**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.

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**VISUALIZATION**

- **Original Image**: Normal fundus to generate lesions.
- **WDMT**
- **DRAEM**
- **ReSAD**
- **Ours**
- **GT**

**Abnormal Image**

**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.

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**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.

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**EXPERIMENT**

- **Method**
  - fAnoGAN
  - MemAE
  - WNet
  - DRAEM
  - Les2Void
  - Ours

- **AUROC**
  - 0.75
  - 0.74
  - 0.77
  - 0.82
  - 0.90
  - 0.93

- **ACC**
  - 0.68
  - 0.59
  - 0.56
  - 0.81
  - 0.85
  - 0.85

- **AUPR**
  - 0.04
  - 0.05
  - 0.07
  - 0.25
  - 0.42

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

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

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**ANOMALY GENERATOR**

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

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**LOSS FUNCTION**

- **Reconstruction Loss for Stage One**:
  \[ L_{\text{Rec}} = ||D_r(E_r(I)) - I||_2^2. \]
  where \( E_r \) and \( D_r \) denote encoder and decoder of the reconstruction network.

- **Focal Loss for Stage Two**:
  \[ -(1 - p)^\tau \log(p), \quad M_{G,x,y}^1 = 1, \]
  \[ -p^{\tau} \log(1 - p), \quad M_{G,x,y}^0 = 0. \]
  where \( p \) represents the probability of anomaly at position \((x, y)\) predicted by the model, and \( \tau \) is a tunable focusing parameter.