UNet Neonatal on neonatal data) were trained for this task. They were tested and compared using neonatal test data.

## Results

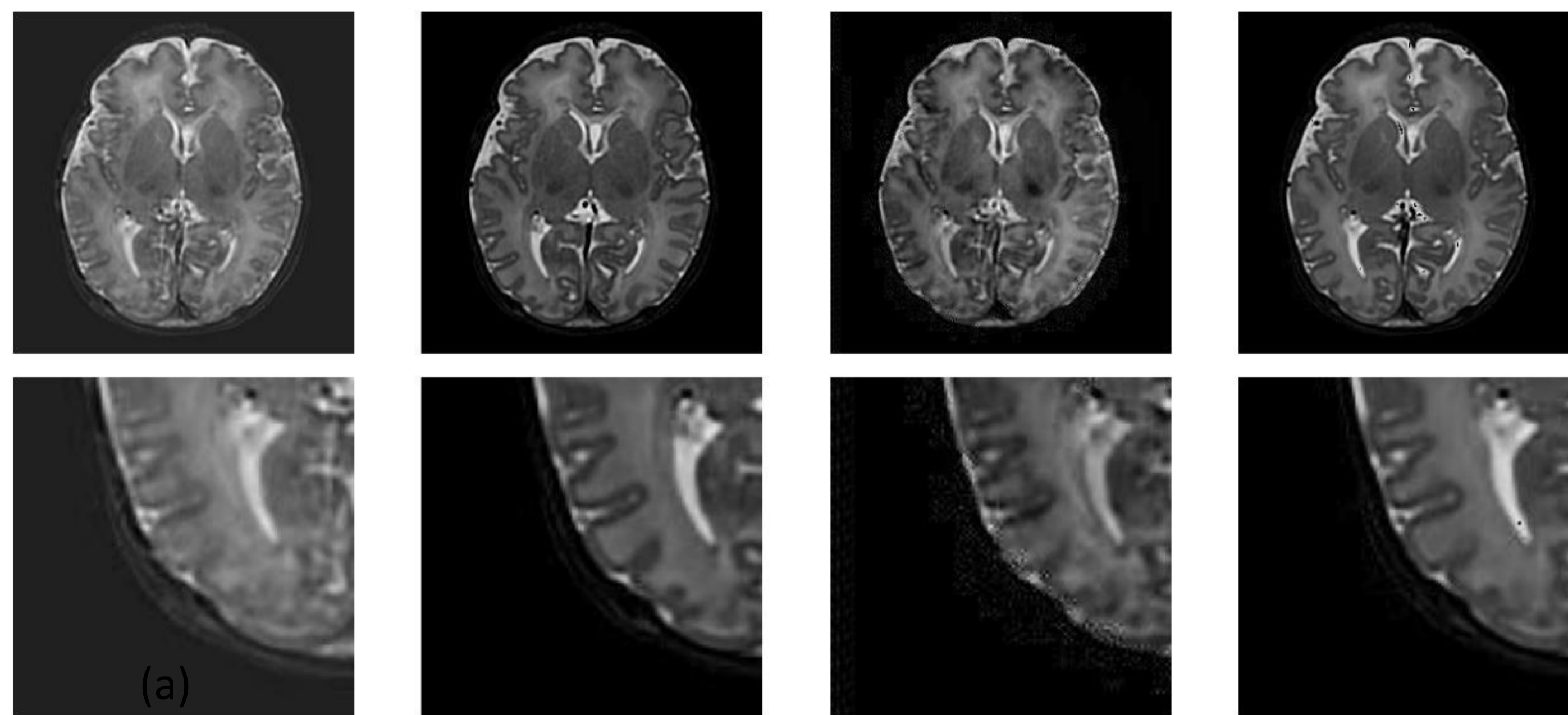


Fig. 3: Comparison of model outputs trained on different datasets. The top row shows the full images, and the bottom row shows the zoomed-in versions. (a) Motion corrupted image, (b) Real neonatal image, (c) Output from the model trained on adult data, (d) Output from the model trained on neonatal data.

Training Dataset	Evaluation Dataset	PSNR	SSIM	MSE
Unet (Neonatal)	Neonatal Validation	30.141	0.91	53.821
Unet (Adult)	Adult Validation	32.836	0.947	25.409
Unet (Neonatal)	Neonatal Test	30.717	0.938	62.448
<b>Unet (Adult)</b>	<b>Neonatal Test</b>	<b>25.839</b>	<b>0.842</b>	<b>147.456</b>

**Table 1: Evaluation** of UNet Models Trained on Adult and Neonatal Data. The metrics used are Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). The intensity and contrast difference between neonatal and adult data contribute to the higher MSE when the adult model is tested with neonatal data. However, a high SSIM score resembles the model's capability of capturing critical structures. This is optimistic because the model predicts on unseen dataset from another distribution.

## Discussion

### Outcomes

- Visually close motion correction w.r.t. to the ground truth while training with a non-augmented adult dataset.
- Potential for domain adaptation using large volume adult datasets.

### Limitations

- Model trained on 2D slices.
- Lacks the spatial information for merging 2D slices to get a 3D scan.

### Future Work

- Introduce adult data augmentation to resemble neonatal data for performance improvement.
- 3D modeling for capturing spatial information.

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