MindEye2: Shared-Subject Models Enable fMRI-To-Image With 1 Hour of Data

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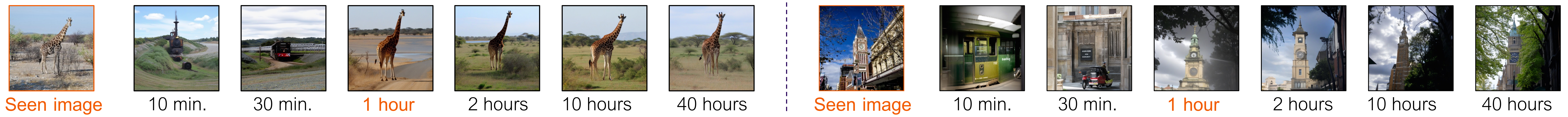
Reconstructions of seen images from human brain activity using ONE hour of fMRI training data (previous work used FORTY hours)



Background

Functional magnetic resonance imaging (fMRI) measures neural activation as changes in blood oxygenation. Decoding seen images from fMRI enables better understanding of brain function and potential for mind-reading applications in brain-computer interfaces. fMRI is expensive and time-consuming so generalization with sparse training data is essential for practical adoption. We used the *Natural Scenes Dataset* (NSD) [1], a public fMRI dataset containing brain responses of human participants looking at naturalistic photographs (MS-COCO).

MindEye2 achieves state-of-the-art across *retrieval* and *reconstruction*, both in 1-hour and 40-hour settings.

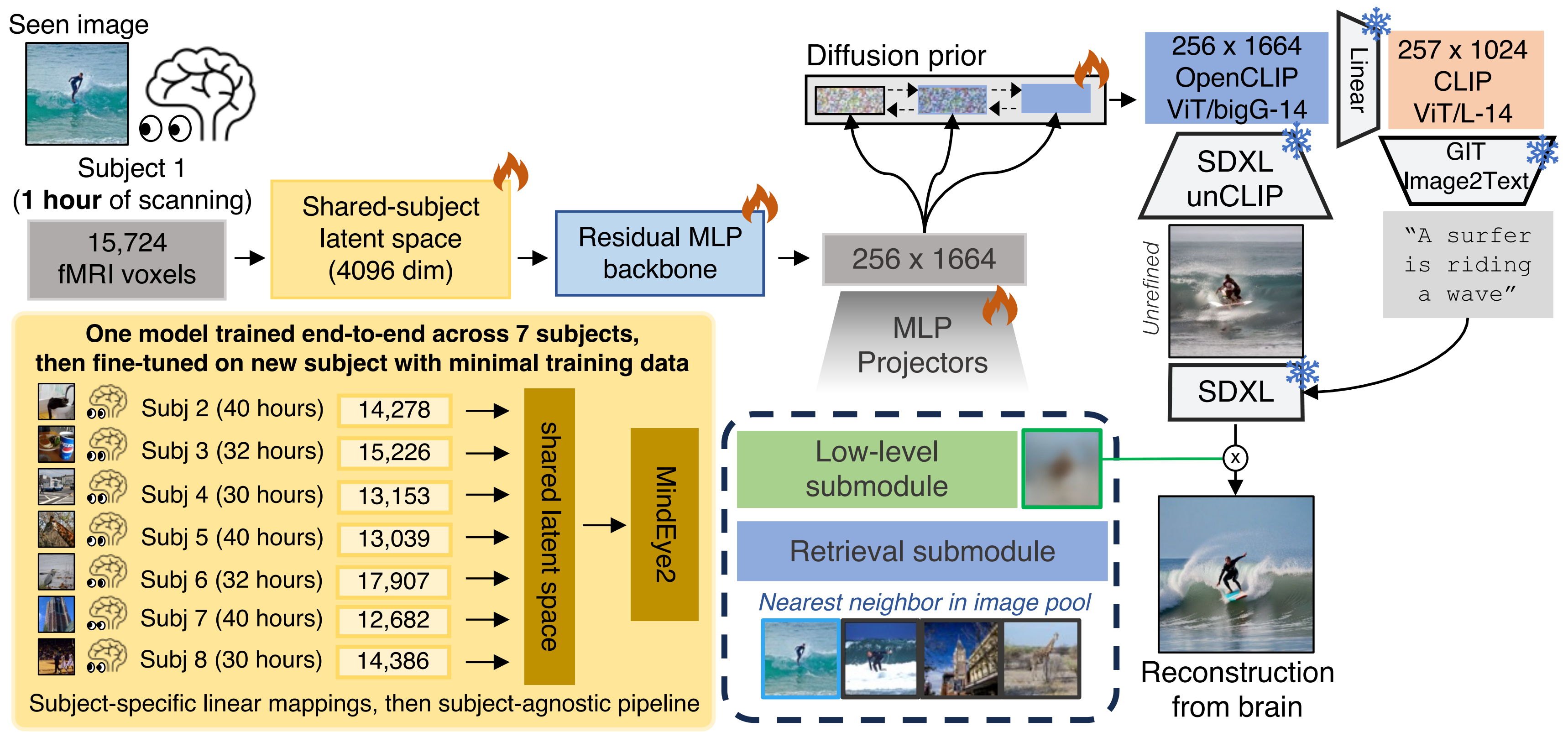
Retrieval: identify the original (or most similar) image out of a pool of candidates (i.e., nearest neighbor)

Reconstruction: recreate the original seen image (i.e., output from latent diffusion model)

Methods

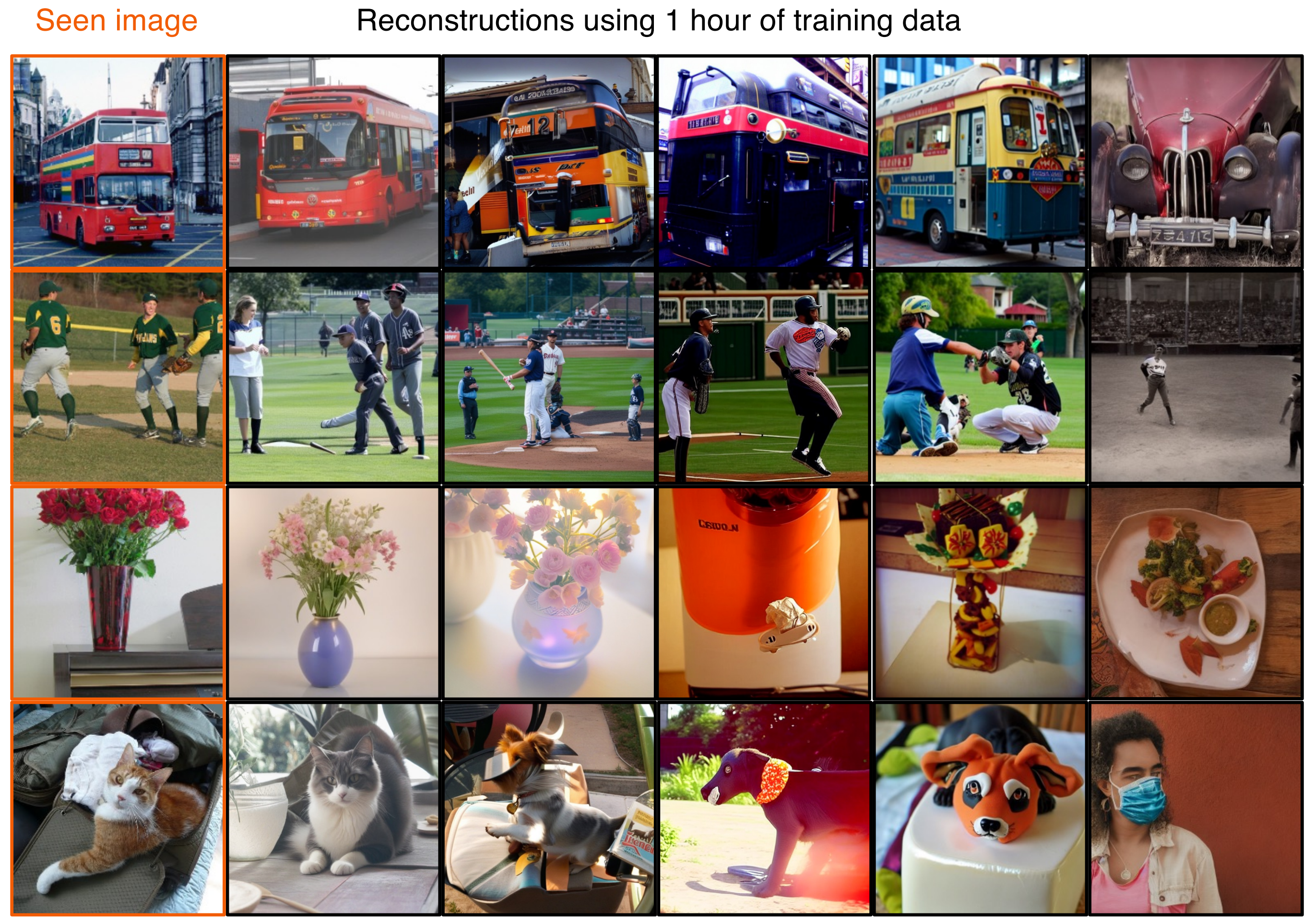
Compared to past work, MindEye2 innovates by:

1. Training model *across* subjects
2. Mapping to stronger CLIP space (OpenCLIP bigG)
3. Fine-tuning a SOTA Stable Diffusion XL [3] unCLIP model
4. Predict image captions from brain for added guidance



Each of 10,000 unique images was viewed 3x for 3 sec. Corresponding fMRI voxels (1.8mm cubes of cortex) were collected for each image presentation. We pretrain our model across 7 subjects and fine-tune on minimal data from a new subject. We linearly map all brain data to a shared-subject latent space, followed by a shared non-linear mapping to OpenCLIP [2] image space. We then map from CLIP space to pixel space by fine-tuning Stable Diffusion XL to accept CLIP latents as inputs instead of text.

Qualitative comparison to past work



MindEye2 | MindEye2 (not pretrained across subjects) | MindEye1 (Scotti et al., 2023) [7] | Brain Diffuser (Ozcelik et al., 2023) | Takagi et al. (2022)

Quantitative comparison to past work

Method	Low-Level				High-Level				Retrieval	
	PixCorr ↑	SSIM ↑	Alex(2) ↑	Alex(5) ↑	Incep ↑	CLIP ↑	Eff ↓	SwAV ↓	Image ↑	Brain ↑
MindEye2	**0.322**	**0.431**	**96.1%**	98.6%	95.4%	93.0%	**0.619**	0.344	**98.8%**	**98.3%**
MindEye2 (unrefined)	0.278	0.328	95.2%	**99.0%**	**96.4%**	**94.5%**	0.622	**0.343**	–	–
MindEye1	0.319	0.360	92.8%	96.9%	94.6%	93.3%	0.648	0.377	90.0%	84.1%
Ozcelik and VanRullen (2023)	0.273	0.365	94.4%	96.6%	91.3%	90.9%	0.728	0.421	18.8%	26.3%
Takagi and Nishimoto (2023)	0.246	0.410	78.9%	85.6%	83.8%	82.1%	0.811	0.504	–	–
MindEye2 (low-level)	0.399	0.539	70.5%	65.1%	52.9%	57.2%	0.984	0.673	–	–
MindEye2 (1 hour)	0.195	0.419	84.2%	90.6%	81.2%	79.2%	0.810	0.468	79.0%	57.4%

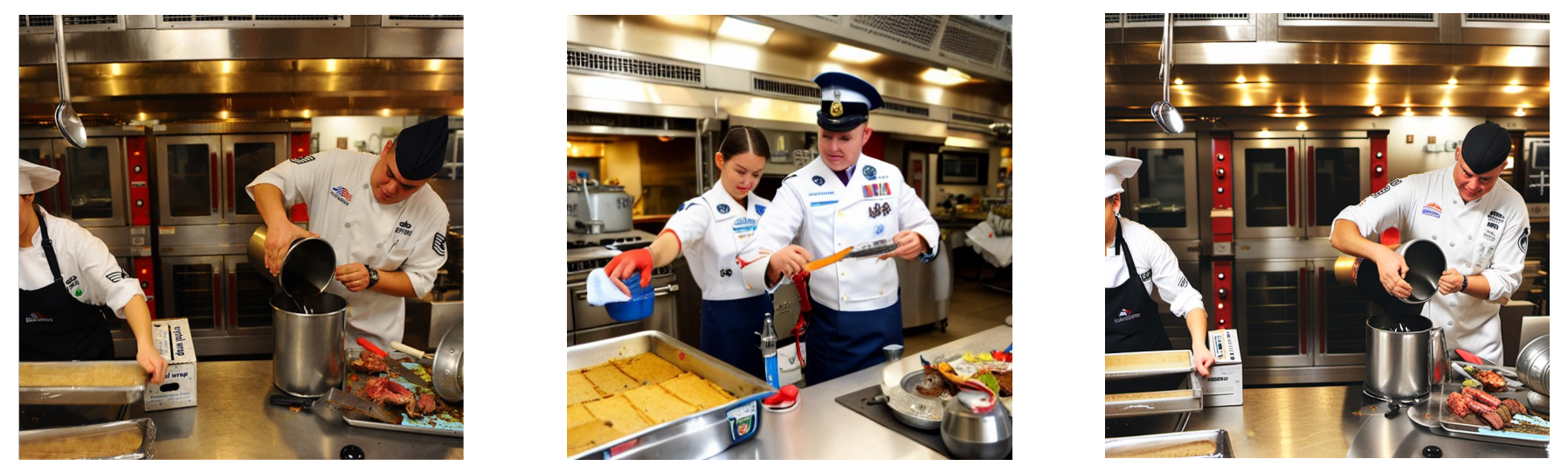
Results are from full 40-hours training data, averaged across the same 4 participants. PixCorr=pixelwise correlation between ground truth and reconstructions; SSIM=structural similarity index metric; EfficientNet-B1 and SwAV-ResNet50 refer to average correlation distance; all other metrics refer to two-way identification (chance = 50%). Image retrieval refers to the percent of the time the correct image was retrieved out of 300 candidates, given the associated brain sample (chance=0.3%); vice-versa for brain retrieval. **Bold**=best performance, underline= 2nd best.

unCLIP comparison

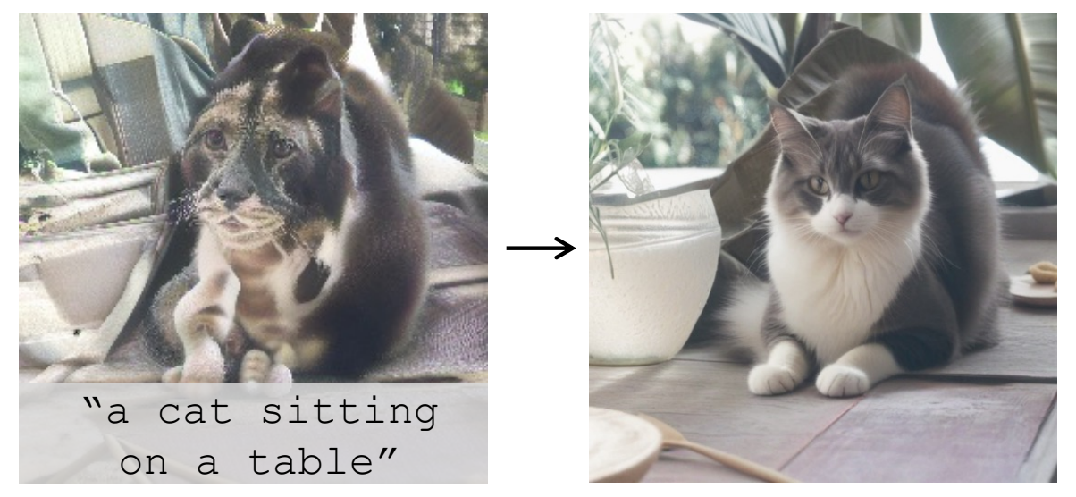
unCLIP models can convert CLIP image embeddings back to pixel space.

We fine-tuned SDXL to support CLIP image embedding input instead of text, raising ceiling reconstruction performance.

Reconstructions from **ground truth** CLIP image embeddings



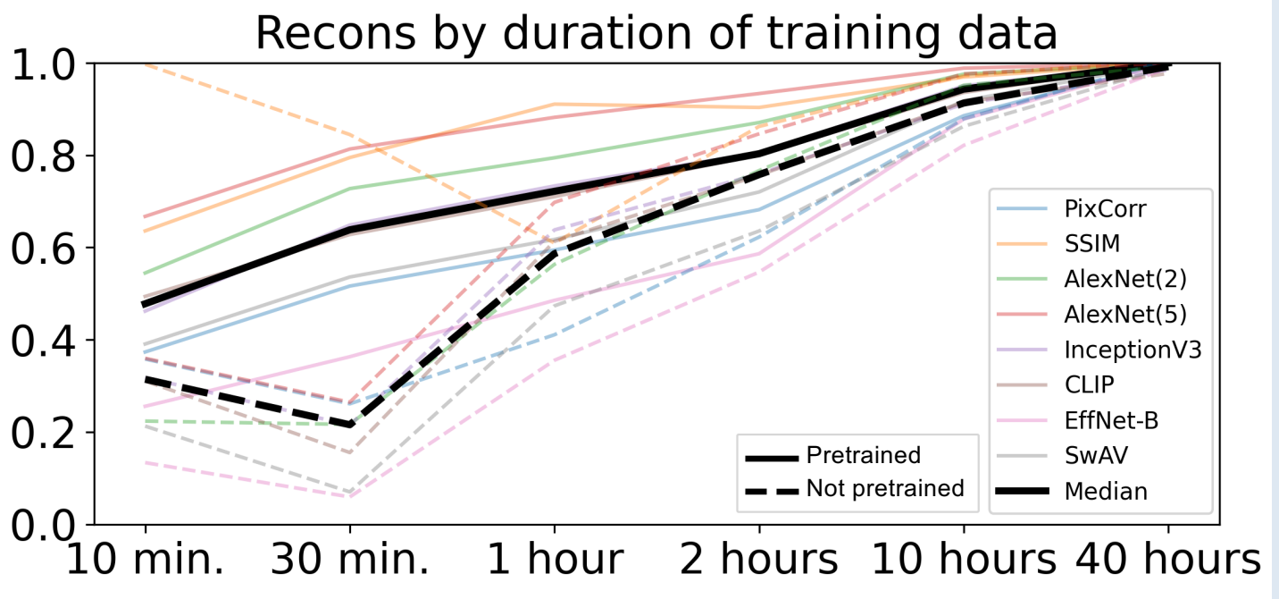
Refinement with image caption prediction



"Unrefined" reconstructions = pixel images output directly from SDXL unCLIP

We observed unrefined reconstructions were SOTA but subjectively distorted. To improve image realism, we use image-to-image [4] with base SDXL, feeding unrefined recons alongside a MindEye2 predicted image caption.

Varying amt. of train data



The 1-hour setting offers a good balance between scan duration and reconstruction performance, with notable improvements from pretraining.

Ablations

Metric		ME2	ME1	CLIP L
Low-Level	PixCorr ↑	**0.292**	0.225	0.243
	SSIM ↑	**0.386**	0.380	0.371
	Alex(2) ↑	**92.7%**	87.3%	84.8%
	Alex(5) ↑	**97.6%**	94.7%	93.7%
High-Level	Incep ↑	**91.5%**	88.9%	87.7%
	CLIP ↑	**90.5%**	86.2%	89.2%
	Eff ↓	**0.700**	0.758	0.744
	SwAV ↓	**0.393**	0.430	0.427
Retrieval	Fwd ↑	**97.4%**	84.9%	89.6%
	Bwd ↑	**95.1%**	70.6%	82.8%

Ablations show importance of both shared-subject modeling and leveraging improved CLIP image space.

ME1 = MindEye1 MLP instead of shared-subject linear mapping
CLIP L = Mapping to CLIP-L instead of OpenCLIP bigG

Conclusions: Benefits & Risks/Limitations

- Potential for new clinical diagnostic methods: reconstructions are expected to be systematically distorted due to mental state.
- Potential to generalize to mental imagery: similar patterns of brain activity are observed across perception and mental imagery [5].
- Real-time brain-computer interfaces [6] e.g., communication with patients in a pseudocoma.

- 1-hour generalization enables practical adoption.
- MindEye2 is limited to natural scene image distributions.
- Data easily becomes too noisy with slight movement or inattention to the task.
- Privacy: IRB approval and participant consent for data sharing was obtained. Medical data should be carefully protected and transparently used.

References. [1] Allen et al. (2022). A massive 7T fMRI dataset to bridge cognitive neuroscience and artificial intelligence. *Nature Neuro.* [2] Ilharco et al. (2021). OpenCLIP. [3] Podell et al. (2023). Sdxl: Improving latent diffusion models for high-resolution image synthesis. *ICLR*. [4] Meng et al. (2022). SDEdit: Guided Image Synthesis and Editing with Stochastic Differential Equations. *ICLR*. [5] Reddy et al. (2010). Reading the mind's eye: Decoding category information during mental imagery. *NeuroImage*. [6] Wallace et al. (2022). RTCloud: A cloud-based software framework to simplify and standardize real-time fMRI. *NeuroImage*. [7] Scotti et al. (2023). Reconstructing the mind's eye: fMRI-to-image with contrastive learning and diffusion priors. *NeurIPS*.