A Multi-task Network with Weight Decay Skip Connection Training for Anomaly Detection in Retinal Fundus Images

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MICCAI2022 Singapore

Abstract

By introducing the skip connection to bridge the semantic gap between encoder and decoder, U-shape architecture has been proven to be effective for recovering fine-grained details in dense prediction tasks. However, such a mechanism cannot be directly applied to reconstruction-based anomaly detection, since the skip connection might lead the model overfitting to an identity mapping between the input and output. In this paper, we propose a weight decay training strategy to progressively mute the skip connections of U-Net, which effectively adapts U-shape network to anomaly detection task. Thus, we are able to leverage the modeling capabilities of U-Net architecture, and meanwhile prevent the trained model from bypassing low-level features. Furthermore, we formulate an auxiliary task, namely histograms of oriented gradients (HOG) prediction, to encourage the framework to deeply exploit contextual information from fundus images. The HOG feature descriptors with three different resolutions are adopted as the auxiliary supervision signals. The multi-task framework is dedicated to enforce the model to aggregate shared significant commonalities and eventually improve the performance of anomaly detection. Experimental results on Indian Diabetic Retinopathy Image Dataset (IDRiD) and Automatic Detection challenge on Age-related Macular degeneration dataset (ADAM) validate the superiority of our method for detecting abnormalities in retinal fundus images.

Motivation

- Auto-encoder networks with **skip connection** (e.g., U-Net) have achieved wide successes in biomedical image segmentation. However, they are not applied in most existing reconstruction-based anomaly detection methods. ***Whether the skip connection can be helpful for improving the anomaly detection performance?***
- Recent research has revealed the effectiveness of histograms of oriented gradients (HOG) prediction for self-supervised representation learning. ***Whether the HOG prediction task can serve the image reconstruction (main task) as auxiliary and assist the anomaly detection?***
- To address the above two questions, we designed a multi-task network with weight decay skip connection (WDMT-Net) for anomaly detection with retinal fundus images.

Conclusion

- A weight decay training strategy was proposed to effectively adapt U-shape network for the anomaly detection task, which prevented the model from overfitting to the identity mapping introduced by skip connections.
- An auxiliary HOG prediction task was integrated to our framework to explore the effectiveness of multi-task learning. Such a multi-task framework was dedicated to enforce the model to aggregate shared commonalities between these two tasks and finally improve the performance of anomaly detection.

Code (Github)

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Method

1. Construct Weight Decay Skip Connection

$$M_i = (\alpha \otimes E_i) \oplus ((1-\alpha) \otimes D_i),$$

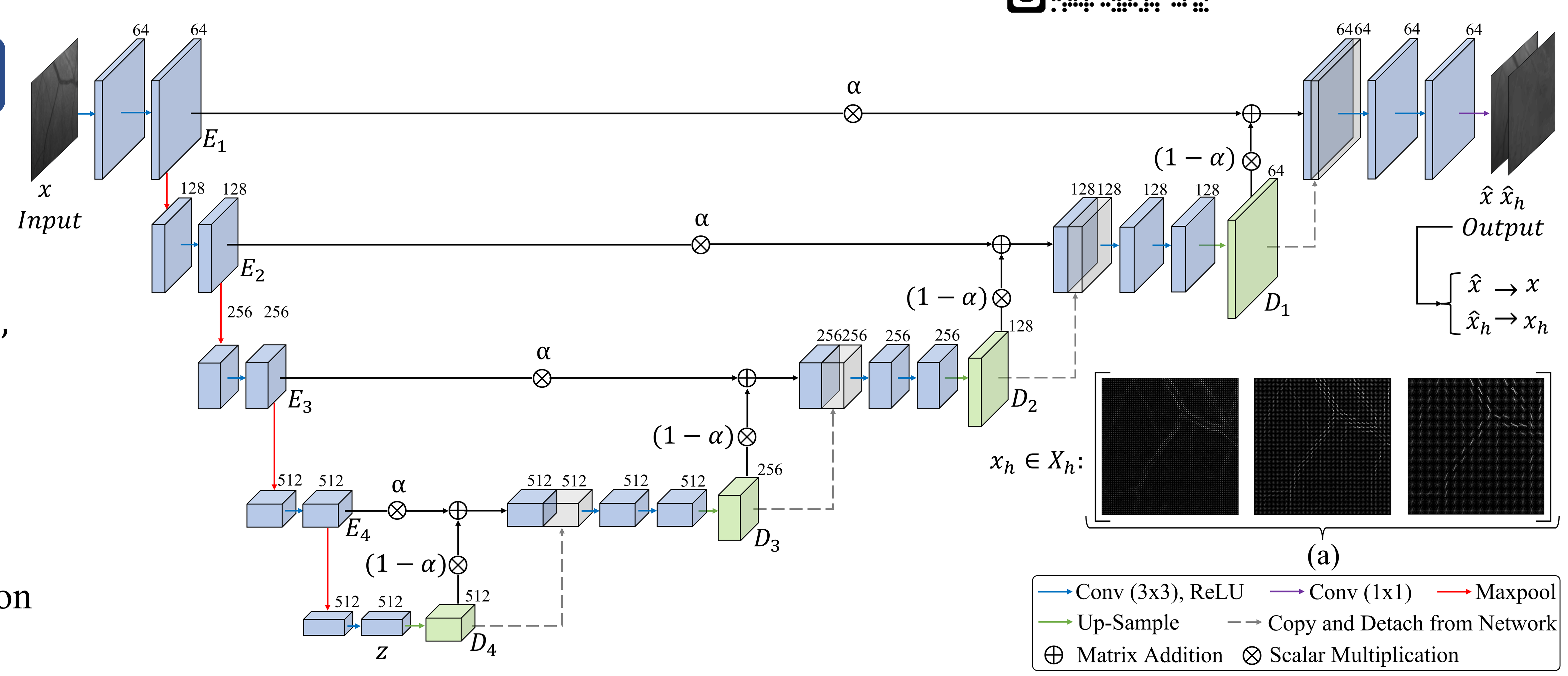
$$D_i' = Concat(M_i, \bar{D}_i),$$

2. Learning Objective

$$\mathcal{L} = \|\hat{x} - x\|_2^2 + \|\hat{x}_h - x_h\|_2^2,$$

3. Score Map for Anomaly Detection

$$\mathcal{A}_M = |\hat{x} - x|$$



(a) Examples of HOG features with different cell sizes: images from left to right are the HOG features obtained by cell sizes of 4×4, 8×8, and 16×16 pixels, respectively.

Experimental Results

Table 1. Ablation study of our WDMT-Net.

Model	Combination			IDRiD [13]			ADAM [4]		
	SC	WD	HOG	AUC	ACC	F1-score	AUC	ACC	F1-score
Auto-Encoder [2]				0.686	0.627	0.537	0.659	0.637	0.469
U-Net [14]	✓			0.553	0.564	0.532	0.610	0.619	**0.530**
WDMT-Net w/o HOG	✓	✓		0.725	0.667	0.680	0.670	0.654	0.484
Auto-Encoder			✓	0.715	0.655	0.664	0.662	0.643	0.470
U-Net	✓		✓	0.640	0.597	0.539	0.656	0.641	0.451
WDMT-Net (*Ours*)	✓	✓	✓	**0.748**	**0.694**	**0.711**	**0.687**	**0.660**	0.474

(SC, WD and HOG represent the used of skip connection, weight decay training strategy and HOG prediction)

Table 2. Impact of the decay rate Δ of the skip connection in our WDMT-Net.

Decay setting	IDRiD [13]			ADAM [4]		
	AUC	ACC	F1-score	AUC	ACC	F1-score
$\Delta = 0.005$	0.729	0.661	0.687	0.676	0.663	0.451
$\Delta = 0.01$	0.738	0.685	0.692	0.678	0.662	**0.482**
$\Delta = 0.025$	0.731	0.674	0.680	0.673	**0.663**	0.465
$\Delta = 0.05$	**0.748**	**0.694**	**0.711**	**0.687**	0.660	0.474
$\Delta = 0.1$	0.724	0.669	0.709	0.674	0.660	0.471

Table 3. Quantitative comparison of our WDMT-Net with the SOTA methods

Method	IDRiD [13]			ADAM [4]		
	AUC	ACC	F1-score	AUC	ACC	F1-score
Auto-Encoder [2]	0.686	0.627	0.537	0.659	0.637	0.469
MemAE [6]	0.647	0.592	0.567	0.667	0.647	0.439
BiO-Net [20]	0.606	0.563	0.519	0.642	0.612	0.481
Attn U-Net [11]	0.581	0.555	0.558	0.645	0.617	0.408
AnoGAN [17]	0.630	0.618	0.579	0.677	**0.661**	0.455
f-AnoGAN [16]	0.698	0.686	0.637	0.662	0.638	0.455
GANomaly [1]	0.652	0.633	0.658	0.673	0.618	**0.539**
Sparse-GAN [22]	0.663	0.638	0.651	0.667	0.627	0.500
ProxyAno [23]	0.701	0.682	0.649	0.675	0.648	0.451
WDMT-Net (*Ours*)	**0.748**	**0.694**	**0.711**	**0.687**	0.660	0.474