模式识别与神经计算研究组

PAttern Recognition and NEural Computing

Active Image Synthesis for Efficient Labeling

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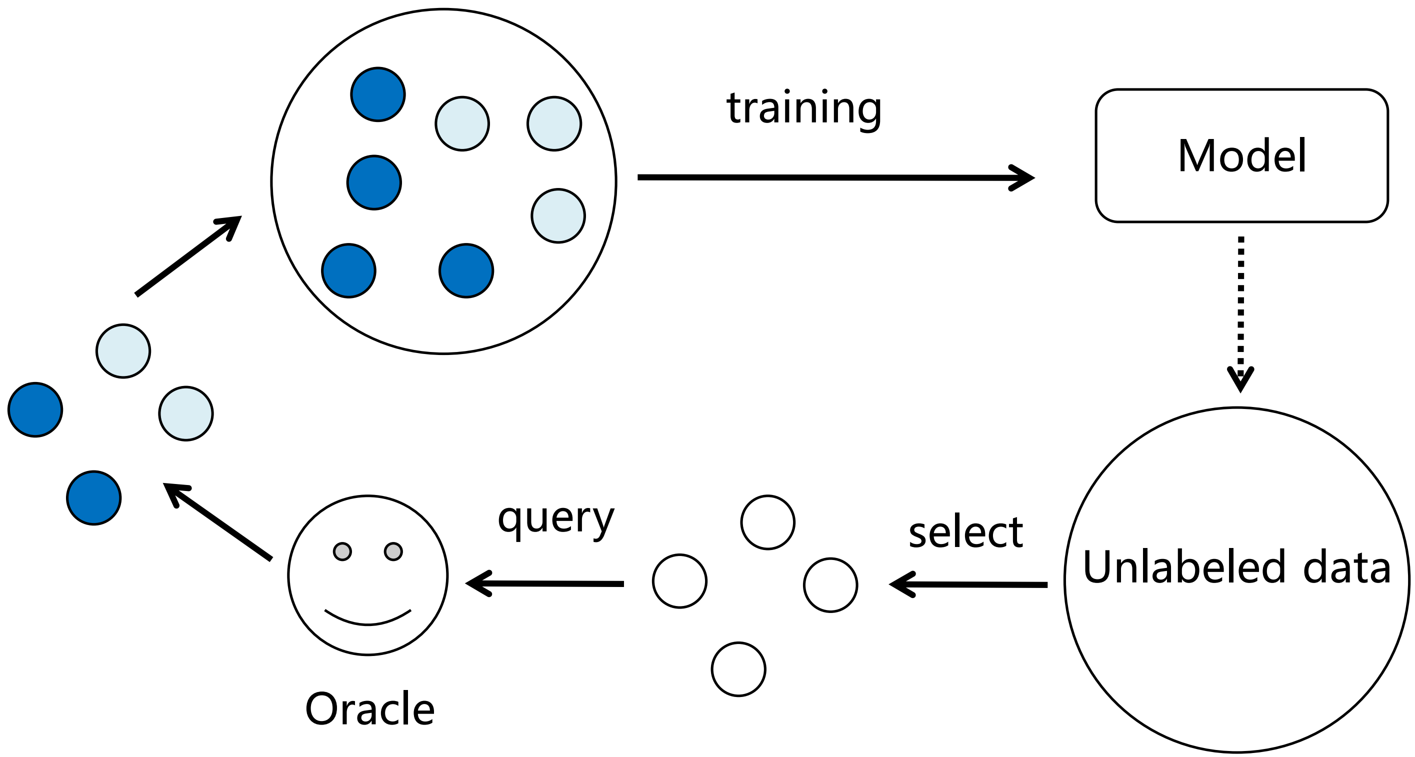
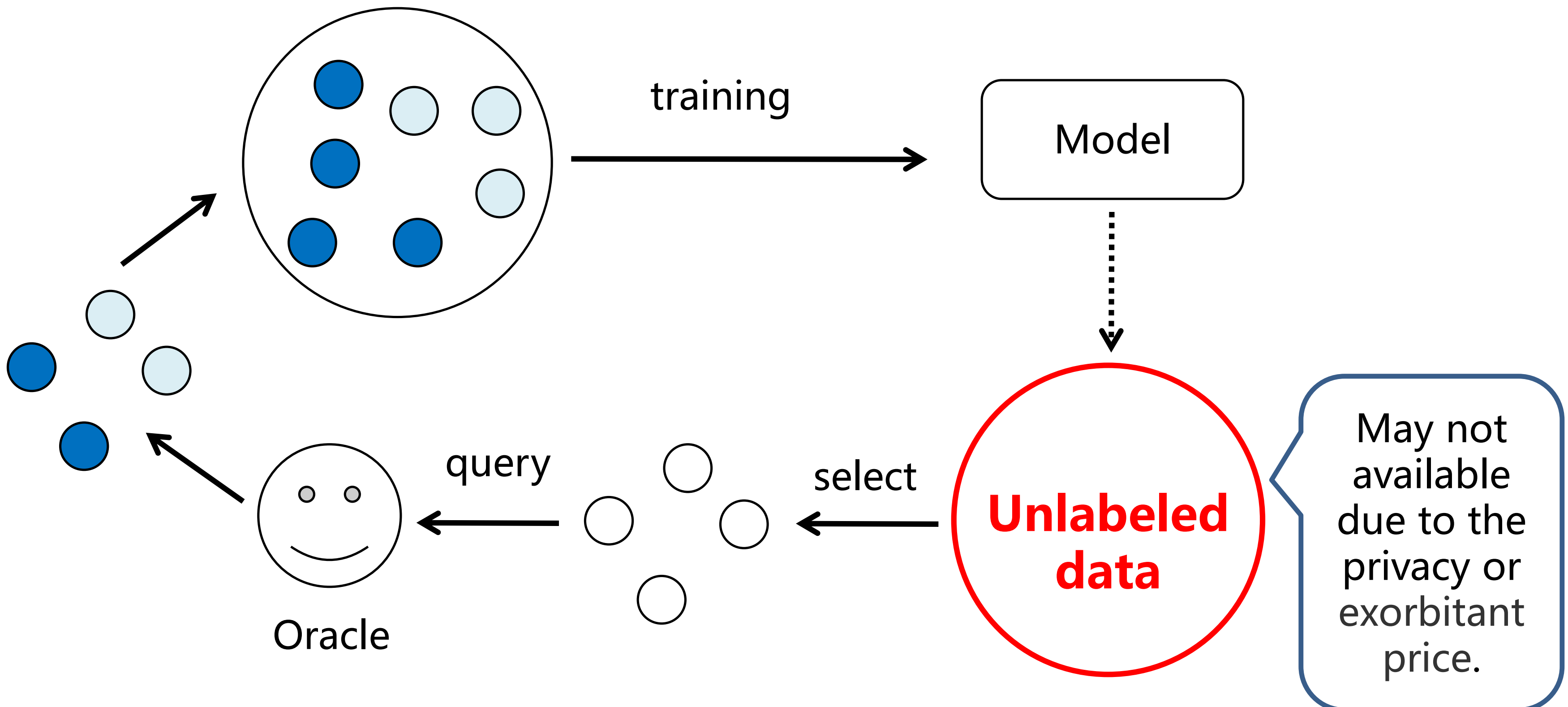
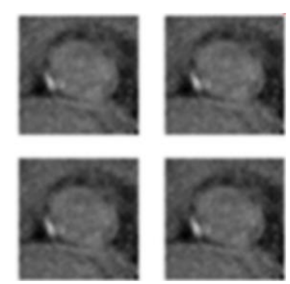


Goal: query less for more.

Introduction



A hospital may only have around **a hundred** historical records of pre-surgical CT scans of aortic stenosis **over the years.**



Main Contributions

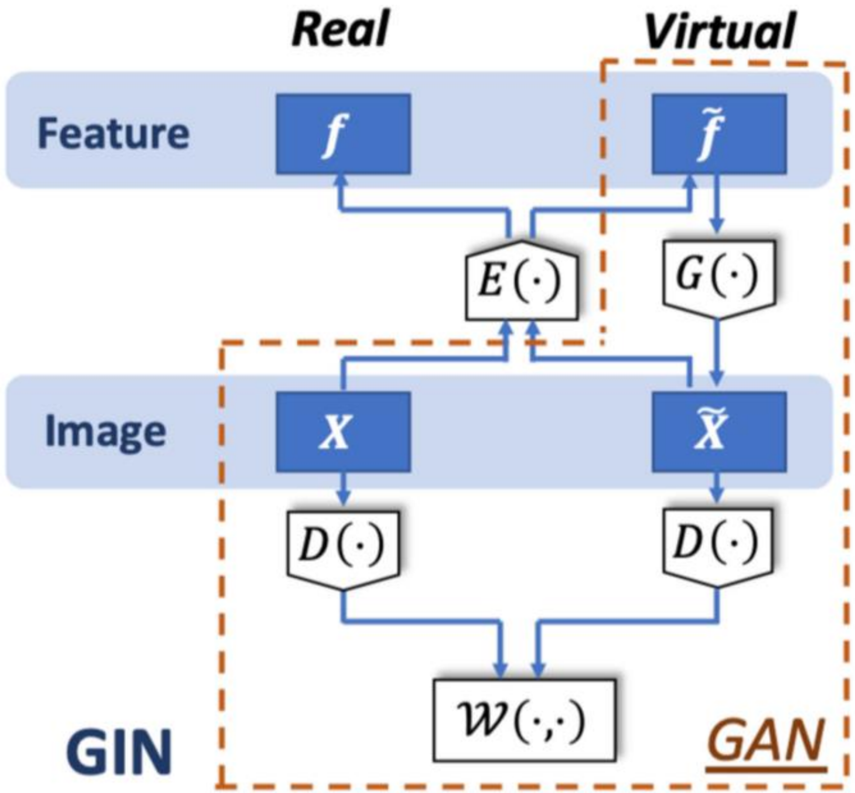
- Propose a generative invertible network (GIN) to generate images with small training data.
- Propose an active sampling method to select informative features from the embedded feature space.
- Conduct experiment on a real aortic stenosis dataset to demonstrate the superiority.

- **Further learn a encoder to inversely map the images to the latent feature vectors (for AL).**

$$\min_{E(\cdot)} \mathbb{E}_{\mathbf{X}\sim\mathcal{X}_n} ||E(\mathbf{X}) - f||_2^2,$$

However, the difficulty is that the feature f for the actual image X is unknown

$$E(\cdot) = \underset{E(\cdot)}{\operatorname{argmin}}\, \mathbb{E}_{u\sim\mathcal{U}} ||E(G(u)) - u||_2^2,$$



Theorem 1. *Denote the target distribution measuring as $\mathcal{X}$ on image space $\{\mathbb{X}, \mathcal{B}[\mathbb{X}]\}$. Assume the generator $G(\cdot)$ is obtained by (3) with the training error $< \epsilon$ and encoder $E(\cdot)$ is obtained by (5) with the training error $< \delta$. If both $G(\cdot)$ and $E(\cdot)$ are Lipschitz-L continues, then the reconstruction error $\mathbb{E}_{x \sim \mathcal{X}} [G(E(x)) - x]^2$ can be bounded by $(L^2 + L + 1)\epsilon + L\delta$.*

$$\min_{G(\cdot)} \max_{D(\cdot)} \mathbb{E}_{x \sim \mathcal{X}_n}[D(x)] - \mathbb{E}_{u \sim \mathcal{U}}[D(G(u))], \tag{3}$$

$$E(\cdot) = \operatorname*{argmin}_{E(\cdot)} \mathbb{E}_{u \sim \mathcal{U}} \|E(G(u)) - u\|_2^2, \tag{5}$$

Active sampling

- **Notations**

for any $f_0 \in \mathbb{F}$ where $\mathbb{F} = [-1, 1]^r$ is the feature space.

For any input image $\mathbf{X}_0 \in \mathbb{X}$, let $y_0 = C(\mathbf{X}_0)$ where $C(\cdot) : \mathbb{X} \mapsto [0, 1]^K$ is the classifier trained with the limited real data

- **Entropy definition**

$$H(\mathbf{X}_0) = -\sum_{k=1}^{K} y_0[k] \log (y_0[k]),$$

- **Entropy for synthesis images**

$$h(f_0) = H(G(f_0)) = -\sum_{k=1}^{K} E(G(f_0))[k] \log (E(G(f_0))[k]). \quad (7)$$

Active sampling

- **Select uncertain features**

$$f'_{1:m} = \operatorname*{argmin}_{f'_{1:m}} dist(\mathcal{F}'_m, \mu_h).$$

where $f'_{1:m} = \{f'_i\}_{i=1}^m$

The entropy $h(\cdot) : \mathbb{F} \mapsto [0, \log K]$ can also be viewed as a (unnormalized) probability density on the measurable space $\{\mathbb{F}, \mathcal{B}[\mathbb{F}]\}$. We denote this *uncertainty measure* as μ_h.

- **Take the energy distance**

$$D^2(F,G) = 2\,\mathrm{E}\,\|X - Y\| - \mathrm{E}\,\|X - X'\| - \mathrm{E}\,\|Y - Y'\| \geq 0,$$

$$\min_{f'_{1:m}} \sum_{i=1}^{m} \mathbb{E}_{\gamma \sim \mu_h} \|f'_i - \gamma\|_2 - \frac{1}{2m} \sum_{i=1}^{m} \sum_{j=1}^{m} \|f'_i - f'_j\|_2.$$

Active sampling

- **Incorporate the real images**

$$\min_{f'_{1:m}} \sum_{i=1}^{m} \mathbb{E}_{\gamma \sim \mu_h} \| f'_i - \gamma \|_2 - \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \frac{\| f'_i - f'_j \|_2}{2(m+n)}, \tag{10}$$

actual images with indies $i = m+1, \ldots, m+n$.

- **Generate images with $G(f')$**

- **labeling by an oracle**

Overall framework

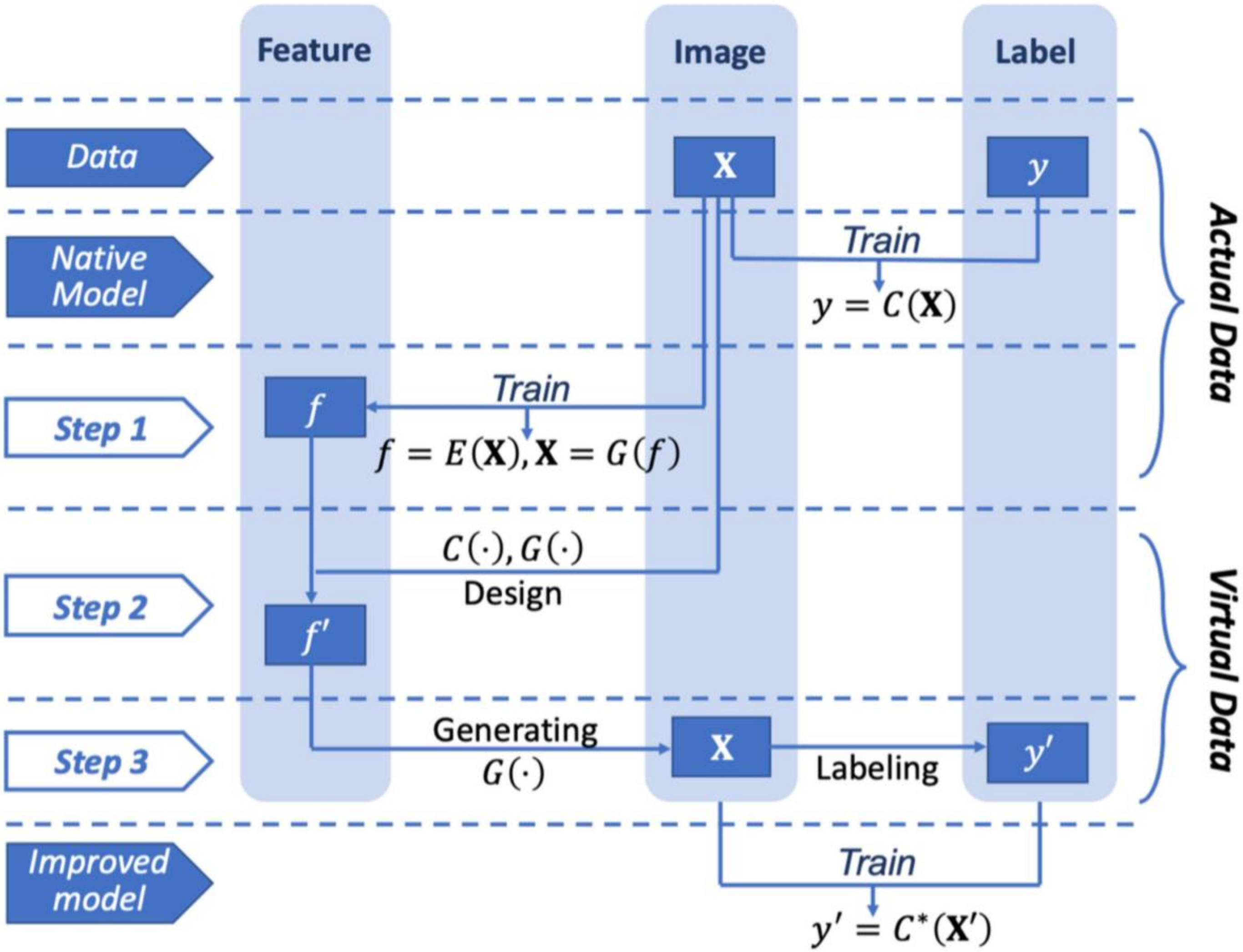
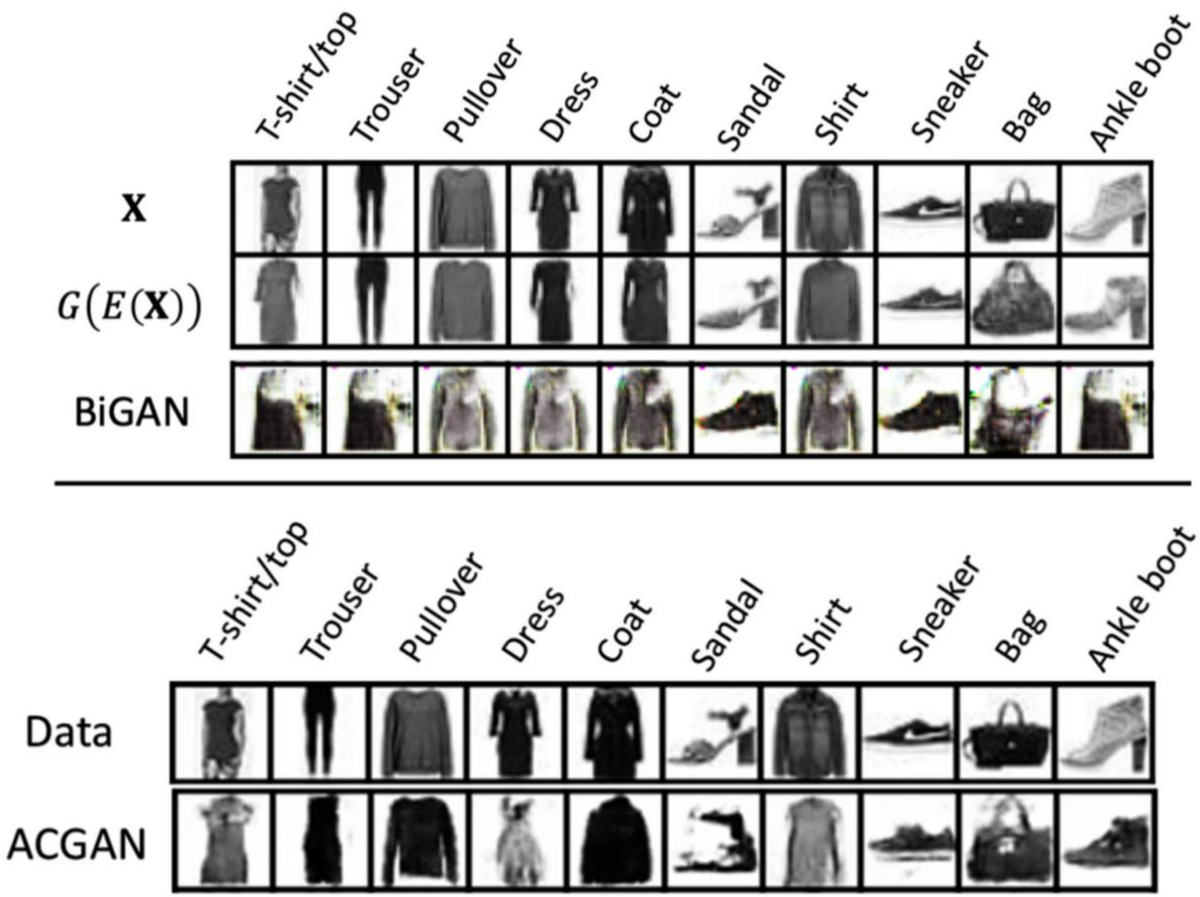


Fig. 2. The proposed three-step framework AISEL to efficiently sample AISEL dataset and improve classification.

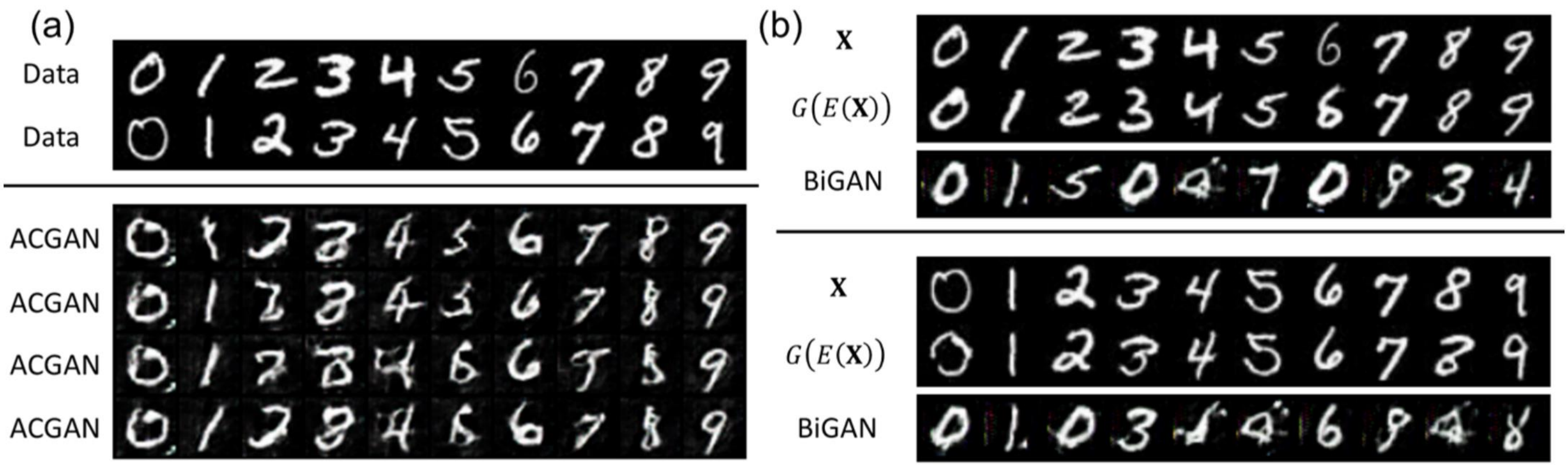
- **Toy Computer Vision Applications (Fashion and MNIST datasets). Visualization of image synthesis**

- 400 data is available for training

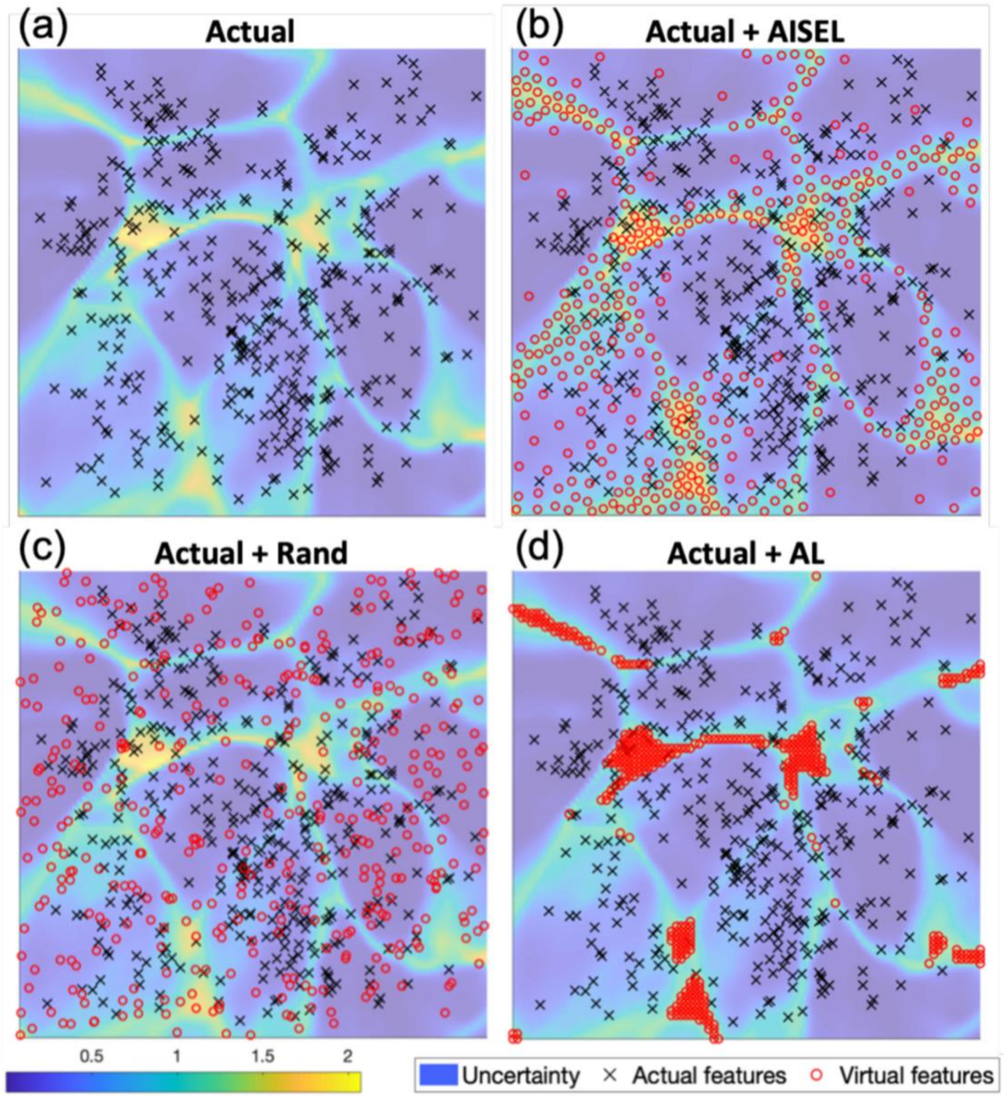


Experiments

- **Visualization of image synthesis**



- **Visualization of active sampling (Fashion dataset)**



Note that the **labels are obtained by the oracle model** (using all 60,000 training data and WideResNet architecture)

AL method select data by uncertainty.

- **The Classification Accuracy on Fashion and MNIST**

Finetune pretrained ResNet18 (ImageNet)

Augment training data with generated images

Random sampling features for image synthesis

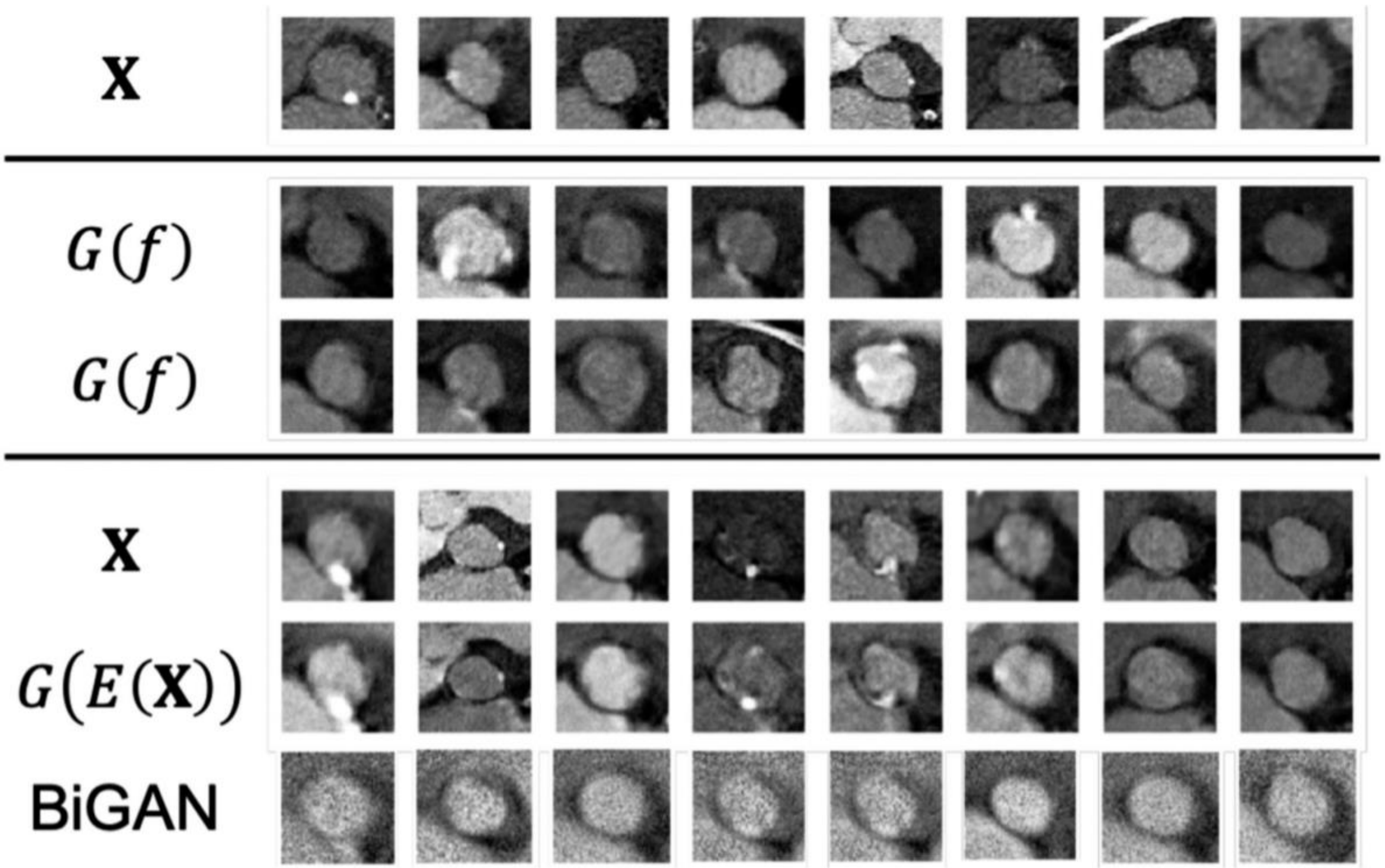
	Native (400)	Transfer	ACGAN	Rand (+400)	Rand (+5000)
Fashion	**72.8%**	74.3%	72.3%	76.4%	80.7%
MNIST	**88.2%**	87.4%	85.9%	90.2%	91.6%

Query by uncertainty

Use real images

	AISEL (+400)	AL (+400)	Oracle (800)	Oracle (all)
Fashion	**81.9%**	78.2%	81.3%	96.7%
MNIST	**91.2%**	90.4%	91.3%	99.2%

- **The visualization on aortic stenosis dataset**
  - 168 CT scan data. 75% for training.



- **The Classification Accuracy on aortic stenosis dataset**

	Native Model (126)				Randomly Generated (+1134)			
Fold	Accu.	Sens.	Spec.	F1	Accu.	Sens.	Spec.	F1
1	64.29	52.17	78.95	61.54	69.05	60.87	78.95	68.29
2	56.96	47.26	66.67	48.65	64.29	61.90	66.67	60.00
3	57.14	50.00	63.64	52.63	71.43	52.94	84.00	58.82
4	59.52	55.00	63.64	56.41	64.29	60.00	68.18	60.00
Ave	**59.48**	51.11	68.23	54.81	**67.27**	58.93	74.45	61.78

	AISEL (+1134)				Randomly Generated (+10000)			
Fold	Accu.	Sens.	Spec.	F1	Accu.	Sens.	Spec.	F1
1	76.19	73.91	78.95	74.42	78.57	78.26	78.95	77.27
2	73.81	76.19	71.43	71.43	76.19	71.43	80.95	73.17
3	80.95	76.47	84.00	76.92	85.71	82.35	88.00	82.05
4	71.43	75.00	68.18	69.77	73.81	70.00	77.27	70.00
Ave	**75.60**	75.39	75.64	73.14	**78.57**	75.51	81.29	75.62

Conclusion

- **This paper proposes an active image synthesis method to generate informative images.**

- **Propose a generative invertible network (GIN) to generate images with small training data, and map the real images to the latent features.**

- **Propose an active sampling method which considers both uncertainty and diversity (by energy distance) to select informative features for image generation.**

THANKS