ReSynthDetect: A Fundus Anomaly Detection Network with Reconstruction and Synthetic Features

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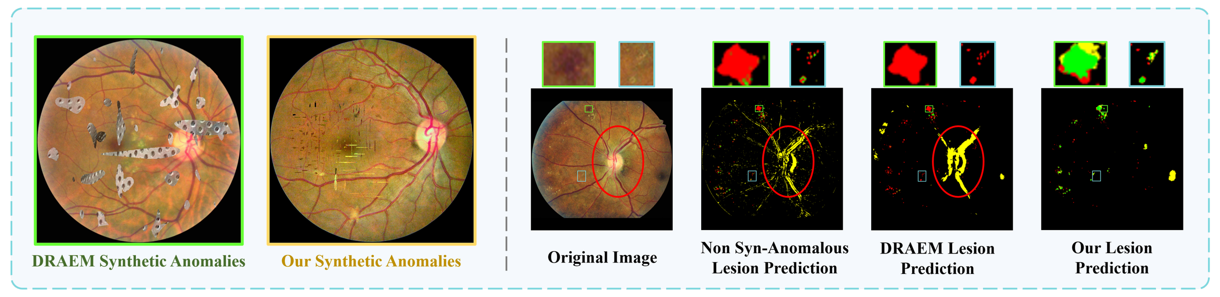
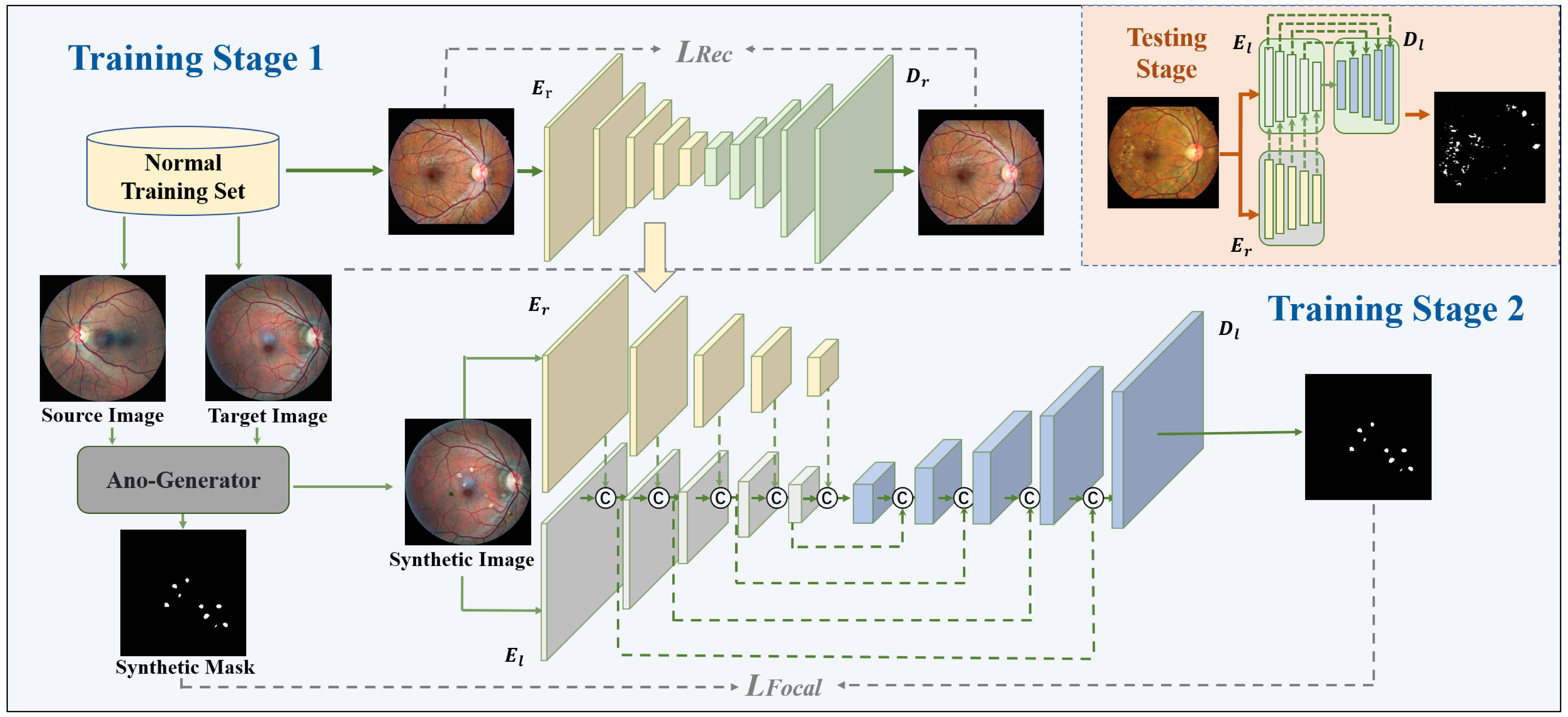
Overview



Problem: •Recent anomaly detection works can hardly learning *abnormality representations* and distinguishing *subtle lesions*
•*Existing* synthetic based anomaly detection works may produce *inconsistent anomalies*.
Challenge: Abnormality Representations.
Method: •ReSynthDetect, a novel method that combines *reconstruction* and *synthetic* features to detect anomalies.
•Consistent anomaly generator capable of producing *diverse and consistent* synthetic anomalies in fundus images.
Results: Our experiments reveal significant improvements, with a 9% increase in AUROC on EyeQ and a 17.1% boost in AUPR on IDRiD.

Our Model



Stage 1 : We train an autoencoder to reconstruct input images, thereby acquiring reconstruction features.
Stage 2 : Guided by these reconstruction features, we develop a localization network dedicated to the proxy task of localizing synthetic anomalies.

Loss Function

- Reconstruction Loss for Stage One:

$$L_{Rec} = \|D_r(E_r(\boldsymbol{I})) - \boldsymbol{I}\|_2^2.$$

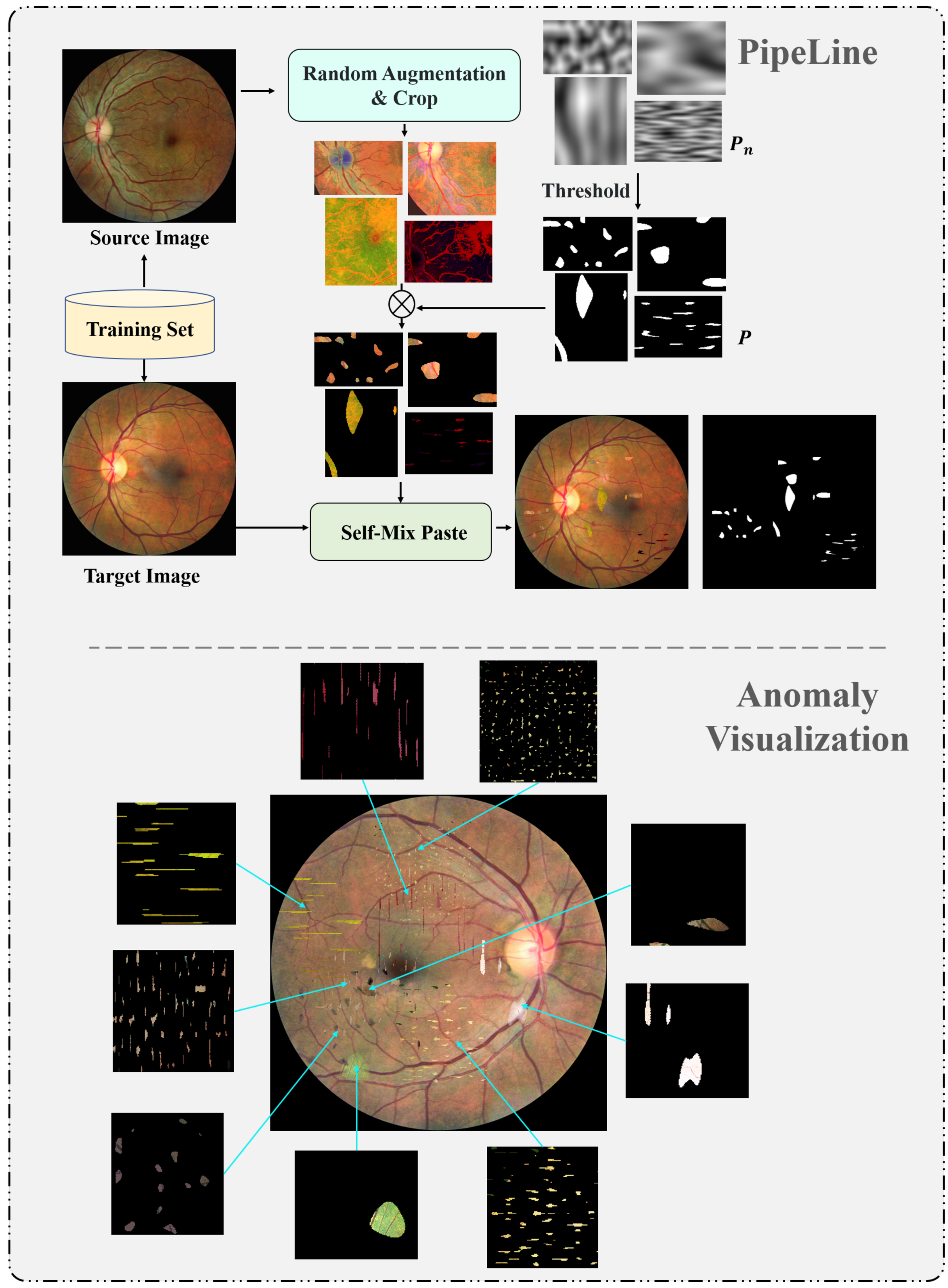
where E_r and D_r denote encoder and decoder of the reconstruction network.

- Focal Loss for Stage Two:

$$\begin{cases} -(1-p)^\tau \log(p), & M_G^{x,y} = 1, \\ -p^\tau \log(1-p), & M_G^{x,y} = 0. \end{cases}$$

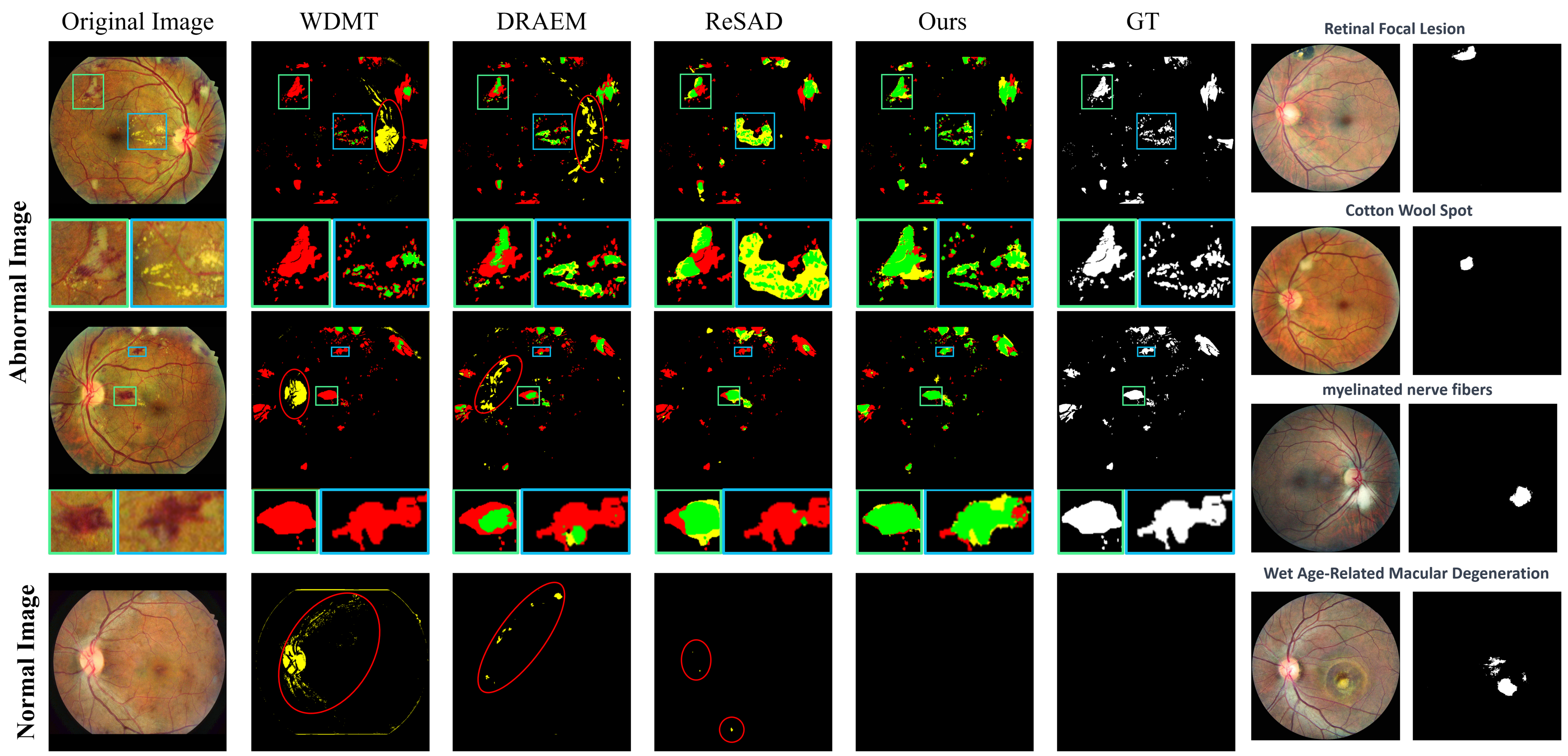
where p represents the probability of anomaly at position (x, y) predicted by the model, and τ is a tunable focusing parameter.

Anomaly Generator



Source : Normal fundus to generate lesions.
Fusion : Fusion map for consistent Anomaly.
Mask : Random Perlin noise for shape diversity.

Visualization



Existing methods WDMT and DRAEM misclassify normal fundus structures as anomalies. ReSAD lacks precise localization, leading to more false positives.
Our method outperforms baseline methods, detecting various lesion types with fine-grained localization. Demonstrates strong generalization across multiple lesion types.

Experiment

Method	0&1	0&2	0&3	0&4	0&all
fAnoGAN	0.50	0.49	0.52	0.57	0.51
MKD	0.58	0.54	0.62	0.70	0.54
DRAEM	0.58	0.65	0.74	0.71	0.61
Les2Void	0.56	0.62	0.87	0.90	0.63
Ours	0.55	**0.76**	**0.94**	**0.91**	**0.72**

•**Image-level**:Our approach surpasses the previous best SOTA method by 9% on EyeQ.

Method	AUROC	ACC	AUPR
fAnoGAN	0.75	0.68	0.04
MemAE	0.74	0.59	0.05
WDNet	0.77	0.56	0.07
DRAEM	0.82	0.74	0.10
ReSAD	0.90	0.81	0.25
Ours	**0.93**	**0.85**	**0.42**

•**Pixel-level**:Our approach yields a 2.6% higher AUROC, 4% higher ACC, and a 17.1% AUPR boost on IDRiD anomaly detection.