Know Your Space

Inlier and Outlier Construction for Calibrating Medical OOD Detectors

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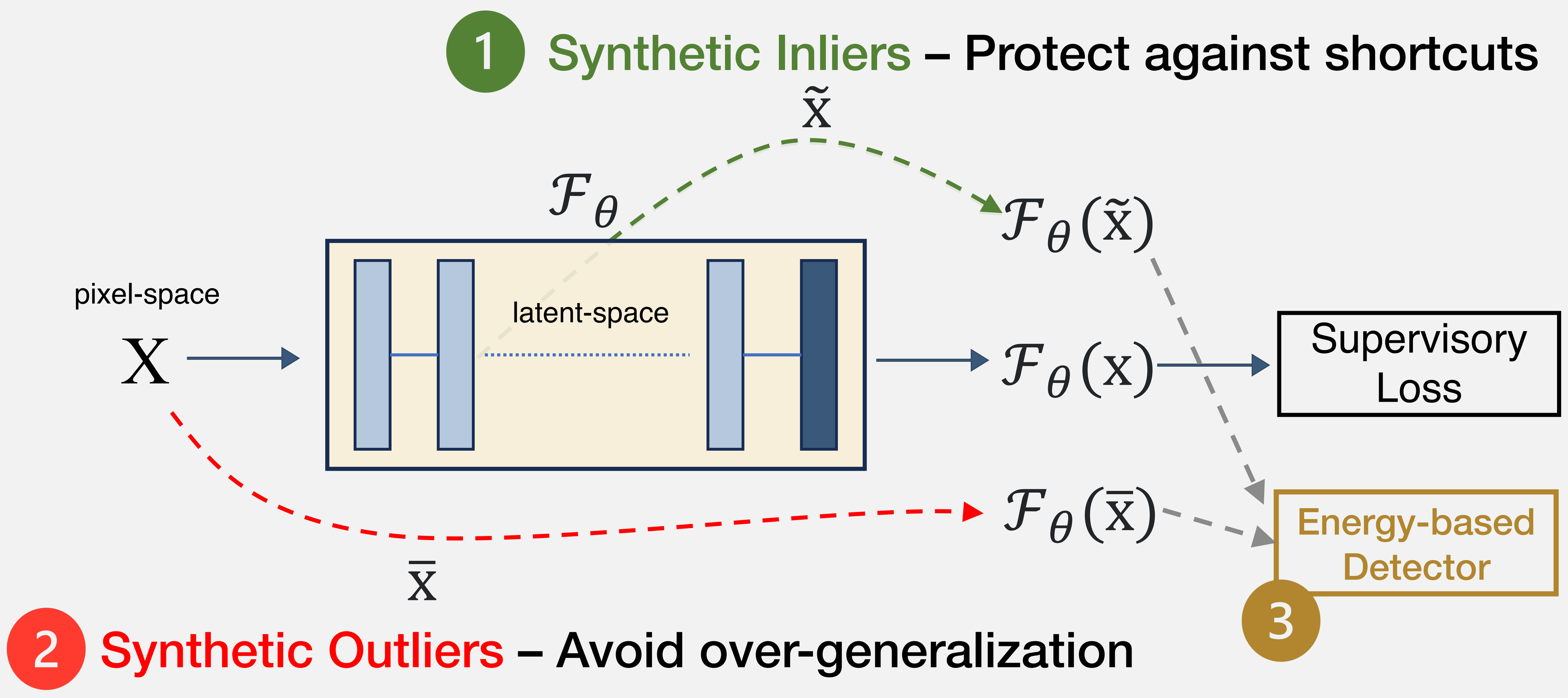
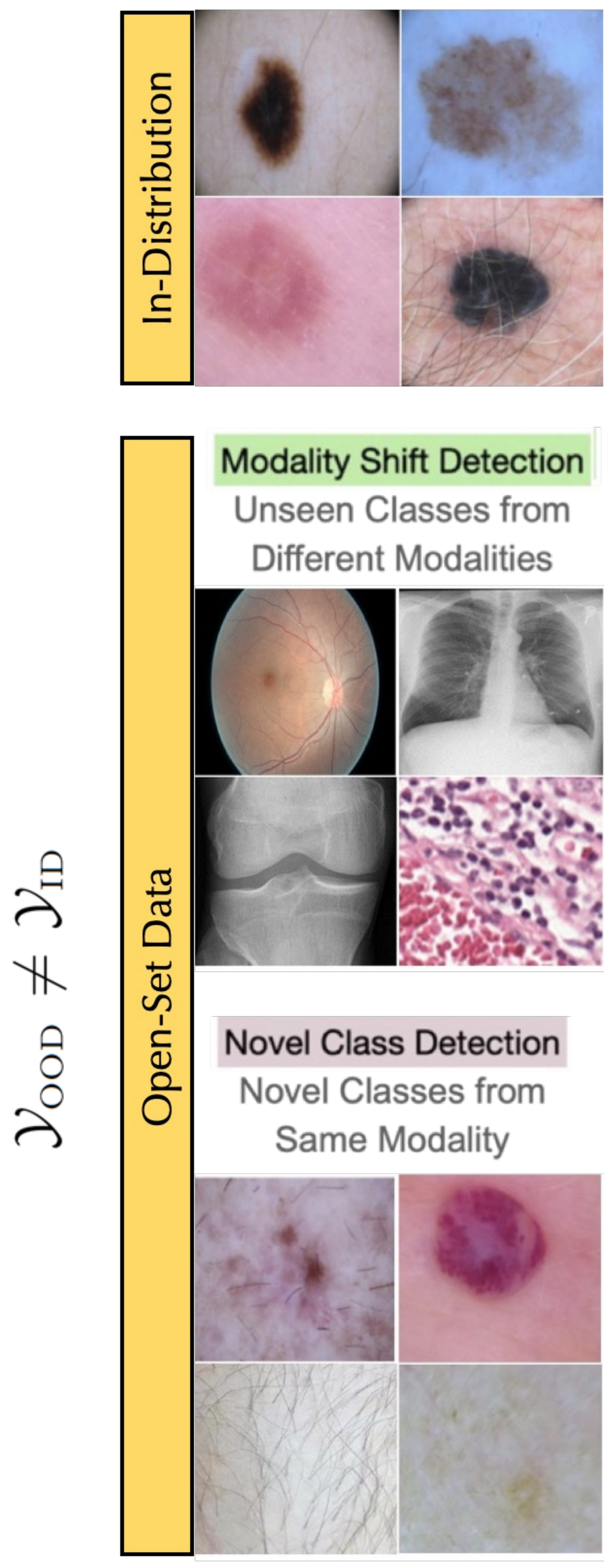
Synthetic Data Generation to Enable Open-Set Recognition without Hurting ID Accuracy



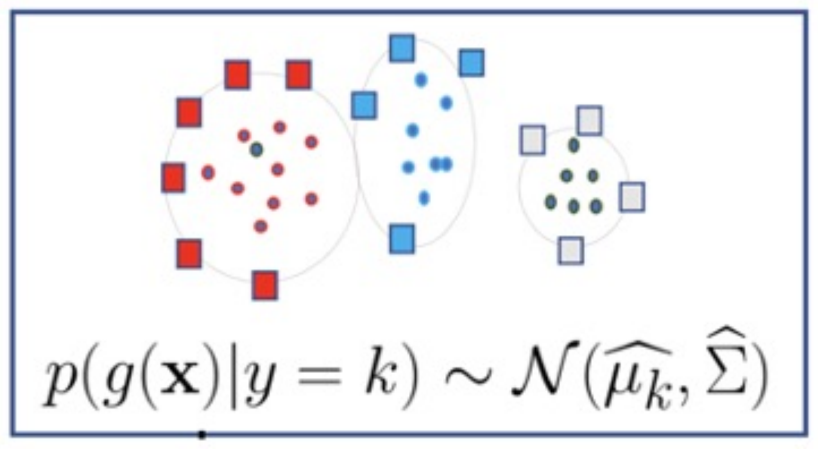
1. **Synthesize inliers in the latent space**
   Sample low-likelihood regions from class-specific feature distributions
2. **Synthesize outliers in the pixel space**
   Highly diverse set of outliers to ensure the OOD subspace does not overlap with the ID subspace
3. **Train energy-based OOD detector**
   Margin-based losses to calibrate the OOD detector to accept synthetic inliers and reject outliers

Open-Set Recognition

SoTA OOD calibration methods fail on medical open-set recognition!

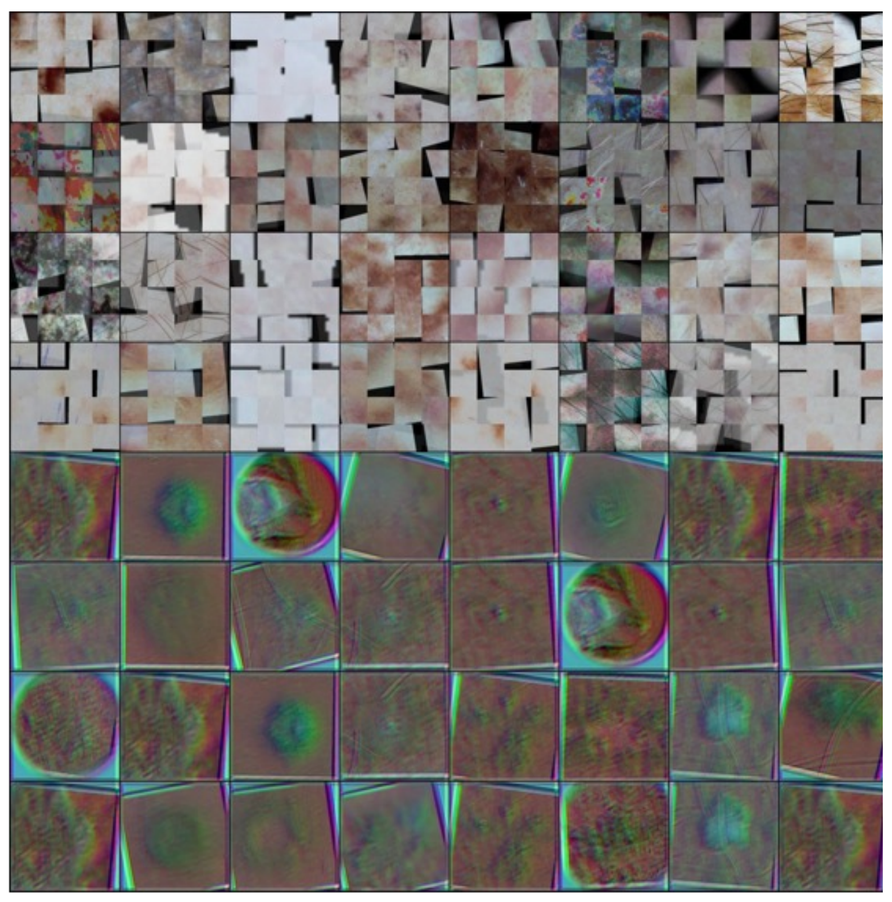


Inlier Synthesis



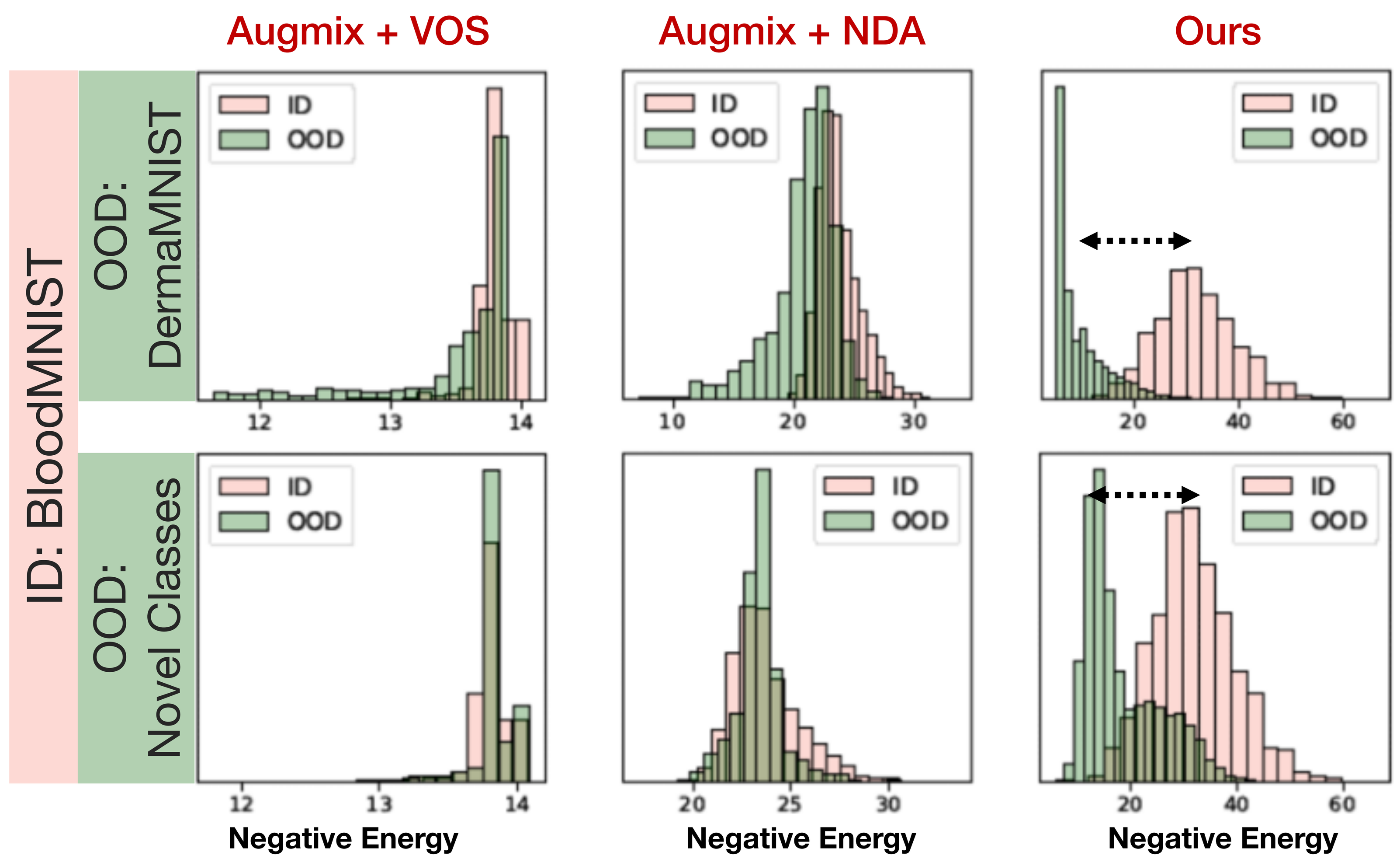
Push the tail samples closer to the class-specific prototypes

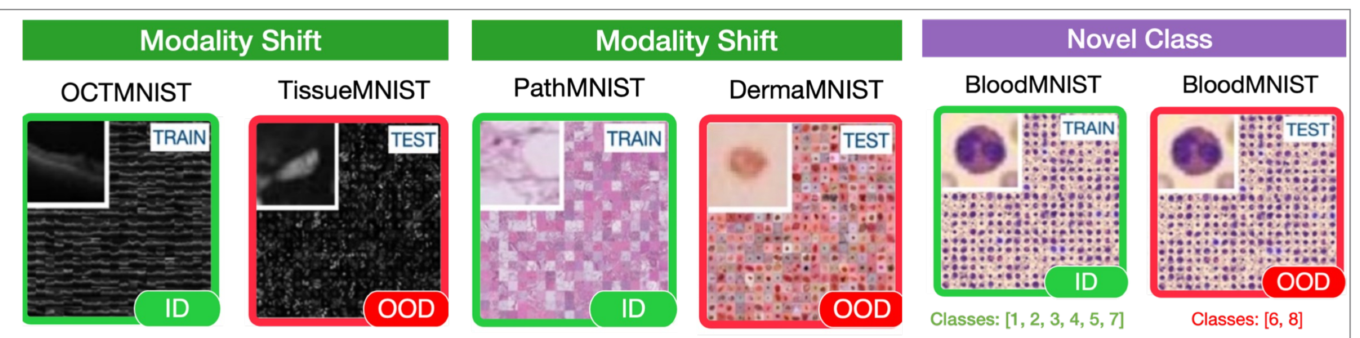
Outlier Synthesis



High-severity compositional image manipulations
(e.g., Augmix, RandConv)

Results





OOD Rejection AUROC (%)	Modality Shift	Modality Shift	Novel Class
G-ODIN	49.7	75.4	53.9
Augmix + VOS	62.0	39.8	38.2
Augmix + NDA	90.9	43.5	53.5
Ours	97.5	98.1	89.1

Across a large suite of benchmarks, we achieve 15%-25% AUROC improvement over SoTA methods.

Lawrence Livermore National Laboratory

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