深圳大学
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Semi-Supervised GANs with Complementary Generator Pair for Retinopathy Screening

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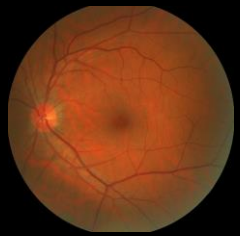
Background

- Several typical types of retinopathy are major causes of blindness

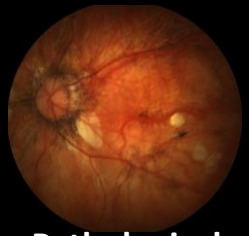
- Visible retinal microvascular changes may reflect the pathophysiological process of systemic diseases

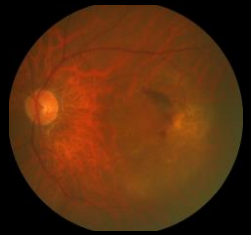
Background

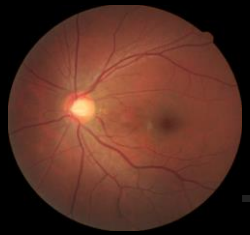
- **Challenge**
  - Some scattered micro-aneurysm lesions may only occupy dozens of pixels.
  - Due to privacy and high labor-cost of reliable annotation, labeled fundus images are incredibly scarce compared to natural images, while a plethora of unlabeled fundus images is unused.


Health


High Myopia


Pathological Myopia

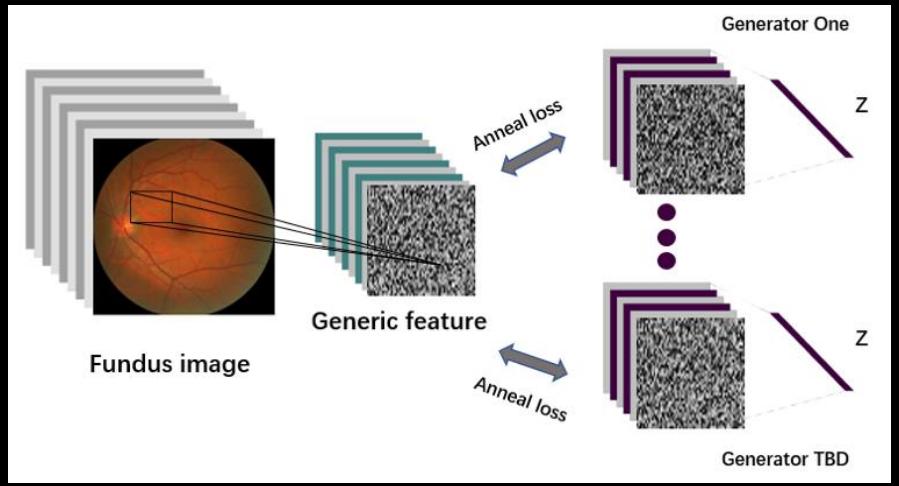

AMD

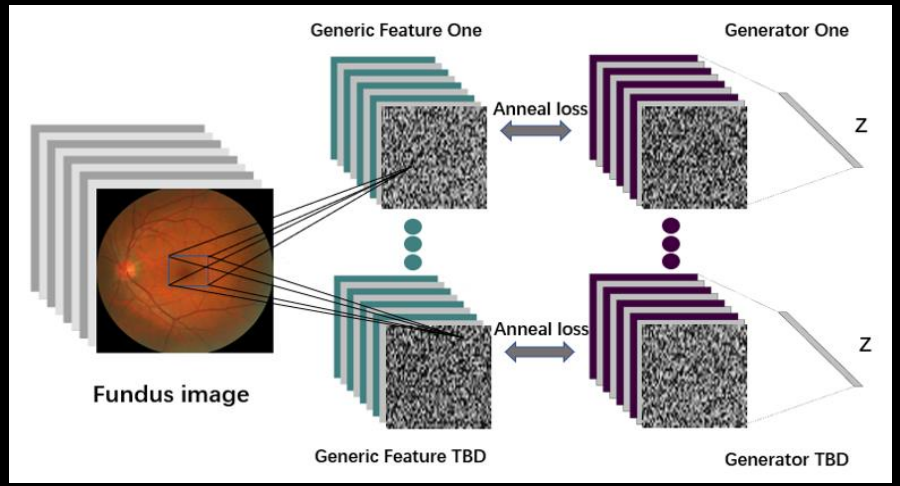

Glaucoma

Method

- **Feature Extractor**

	B0	B1	B2	B3	B4	B5	B6	B7	B8	L2-475	L2
Baseline preprocessing	76.8% (ckpt)	78.8% (ckpt)	79.8% (ckpt)	81.0% (ckpt)	82.6% (ckpt)	83.2% (ckpt)					
AutoAugment (AA)	77.3% (ckpt)	79.2% (ckpt)	80.3% (ckpt)	81.7% (ckpt)	83.0% (ckpt)	83.7% (ckpt)	84.2% (ckpt)	84.5% (ckpt)			
RandAugment (RA)						83.9% (ckpt)		85.0% (ckpt)	85.4% (ckpt)		
AdvProp + AA	77.6% (ckpt)	79.6% (ckpt)	80.5% (ckpt)	81.9% (ckpt)	83.3% (ckpt)	84.3% (ckpt)	84.8% (ckpt)	85.2% (ckpt)	85.5% (ckpt)		
NoisyStudent + RA	78.8% (ckpt)	81.5% (ckpt)	82.4% (ckpt)	84.1% (ckpt)	85.3% (ckpt)	86.1% (ckpt)	86.4% (ckpt)	86.9% (ckpt)	-	88.2% (ckpt)	88.4% (ckpt)





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Method

- **Generative Adversarial Networks**

$$\min_G \max_D V(G,D) = E_{x \in P_{\text{data}}(x)}[\log D(x)] + E_{z \in P(z)}[\log(1 - D(G(z)))]$$

$$\begin{cases} \max_D V(D) = \frac{1}{\mathrm{m}} \sum_{i=1}^{m} [\log D(x^{(i)}) + \log(1 - D(G(z^{(i)})))] \\ \min_G V(G) = \frac{1}{m} \sum_{i=1}^{m} \log(1 - D(G(z^{(i)}))) \end{cases}$$

- **Semi-supervised GANs**

$$L_{Total} = L_{Supervised} + L_{Minmax}$$

$$\begin{cases} L_{Supervised} = -E_{x,y \sim P_{data}(x)} \log[D(y|x, y < K+1)] \\ \min_G \max_D V(G,D) = E_{x \in P_{\text{data}}(x)}[\log D(x)] + E_{z \in P(z)}[\log(1 - D(G(z)))] \end{cases}$$

Method

- **Convergence conditions**

① For $x,\ y\ \epsilon\ P_{data}(x)$, while $y \neq k$, $w_y{}^T f(x) > w_k{}^T f(x)$

② For $z\ \epsilon\ P_{noise}(z)$, $w_{K+1}{}^T f(G(z)) > \max_{k=1}^{K} w_k{}^T f(G(z))$

③ For $x\ \epsilon\ P_{data}(x)$, $\max_{k=1}^{K} w_k{}^T f(x) > w_{K+1}{}^T f(x)$

Improved Method:

- Ent: $$\max_D\ E_{x\epsilon P_{data}}\left[\sum_{k=1}^{K} D_k(x)\log D_k(x)\right]$$
- Dynamic CE: $$\max_D\ E_{x\epsilon P_{data}}[\log D_i(x) | i = y_{\max}(x)]$$

Method

- “Bad” Generator

$$L_{Generator}^{Bad} = L_{FM} + L_{PT}$$

$$= \left\| E_{z \epsilon P_{noise}} f(G(z)) - E_{x \epsilon P_{unlabeled}} f(x) \right\|^2$$

$$+ \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} \left(\frac{f(G(z)_i)^T f(G(z)_j)}{\|f(G(z)_i)\| \|f(G(z)_j)\|} \right)^2$$

- “Good” Generator

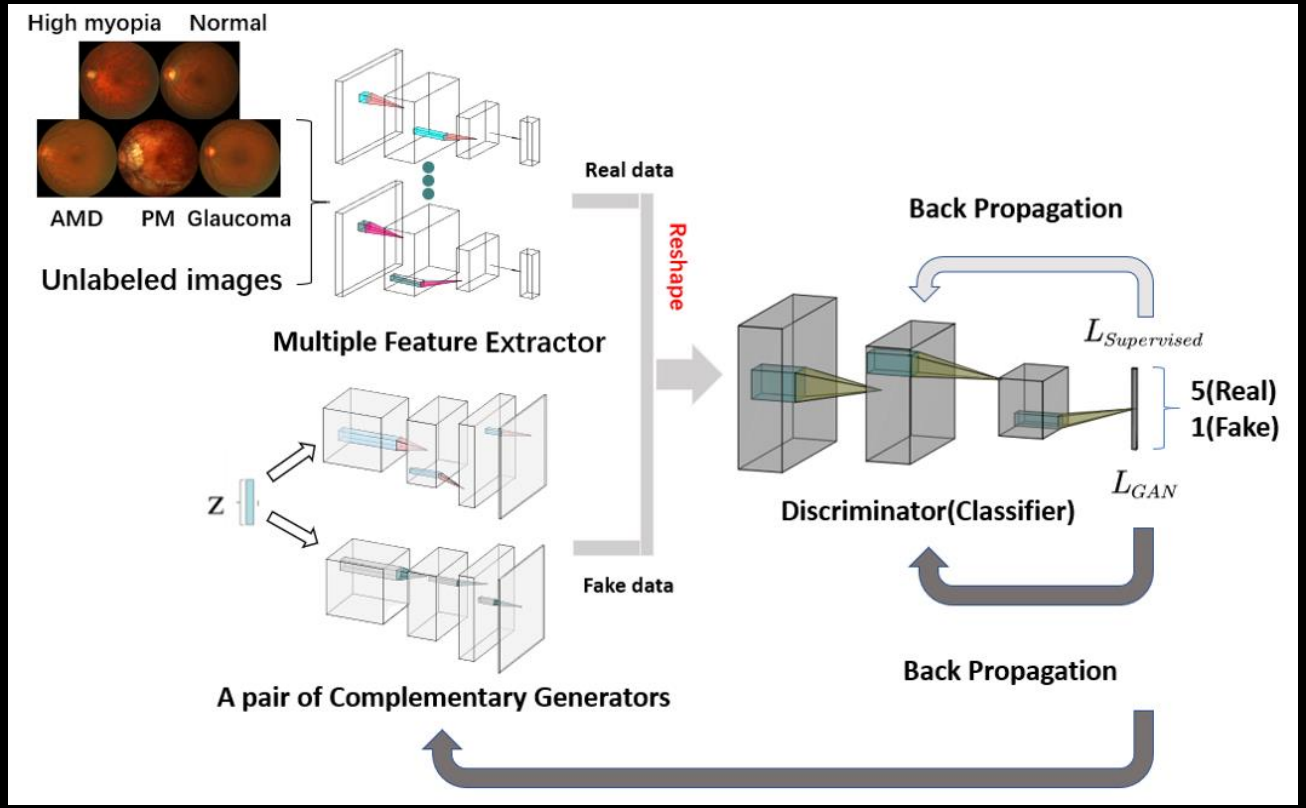
$$L_{Generator}^{Good} = - E_{z \epsilon P_{noise}} [\log D_i(G(z)) | i = y_{\max}(G(z))]$$

Where:

$$y_{\max}(x) = arg \max_{y \epsilon \{1, \ldots, K\}} D_k(x)$$

Method

The framework of our proposed GBGANs



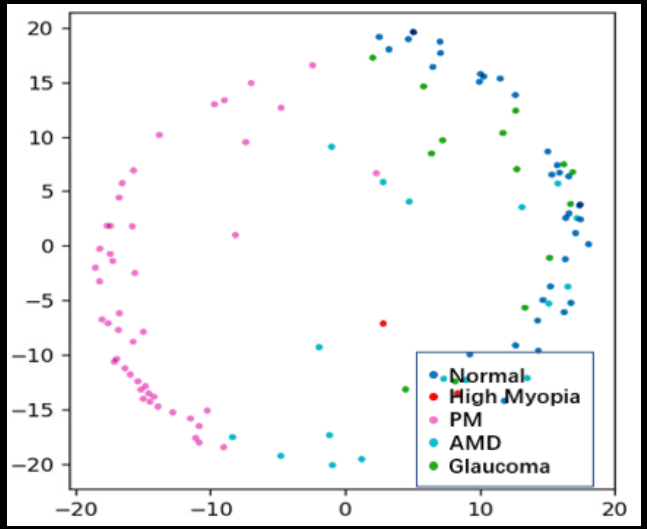
Dataset

Type	Source	Amount	Total
Health	iChallenge-PM	161	569
High Myopia		26	
Pathological Myopia		213	
Glaucoma	iChallenge-GON	87	
AMD	iChallenge-AMD	87	
Unlabeled	iChallenge	2631	2631

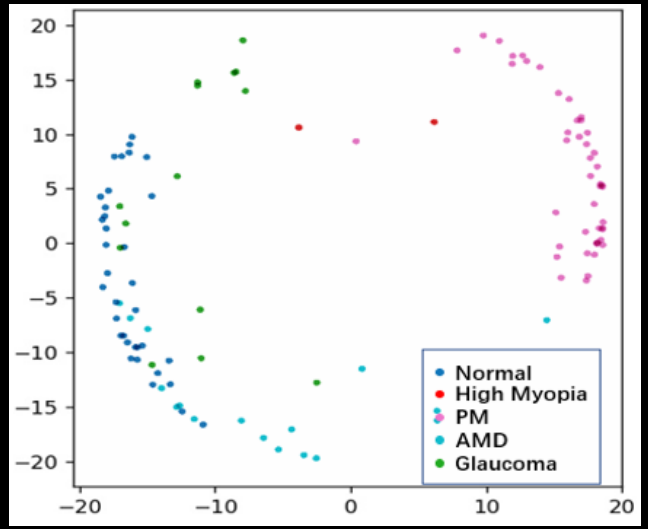
All of the 3200 images are all centered at the posterior pole with both macula and optic disc in the field, each image was cropped to a square shape which included the most tightly contained circular area of the retinal fundus, and the image sizes are 1444 × 1444, 1634 × 1634 and 2124 × 2056 respectively.

Result

Dimensionality reduction by t-SNE.

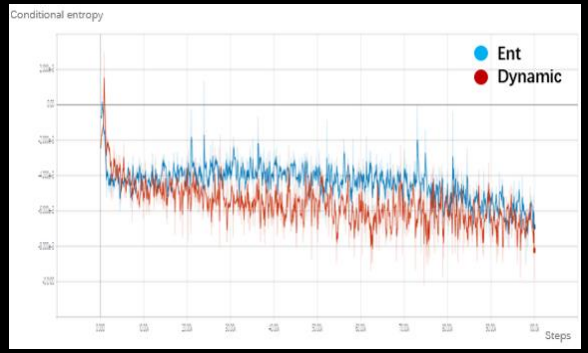


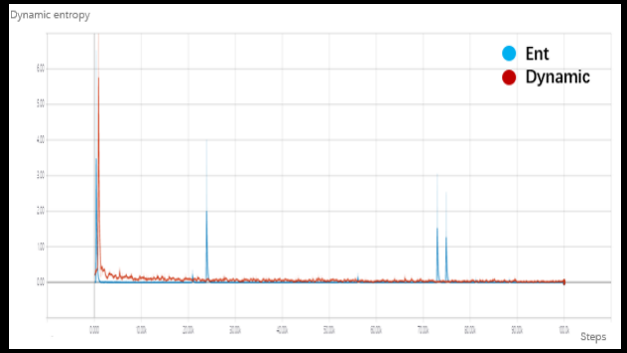
(a) Pooled features extracted by the feature extractor



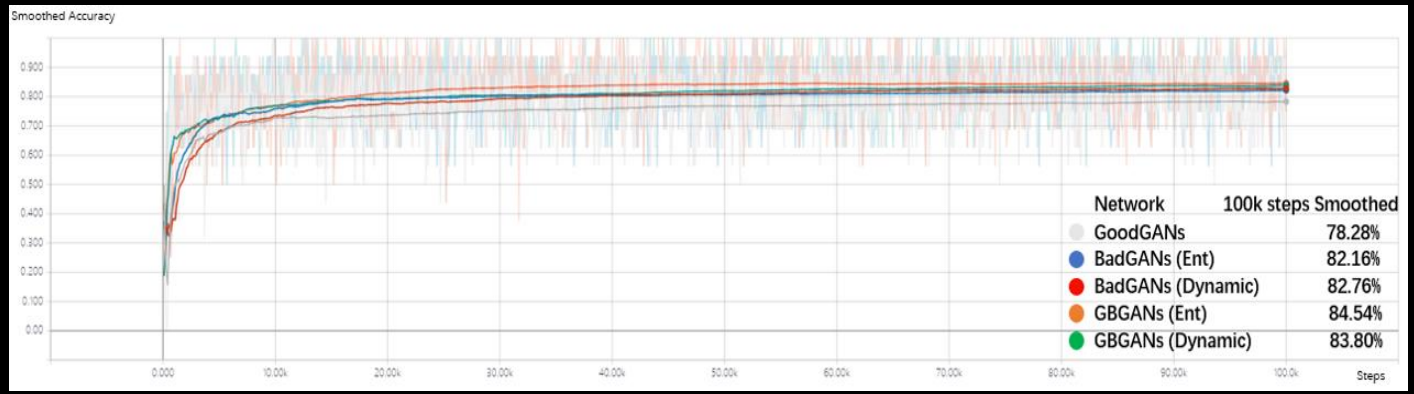
(b) Flattened features learned by the discriminator

Result





Trend of conditional entropy and dynamic entropy during the training process.

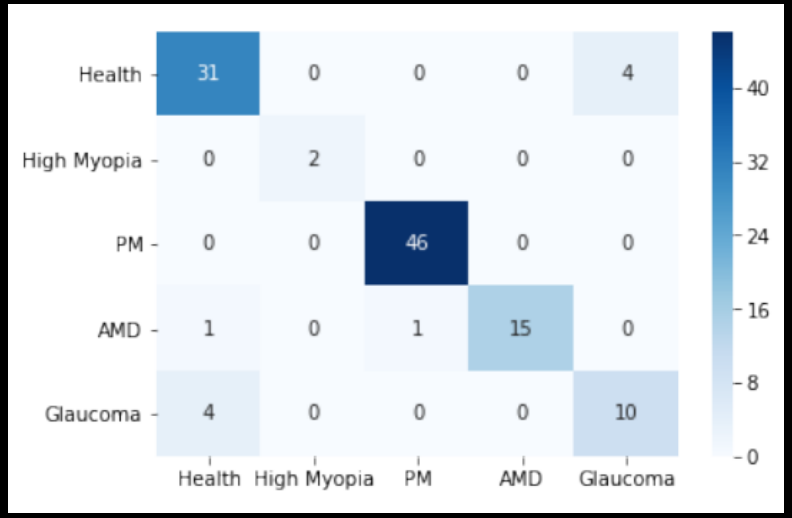


Comparison on the trend of smoothed accuracy on validation set among GoodGANs (AMGANs), BadGANs, and our GBGANs during the training process.

Result

Comparison with other SSL-GANs based methods for retinopathy screening.

Method	Accuracy	Macro-F1	Cohen kappa score
SSGANs	0.8722	0.8711	0.8260
FMGANs	0.8860	0.8158	0.8375
AMGANs(GoodGANs)	0.8421	0.8114	0.7689
BadGANs	0.9035	0.8645	0.8634
GBGANs(Our method)	**0.9123**	**0.9029**	**0.8750**



Confusion matrix of retinopathy screening results.

Thanks!