A. Supplementary Materials

A.1. AUCp Metric Calculation

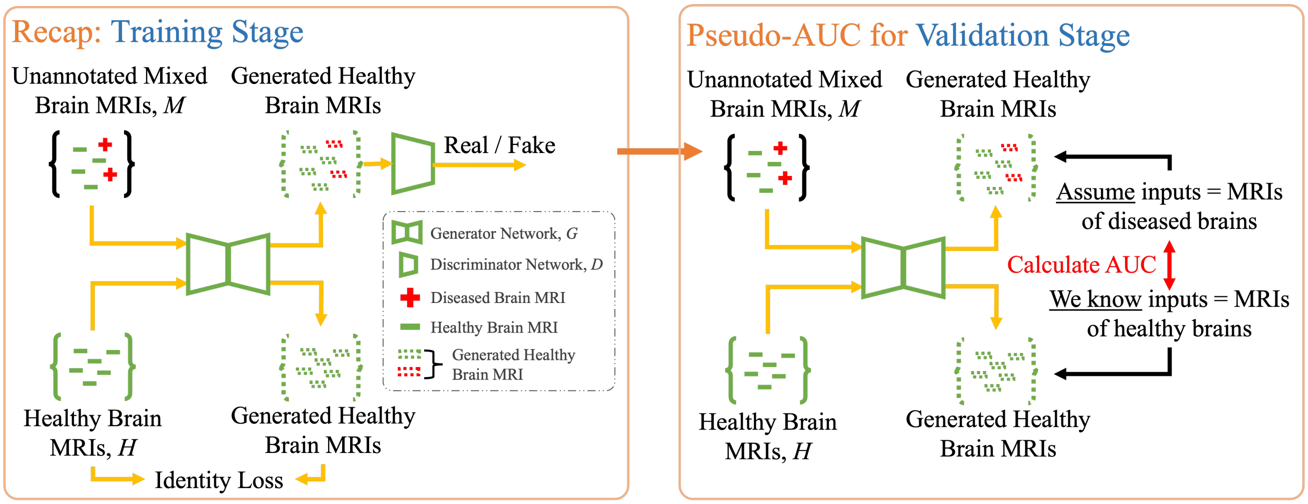

Figure 4. An overview of the proposed AUCp metric calculation. To calculate AUCp, we first generate the *disease detection scores* for each model, as discussed in Sec. 3.3. As we already know that the set H contains only healthy-brain MRIs, we assume the labels for MRIs in the unannotated mixed brain MRI set, M, to be diseased brains. Then, we use these *imperfect* annotations as ground truths along with the *disease detection scores* in the traditional AUC calculation resulting in AUCp scores. Once the AUCp scores are available for all the models, we select a model with the highest AUCp score for inference. In Sec. 6.3, we have also shown that AUCp sets a better-performing model for inference compared to FID, commonly used in existing works [34].

A.2. Neural Network Architectures

A detailed neural network architecture for the discriminator is provided in Tab. 3 and for the generator is provided in Tab. 4. Both these networks are adopted from [13, 35, 34] with slight modification.

Type	Operations	Input Shape	Output Shape
Input layer	Conv2d (OC=64, KS=4, S=2, P=1), LeakyReLU (NS=0.01)	$(h, w, 3)$	$(\frac{h}{2}, \frac{w}{2}, 64)$
Hidden layers	Conv2d (OC=128, KS=4, S=2, P=1), LeakyReLU (NS=0.01)	$(\frac{h}{2}, \frac{w}{2}, 64)$	$(\frac{h}{4}, \frac{w}{4}, 128)$
	Conv2d (OC=256, KS=4, S=2, P=1), LeakyReLU (NS=0.01)	$(\frac{h}{4}, \frac{w}{4}, 128)$	$(\frac{h}{8}, \frac{w}{8}, 256)$
	Conv2d (OC=512, KS=4, S=2, P=1), LeakyReLU (NS=0.01)	$(\frac{h}{8}, \frac{w}{8}, 256)$	$(\frac{h}{16}, \frac{w}{16}, 512)$
	Conv2d (OC=1024, KS=4, S=2, P=1), LeakyReLU (NS=0.01)	$(\frac{h}{16}, \frac{w}{16}, 512)$	$(\frac{h}{32}, \frac{w}{32}, 1024)$
	Conv2d (OC=2048, KS=4, S=2, P=1), LeakyReLU (NS=0.01)	$(\frac{h}{32}, \frac{w}{32}, 1024)$	$(\frac{h}{64}, \frac{w}{64}, 2048)$
Output layer (D_{src})	Conv2d (OC=1, KS=3, S=1, P=1)	$(\frac{h}{64}, \frac{w}{64}, 2048)$	$(\frac{h}{64}, \frac{w}{64}, 1)$

Table 3. Discriminator network architecture. OC, KS, S, P, and NS stand for output channels, kernel size, stride, padding, and negative slope, respectively.

Type	Operations	Input Shape	Output Shape
Encoder	Conv2d (OC=64, KS=7, S=1, P=3), IN, ReLU	$(h, w, 3)$	$(h, w, 64)$
	Conv2d (OC=128, KS=4, S=2, P=1), IN, ReLU	$(h, w, 64)$	$(\frac{h}{2}, \frac{w}{2}, 128)$
	Conv2d (OC=256, KS=4, S=2, P=1), IN, ReLU	$(\frac{h}{2}, \frac{w}{2}, 128)$	$(\frac{h}{4}, \frac{w}{4}, 256)$
Bottleneck	Residual Block: Conv2d (OC=256, KS=3, S=1, P=1), IN, ReLU	$(\frac{h}{4}, \frac{w}{4}, 256)$	$(\frac{h}{4}, \frac{w}{4}, 256)$
	Residual Block: Conv2d (OC=256, KS=3, S=1, P=1), IN, ReLU	$(\frac{h}{4}, \frac{w}{4}, 256)$	$(\frac{h}{4}, \frac{w}{4}, 256)$
	Residual Block: Conv2d (OC=256, KS=3, S=1, P=1), IN, ReLU	$(\frac{h}{4}, \frac{w}{4}, 256)$	$(\frac{h}{4}, \frac{w}{4}, 256)$
	Residual Block: Conv2d (OC=256, KS=3, S=1, P=1), IN, ReLU	$(\frac{h}{4}, \frac{w}{4}, 256)$	$(\frac{h}{4}, \frac{w}{4}, 256)$
	Residual Block: Conv2d (OC=256, KS=3, S=1, P=1), IN, ReLU	$(\frac{h}{4}, \frac{w}{4}, 256)$	$(\frac{h}{4}, \frac{w}{4}, 256)$
	Residual Block: Conv2d (OC=256, KS=3, S=1, P=1), IN, ReLU	$(\frac{h}{4}, \frac{w}{4}, 256)$	$(\frac{h}{4}, \frac{w}{4}, 256)$
Decoder	ConvTranspose2d (OC=128, KS=4, S=2, P=1), IN, ReLU	$(\frac{h}{4}, \frac{w}{4}, 256)$	$(\frac{h}{4}, \frac{w}{4}, 128)$
	ConvTranspose2d (OC=64, KS=4, S=2, P=1), IN, ReLU	$(\frac{h}{2}, \frac{w}{2}, 128)$	$(h, w, 64)$
	ConvTranspose2d (OC=1, KS=7, S=1, P=3)	$(h, w, 64)$	$(h, w, 1)$

Table 4. Generator network architecture. OC, KS, S, P, and IN stand for output channels, kernel size, stride, padding, and instance norm, respectively.

A.3. Receiver Operating Characteristic Curves

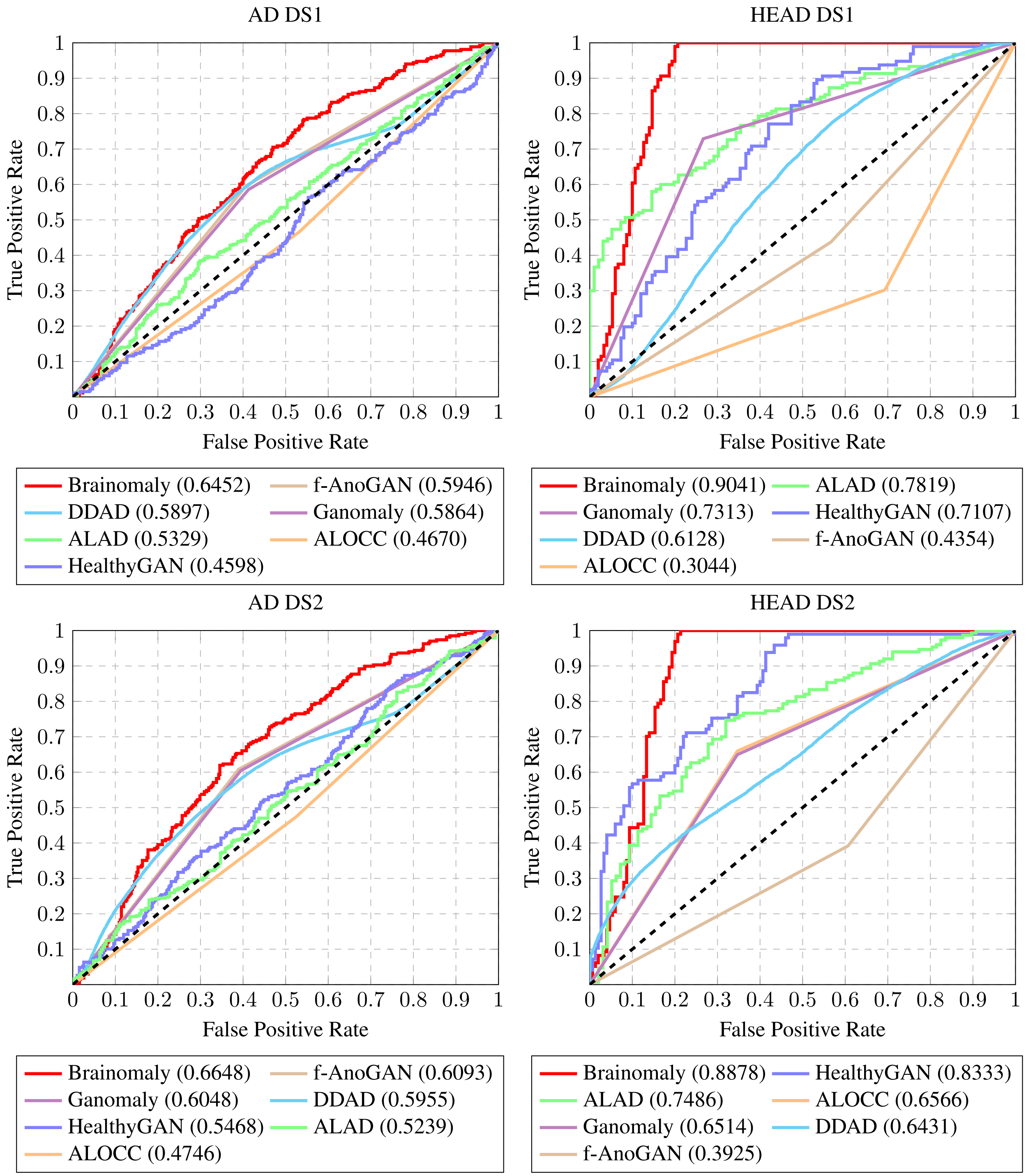

Figure 5. Receiver operative characteristics analyses for Alzheimer's disease and headache detection. *AD DS1* and *AD DS2* on the left compares Alzheimer's disease detection performances and *HEAD DS1* and *HEAD DS2* on the right compares headache detection performances. As discussed in Sec. 6, Brainomaly outperforms the existing methods across the tasks.