

## INTRODUCTION

- MRI scans => expensive. High quality MRI scans are even more expensive.
- HydraNet** can save time and money, and help doctors make better diagnoses
- HydraNet** uses multi-branch architecture to denoise images
- HydraNet** increases quality of brain scans at no cost to MRI technicians

HydraNet addresses the fundamental issue of denoising medical images, which are much more difficult to predict and denoise than natural images.

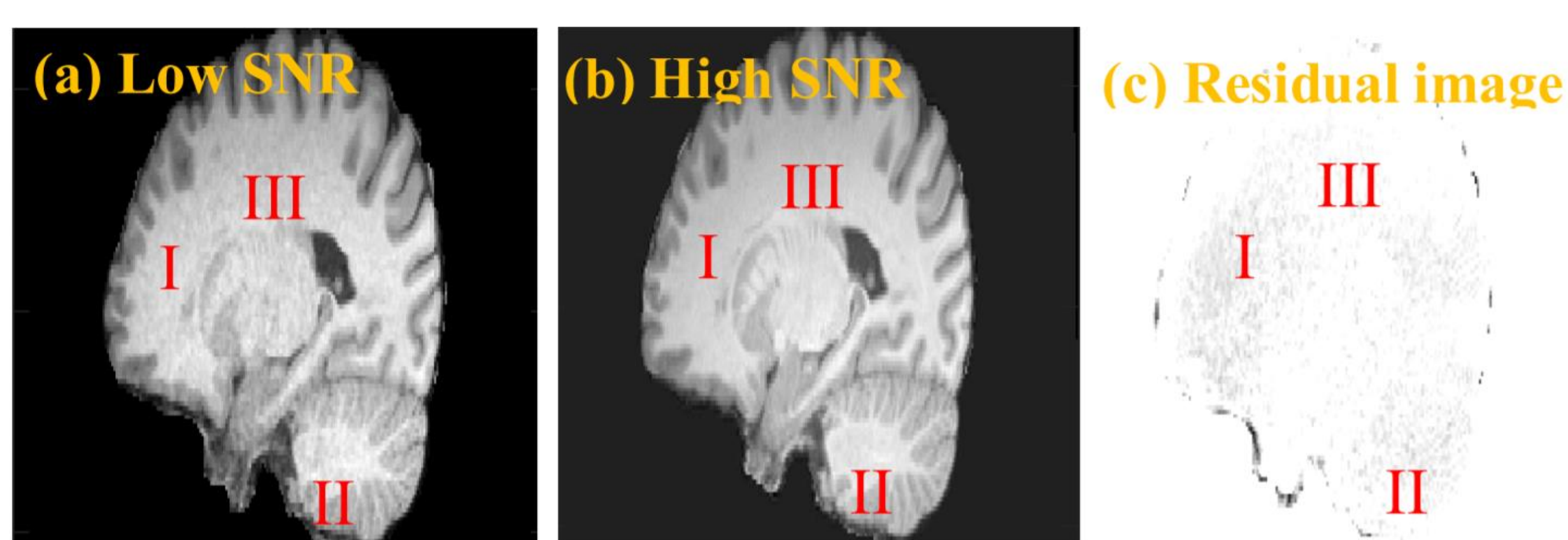


Fig. 1: Residual between low SNR and high SNR MRI scans



Fig. 2: Residual between low SNR and high SNR Natural Images

The noise distribution from MRI images (Fig. 1) is not uniform, in contrast to natural images (Fig. 2). This makes them harder to denoise.

- Existing Deep Learning Methods are trained by adding Additive white Gaussian noise (AWGN) to clear images and attempting to recover the original images.
- This process breaks down for medical images,
- Noise distribution in MRI is **not** Gaussian, **not** spatially invariant.
- Noise can't be predicted or duplicated by synthetic addition
- HydraNet is trained with **real noise** to overcome this issue.

## METHODS

- HydraNet** consists of  $n$  denoiser networks
- Each denoiser => **DnCNN** [1]
- Denoisers specialize for specific noise characteristics
- Run-time => **volumes** split into **slices**, further split into **patches**, passed to denoisers via **estimated noise**

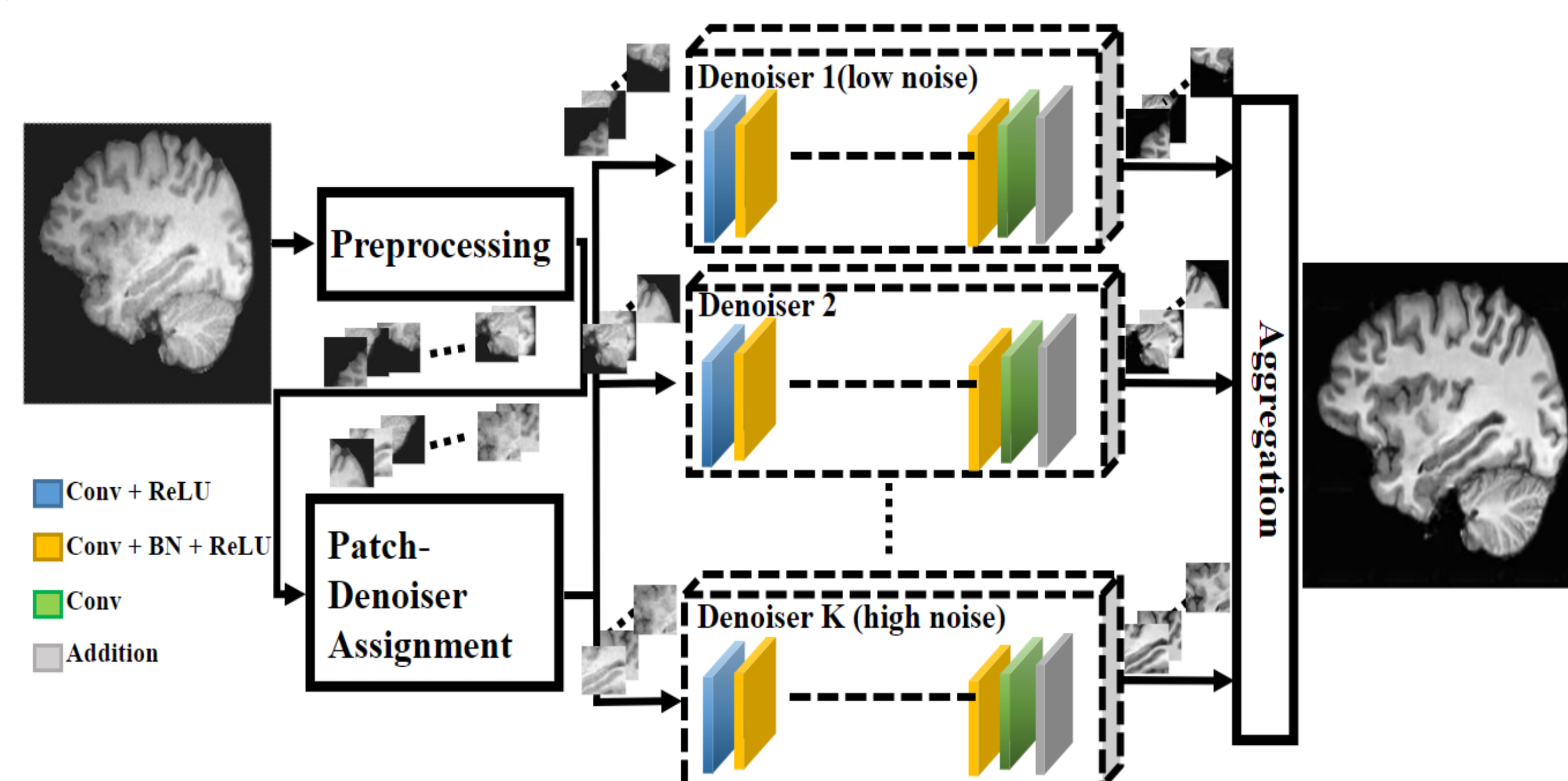


Fig. 3: HydraNet Architecture

We experiment with 3 estimates of noise characteristics:

1. Peak Signal to Noise Ratio (*High PSNR  $\approx$  High Noise*)
2. Residual Standard Deviation (*High  $\sigma \approx$  High Noise*)
3. Slice Location (*Fig. 4*) (*Similar Regions  $\approx$  Similar Noise*)

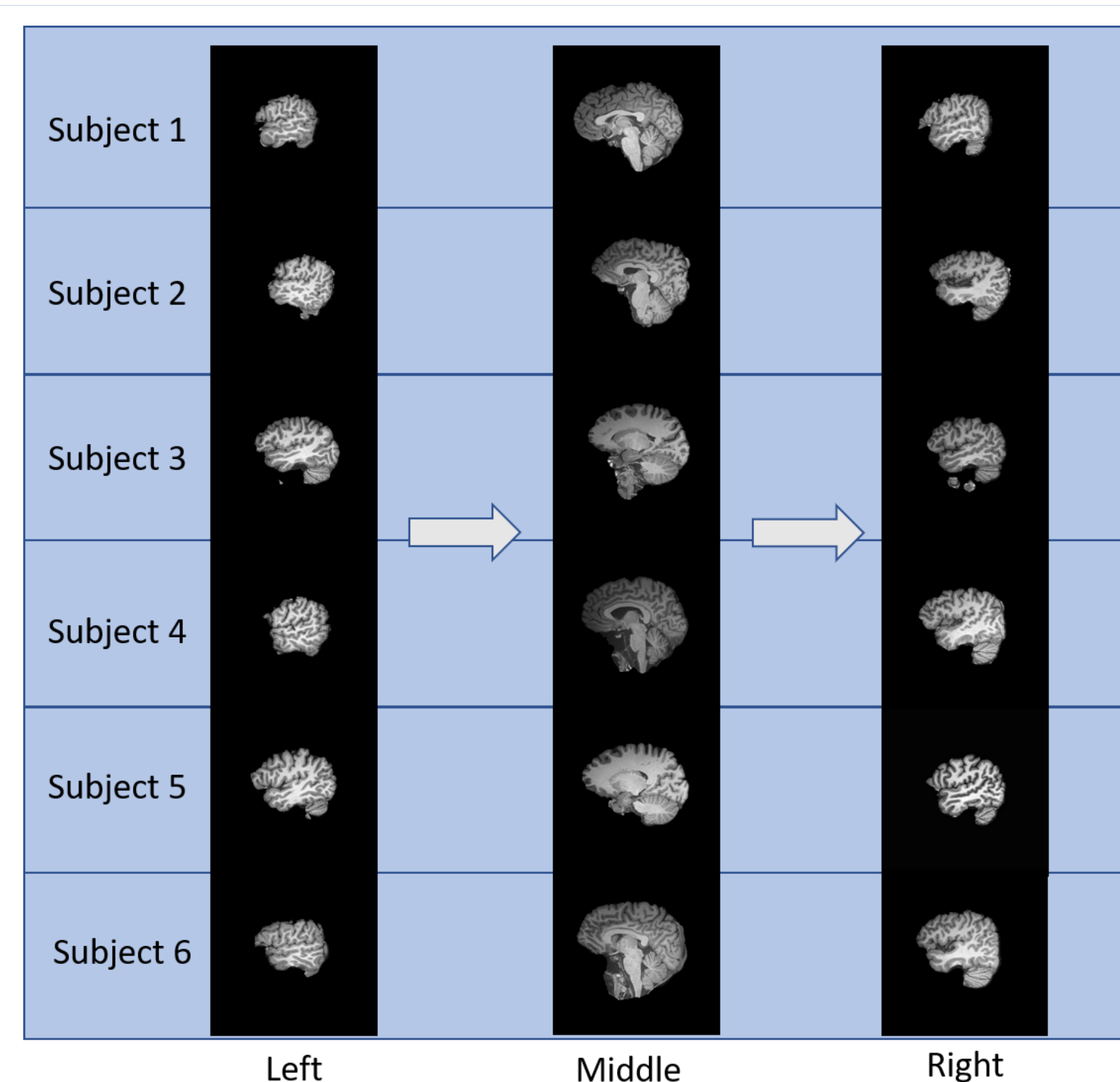


Fig. 4: Sample slices from left, middle, and right portions of each MRI subject, showcasing qualitative correlation between regions

Hypotheses:

1. Multiple specialized denoisers can perform better than a single general denoiser
2. Real noise in training data produces better models
3. Good metrics are used to predict noise characteristics

## RESULTS

- 3 HydraNet experiments compared with **DnCNN** [1] and **BM3D** [2] on 2 MRI subjects
- Superior **qualitatively** (Fig. 5) & **quantitatively** (Fig. 6)

Shown in (Fig. 5), HydraNet learns to simultaneously denoise the highly complex teal regions and the simpler blue regions with comparable efficacy

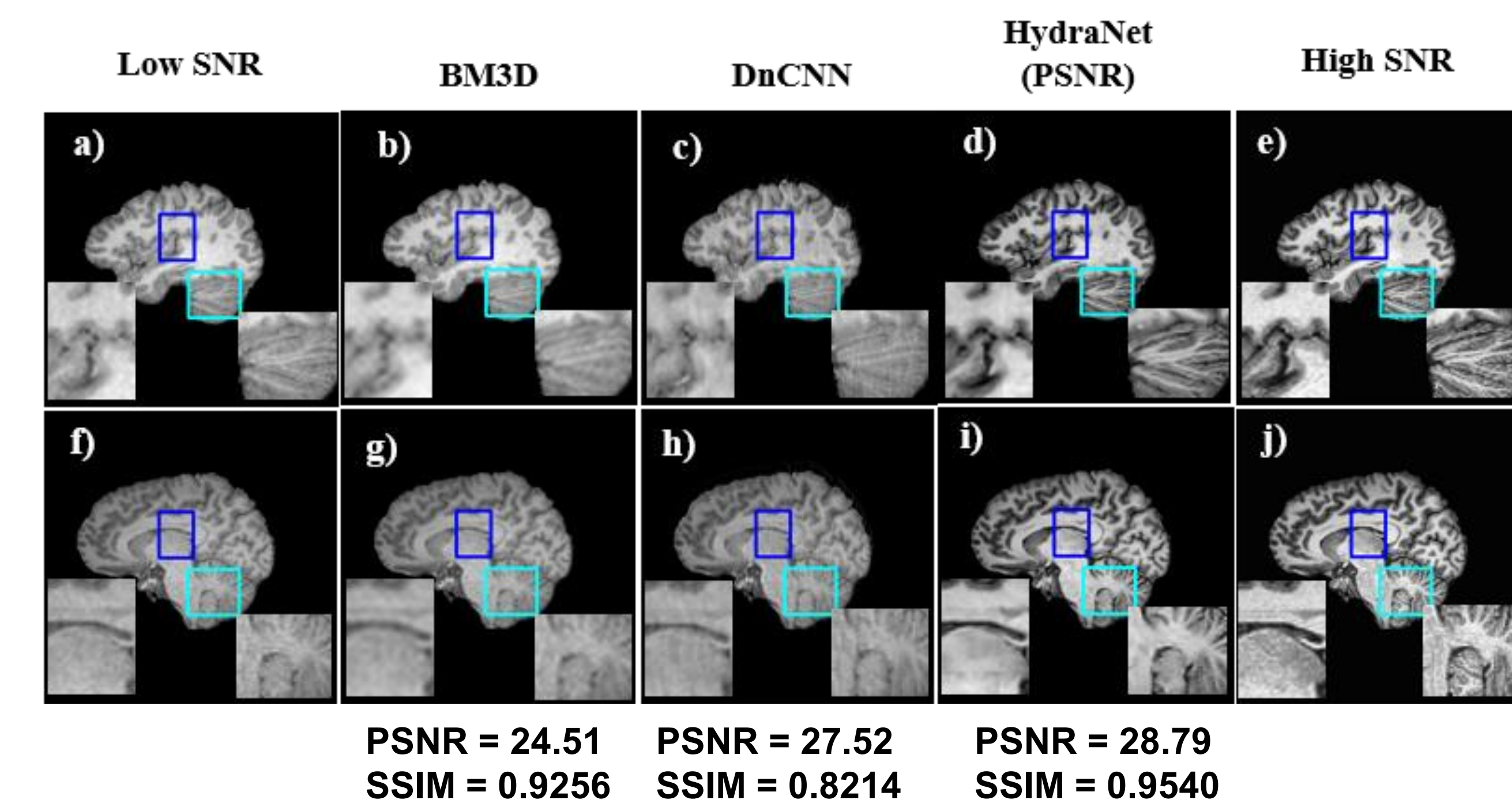


Fig. 5: Denoising Results for sample MRI slices from each of **BM3D**, **DnCNN**, and **HydraNet**

Method	SSIM	PSNR (dB)
HydraNet (PSNR)	0.9540	28.790
HydraNet (Residual std)	0.9527	27.855
HydraNet (Location)	0.9592	28.420
DnCNN	0.8214	27.520
BM3D-Brushlet	0.9256	24.51

Fig. 6: Quantitative Results for **BM3D**, **DnCNN**, and **HydraNet**

## CONCLUSIONS

1. HydraNet takes a promising step towards effective denoising of medical images
2. Providing real noisy data is essential for training/evaluating deep-learning-based denoisers.
3. More work is needed to establish metrics for evaluating noise in both natural and medical images

In future work, we plan to generalize HydraNet to a 3-dimensional architecture with 3D Convolutions for faster training, inference, and superior results.

## REFERENCES

1. Zhang, K. et. al. IEEE TIP 26(7), 3142–3155 (2017)
2. Ahn, B, arxiv: 1704.00524, 2017
3. Hor'e, A. et. al. ICPR, 2366–2369 (2010).
4. Zhou, W., et. al. IEEE TIP 13(4), 600–612 (2004)