RFormer: Transformer-based Generative Adversarial Network for Real Fundus Image Restoration on A New Clinical Benchmark

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Abstract

Ophthalmologists have used fundus images to screen and diagnose eye diseases. However, different equipments and ophthalmologists pose large variations to the quality of fundus images. Low-quality (LQ) degraded fundus images easily lead to uncertainty in clinical screening and generally increase the risk of misdiagnosis. Thus, real fundus image restoration is worth studying. Unfortunately, real clinical benchmark has not been explored for this task so far. In this paper, we investigate the real clinical fundus image restoration problem. Firstly, We establish a clinical dataset, Real Fundus (RF), including 120 low- and high-quality (HQ) image pairs. Then we propose a novel Transformer-based Generative Adversarial Network (RFormer) to restore the real degradation of clinical fundus images. The key component in our network is the Window-based Self-Attention Block (WSAB) which captures non-local self-similarity and long-range dependencies. To produce more visually pleasant results, a Transformer-based discriminator is introduced. Extensive experiments on our clinical benchmark show that the proposed RFormer significantly outperforms the state-of-the-art (SOTA) methods. In addition, experiments of downstream tasks such as vessel segmentation and optic disc/cup detection demonstrate that our proposed RFormer benefits clinical fundus image analysis and applications. The dataset, code, and models will be released.

1. introduction

Due to the safety and cost-effectiveness in acquiring, fundus images are widely used by ophthalmologists for early eye disease detection and diagnosis, including glaucoma [11, 43, 49, 54], diabetic retinopathy [24, 29, 48], cataract [15, 76], and age-related macular degeneration [2, 51]. However, different equipments and ophthalmologists pose large variations to the quality of fundus images. A screening study of 5,575 patients found that about 12% of fundus images are of inadequate quality to be readable by ophthalmologists [52]. We analyze the factors causing the degradation in real fundus image capturing. Firstly, patients, especially infant patients, do not cooperate with the capturing process of fundus images. Specifically, most patients are reluctant to undergo pupil dilation, which causes

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Secondly, by a bright light during flash photography. Patients usually cannot resist the eye-closing reflex caused by low-quality (LQ) fundus images. Besides, infant patients are under-developed or developing countries. As a result, low-precision and portable fundus cameras are used to capture LQ fundus images. These LQ fundus images easily mislead the clinical diagnosis and lead to unsatisfactory results of downstream tasks like blood vessels segmentation. Various markers and biomarkers of the retina (e.g., hemorrhage, microaneurysm, exudate, optic nerve and cup) are essential in different diseases. Hence, it is necessary to ensure the prominence and visibility of each marker for precise clinical diagnosis. Thus, when LQ fundus images are captured, ophthalmologists often repeat dozens of shots until HQ fundus images are obtained. Nonetheless, this repeated capturing process harms patients, degrades hospital efficiency, prevents reliable diagnosis of ophthalmologists, and impacts automated image analysis systems.

We observe the clinical fundus images and find that the main degradation types of LQ images include out-of-focus blur, motion blur, artifact, over-exposure, and over-darkness. Compared with other types of degradation, blur, especially out-of-focus blur, poses the most severe threat to image analysis and clinical diagnosis. An example is shown in Fig. 2, where the uneven illumination, haze, and out-of-focus blur are presented in (a), (b), and (c). It can be observed that the performance of blood vessel segmentation only collapses on out-of-focus blurred fundus images.

Traditional fundus image restoration methods [18, 31] are mainly based on hand-crafted priors. These model-based methods achieve unsatisfactory performance and generality due to the poor representing capacity. Recently, deep Convolutional Neural Networks (CNNs) have been applied to learn the end-to-end mapping function of fundus image restoration. Although impressive results have been achieved, the CNN-based methods [13, 45, 47, 56, 58, 68, 78] show limitations in capturing long-range dependencies. In recent years, the natural language processing (NLP) model, Transformer [63] has been introduced into computer vision and outperformed CNN methods in many tasks. The Multi-head Self-Attention (MSA) module in Transformer excels at modeling non-local similarity and long-range dependencies. This advantage of Transformer may provide a possibility to address the limitations of CNN-based methods.

Existing deep learning methods rely on a large amount of LQ and HQ fundus image pairs. Unfortunately, real clinical benchmark has not been explored for fundus image reconstruction. There remains a data-hungry problem. As shown in Fig. 1 (b), to get more image pairs, artificial degradation models such as Gaussian filter are used to synthesize LQ fundus images from their HQ counterparts. However, as depicted in Fig. 1 (c), artificial degradation is fundamentally different from clinical degradation. As shown in Fig. 1 (d), the two CNN-based methods [13, 58] trained with synthesized data fail in real fundus image restoration.

In this paper, we investigate the real fundus image restoration problem, which has not been studied in the literature. Our work is the first attempt. To begin with, we establish a clinical benchmark, Real Fundus (RF), including 120 LQ and HQ real clinical fundus image pairs to alleviate the data-hungry issue. Based on this dataset, we propose a novel method, namely Transformer-based Generative Adversarial Network (RFormer), for real fundus image restoration. Specifically, the generator and discriminator are built up by the basic unit, Window-based Self-Attention Blocks (WSABs). The self-attention mechanism equipped with each basic block excels at capturing the non-local self-similarity and long-range dependencies, which are the main limitations of existing CNN-based methods. In particular, the generator adopts a U-shape structure to aggregate multi-resolution contextual information. Unlike previous CNN-based Generative Adversarial Networks (GANs), we adopt a Transformer-based discriminator to extract non-local image prior information and thus improve the ability of discriminator to distinguish restored fundus images from the ground-truth HQ fundus images. Our Transformer-based adversarial training scheme encourages the generator to create more plausible-looking natural and visually-pleasant images with more detailed contents and structural textures.

Our contributions can be summarized as follows:

- We establish a new clinical benchmark, RF, to evaluate fundus image restoration algorithms in real clinical scenes. To the best of our knowledge, this is the first real fundus image dataset in the literature.
- We propose a novel Transformer-based method, RFormer, for real fundus image restoration. To the best of our knowledge, it is the first attempt to explore the potential of Transformer for this task in the literature.
- Comprehensive experiments demonstrate that our RFormer significantly outperforms SOTA algorithms. Extensive experiments of downstream tasks further validate the effectiveness of our method.

2. Related Work

2.1. Fundus Image Restoration

Traditional fundus image restoration and enhancement methods [18, 31] are mainly based on hand-crafted priors.
2.2. Generative Adversarial Network

Generative Adversarial Network (GAN) is firstly introduced in [23] and has been proven successful in image synthesis [22, 32, 81], and translation [32, 81]. Subsequently, GAN is applied to image restoration and enhancement, e.g., super resolution [3, 26, 28, 37, 56, 65, 78], deraining [53], enlighten [35, 73], dehazing [25, 27, 40], image inpainting [74, 79], style transfer [38, 81], image editing [71, 72], and mobile photo enhancement [12, 75]. Although GAN is widely applied in low-level vision, few works are dedicated to improving the underlying framework of GAN, such as replacing the traditional CNN framework with Transformer. Jiang et al. [34] propose the first Transformer-based GAN, TransGAN, for image generation. Nonetheless, to the best of our knowledge, the Transformer-based GAN has not been involved in fundus image restoration.

2.3. Vision Transformer

Transformer is firstly proposed by [63] for machine translation. Recently, Transformer has achieved great success in high-level vision, such as image classification [1, 16, 17, 44, 69], semantic segmentation [7, 44, 69, 80], human pose estimation [5, 6, 39, 41, 46, 70], object detection [9, 14, 30, 44, 82], etc. Due to the advantage of capturing long-range dependencies and excellent performance in many high-level vision tasks, Transformer has also been introduced into low-level vision [8, 10, 42, 67]. SwinIR [42] uses Swin Transformer [44] blocks to build up a residual network and achieve SOTA results in natural image restoration. Chen et al. [10] propose a large model IPT pre-trained on large-scale datasets with a multitask learning scheme. MST [4] presents a spectral-wise Transformer for hyperspectral image reconstruction. Although Transformer has achieved impressive results in many tasks, its potential in fundus image restoration remains under-explored.

3. Methodology

3.1. RFormer Architecture

The architecture of RFormer is shown in Fig. 3, where (a) and (b) depict the generator and discriminator. Fig. 3 (c) shows the proposed Window-based Self-Attention Blocks (WSABs), which consists of a Feed-Forward Network (FFN) (detailed in Fig. 3 (d)), a Window-based Multi-head Self-Attention (W-MSA), and two layer normalization.
The generator adopts a U-shaped [55] architecture including an encoder, a bottleneck, and a decoder. The input LQ image is denoted as $I_{LQ} \in \mathbb{R}^{H \times W \times 3}$. Firstly, the generator exploits a projection layer consisting of a $3 \times 3$ convolution (conv) and LeakyReLU to extract shallow feature $I_0 \in \mathbb{R}^{H \times W \times C}$. Secondly, 4 encoder stages are used for deep feature extraction on $I_0$. Each stage is composed of two consecutive WSABs and one downsampling layer. We adopt a $4 \times 4$ conv with stride 2 as the downsampling layer to downscale the spatial size of feature maps and double the channel dimension. Thus, the feature of the $i$-th stage in the encoder is denoted as $X_{i} \in \mathbb{R}^{\frac{H}{2^i} \times \frac{W}{2^i} \times 2^iC}$. Here, $i = 0, 1, 2, 3$ indicates the four stages. Thirdly, $X_3$ undergoes the bottleneck that consists of two WSABs. Subsequently, following the spirits of U-Net, we customize a symmetrical decoder, which also contains 4 stages. Each stage of the decoder is also composed of two WSABs and one upsampling layer. Similarly, the feature maps of the $i$-th stage in the decoder is denoted as $X_i' \in \mathbb{R}^{\frac{H}{2^i} \times \frac{W}{2^i} \times 2^{3-i}C}$. The upsampling layer is a bilinear interpolation followed by a $3 \times 3$ conv layer. To alleviate the information loss caused by downsampling in the encoder, skip connections are used for feature fusion between the encoder and decoder. Finally, after undergoing the decoder, the feature maps pass through a $3 \times 3$ conv layer to generate a residual image $\hat{I} \in \mathbb{R}^{H \times W \times 3}$. Subsequently, the restored fundus image can be obtained by $I_R = I_{LQ} + \hat{I}$.

As shown in Fig. 3 (b), the discriminator aims to distinguish the restored fundus images from ground-truth high-quality fundus images. As analyzed in [32], patch-level GAN is more effective than image-level GAN in capturing high-resolution and fine-grained image information, which is critical for restoring clinical fundus image restoration. Hence, we follow the adversarial training scheme based on image patches as PatchGAN and further propose a Transformer-based discriminator. More specifically, the discriminator employs the same architecture as the encoder in the generator followed by a $3 \times 3$ conv layer. The restored fundus image $I_R \in \mathbb{R}^{H \times W \times 3}$ concatenated with the ground-truth HQ fundus image $I_{HQ} \in \mathbb{R}^{H \times W \times 3}$ undergoes our proposed Transformer-based discriminator to generate the predicted map $F \in \mathbb{R}^{N \times N \times 1}$.

3.2. Window-based Self-Attention Block

The emergence of Transformer provides an alternative to address the limitations of CNN-based methods in modeling non-local self-similarity and long-range dependencies. However, as analyzed in Swin Transformer [44], the computational cost of the standard global Transformer is quadratic to the spatial size of the input feature ($HW$). This burden is nontrivial and sometimes unaffordable. To tackle this problem, we adopt the Window-based Multi-
head Self-Attention (W-MSA) \cite{44} as the self-attention mechanism and integrate it with the basic Transformer unit. The computational complexity of W-MSA is linear to the spatial size, which is much cheaper than that of standard global MSA. The components of our proposed Window-based Multi-head Self-Attention Block (WSAB) are shown in Fig. 3 (c). WSAB consists of a W-MSA, an FFN, and two layer normalization. The details of FFN are shown in Fig. 3 (d). Then WSAB can be formulated as
\[
\begin{align*}
F' &= \text{W-MSA}(\text{LN}(F_{in})) + F_{in}, \\
F_{out} &= \text{FFN}(\text{LN}(F')) + F',
\end{align*}
\]
where $F_{in}$ represents the input feature maps of a WSAB.\text{LN}$(\cdot)$ represents the layer normalization. $F'$ and $F_{out}$ denote the output feature of W-MSA and FFN respectively.

### 3.2.1 Window-based Multi-head Self-Attention

Instead of using global correspondence, we partition the feature map into non-overlapping windows. Subsequently, the token interactions are calculated inside each window. As shown in Fig. 4, given the input feature map $X_{in} \in \mathbb{R}^{H \times W \times C}$ with $H$ and $W$ being the height and the width. We partition $X_{in}$ into $L \times L$ non-overlapping windows. The feature of the $i$-th window is denoted as $X_i \in \mathbb{R}^{L_i \times L_i \times C}$, where $i \in \{1, 2, \cdots, N\}$ and $N = HW/L^2$. $X_i$ is flattened and transposed into $X_i^T \in \mathbb{R}^{L^2 \times C}$. We conduct MSA on $X^T$. Firstly, $X^T$ is linearly projected into query $Q^T$, key $K^T$, and value $V^T \in \mathbb{R}^{L^2 \times C};$

\[
Q^T = X^T W^Q, K^T = X^T W^K, V^T = X^T W^V,
\]

where $W^Q, W^K, W^V \in \mathbb{R}^{C \times C}$ are learnable parameters, denoting the projection matrices of the query, key and value. We respectively split $Q^T, K^T$ and $V^T$ into $k$ heads along the channel dimension: $Q^T = [Q_1^T, \cdots, Q_k^T], K^T = [K_1^T, \cdots, K_k^T]$ and $V^T = [V_1^T, \cdots, V_k^T]$. The dimension of each head is $d_h = C/k$. The Self-Attention (SA) for head $j$ is formulated as

\[
\text{SA}(Q_j^T, K_j^T, V_j^T) = \text{softmax}\left(\frac{Q_j^T K_j^T^T}{\sqrt{d_k}}\right)V_j^T
\]

where $Q_j^T, K_j^T$ and $V_j^T$ respectively represent the query, key and value of head $j$ respectively. The output tokens $X_j^T \in \mathbb{R}^{L^2 \times C}$ of the $j$-th window can be obtained by

\[
X_j^T = \text{Concat}\left(\text{SA}(Q_j^T, K_j^T, V_j^T)\right)W^O + B,
\]

where $\text{Concat}(\cdot)$ denotes the concatenating operation, $B \in \mathbb{R}^{L^2 \times C}$ represents the position embedding, and $W^O \in \mathbb{R}^{C \times C}$ are learnable parameters. We reshape $X_j^T$ to obtain the output window feature map $X_{out} \in \mathbb{R}^{L \times L \times C}$. Finally, we merge all the patch representations $(X_{out}^1, X_{out}^2, X_{out}^3, \cdots, X_{out}^N)$ to obtain the output feature maps $X_{out} \in \mathbb{R}^{H \times W \times C}.$

### 3.2.2 Feed-Forward Network

As illustrated in Fig. 3 (d), the Feed-Forward Network (FFN) is composed of a $1 \times 1$ $\text{conv}$ layer with a GELU activation, a depth-wise $3 \times 3$ $\text{conv}$ layer with a GELU activation, and another $1 \times 1$ $\text{conv}$ layer.

### 3.3. Loss Functions

During the training procedure, we exploit the weighted sum of four loss functions as the overall training objective. They are described and analyzed in the following part.

#### 3.3.1 Charbonnier Loss

The first loss function is the Charbonnier loss between the restored and ground-truth HQ images:

\[
\mathcal{L}_C(I_R, I_{HQ}) = \sqrt{|I_R - I_{HQ}|^2 + \varepsilon^2}
\]

where $I_R$ denotes the restored fundus image, $I_{HQ}$ represents the ground-truth HQ fundus image, and $\varepsilon$ denotes a constant which is empirically set to $10^{-3}$ in experiments.

#### 3.3.2 Fundus Quality Perception Loss

Unlike natural images, fundus images have specific acquisition process and anatomical structures. This indicates fundus images have highly similar styles. Therefore, we exploit high-level feature constraints to improve the perceptual quality and encourage the network to capture the fundus anatomical structures and styles. To this end, we propose Fundus Quality Perception Loss (FQPLoss). More specifically, we adopt VGG-19 \cite{59} as the perception network and pre-train it on the fundus image quality evaluation dataset, Eye-Q \cite{20} with the fundus image quality classification task. The Eye-Q dataset has 28,792 fundus images with three-level quality grading. The perception network trained on the Eye-Q dataset is capable of extracting the difference of high-level features between different qualities of fundus images. Then our FQPLoss can be formulated as

\[
\mathcal{L}_{fqp} = \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} (\phi(I_R(i,j)) - \phi(I_{HQ}(i,j)))^2
\]

where $H$ and $W$ denote the height and width of the fundus image. $\phi(\cdot)$ denotes the feature extraction function of the pre-trained perception network. Our FQPLoss is customized to assess a solution with respect to perceptually relevant characteristics. By minimizing the FQPLoss $\mathcal{L}_{fqp}$, the model is encouraged to capture more high-level discriminative features and generate more visually-pleasant results.

#### 3.3.3 Adversarial Loss

Our proposed Transformer-based discriminator aims to distinguish the restored fundus images from ground-truth HQ fundus images. More specifically, the discriminator outputs
3.3.4 Edge Loss

To enhance the high-frequency edge details, we exploit the edge loss function that focuses on the gradient information of images and enhances edge textures. To be specific, the edge loss function is formulated as

$$L_{edge}(I_R, I_{HQ}) = \sqrt{\|\Delta(I_R) - \Delta(I_{HQ})\|^2 + \epsilon^2}, \quad (8)$$

where $\Delta(\cdot)$ represents the Laplacian operator.

3.3.5 The Overall Loss Function

Finally, the overall training objective is the weighted sum of the above four loss functions:

$$\mathcal{L} = L_1 + \lambda_1 L_{fqp} + \lambda_2 L_{edge} + \lambda_3 (L_{adv}^G + L_{adv}^D), \quad (9)$$

where $\lambda_1, \lambda_2, \lambda_3$ are three hyper-parameters controlling the importance balance of different loss functions. RFormer is end-to-end trained by minimizing $\mathcal{L}$. The weights of the perception network are fixed. Each mini-batch training procedure is divided into two steps: (i) Fix the discriminator and train the generator. (ii) Fix the generator and train the discriminator. This adversarial training scheme encourages the reconstructed fundus images to be more photo-realistic and closer to the real clinical HQ fundus image manifold.

4. Real Fundus

This section introduces our clinical benchmark, Real Fundus (RF), which consists of 120 LQ and HQ clinical fundus image pairs with the spatial size of $2560 \times 2560$. The training and testing subsets are split in proportional to 3:1. Since the blur degradation significantly impacts image analysis, clinical diagnosis and automated image analyzing systems, it is set to the primary degradation type of LQ fundus images. Besides, there are other degradation types such as artifacts and uneven illumination which are inevitably introduced in the fundus image capturing process.

4.1. Data Collecting Process

The collection process of our RF contains three steps: capturing, selecting, and calibrating fundus images.

4.1.1 Capturing

Instead of exploiting artificial degradation models (e.g., Gaussian Filter) to synthesize LQ fundus images as shown in Fig. 1 (b), we directly use the LQ fundus images from the fail cases in practical capturing. As depicted in Fig. 1 (a), the fundus images are captured by ophthalmologists using a ZEISS VISUCAM200 fundus camera. We select clinical fundus images from patients of different ages and different fundus states (e.g., leopard fundus, hemorrhage, microaneurysms, and drusen) to expand the scope of our RF.

4.1.2 Selecting

When LQ fundus images are captured in practice, the operator will repeat capturing until HQ fundus images are obtained. Then we manually select LQ and HQ fundus image pairs of the same eye. To ensure the diversity of RF and avoid similar data, only one image pair is selected with one eye. Note that only HQ clear fundus images captured by experienced ophthalmologists can be used as the ground truths of degraded LQ images. Based on these strict criteria, we finally select 120 LQ and HQ fundus image pairs from the eye hospital database containing more than 30,000 eye instances. Each instance contains multiple fundus images.

4.1.3 Calibrating

After selecting fundus image pairs, we observe two issues in raw unprocessed fundus data. Firstly, the LQ and HQ fundus images are spatially misaligned (as illustrated in Fig. 1(a)). Secondly, there is a large black area around the eyeball. This black area is uninformative and may easily degrade the performance of the restoration model during the training procedure. Thus, to improve the quality of our RF, we calibrate the collected dataset using the software, Photoshop. Specifically, we first spatially align the image pairs and then cut off the black area around the eyeball.

4.2. Comparisons with Synthetic Dataset

4.2.1 LQ Fundus Images

We compare the LQ images from our RF and synthetic dataset in Fig. 1 (c). As can be seen from the zoom-in patches that the artificially synthesized degradation is fundamentally different from the real clinical degradation.
Figure 5. Restored fundus image comparisons of Scene 1 on our RF. Six SOTA methods and our proposed RFormer are included. (a) LQ fundus image. (b) Bicubic+RL [61]. (c) GLCAE [62]. (d) Cofe-Net [58]. (e) ESRGAN [65]. (f) RealSR [33]. (g) I-SECRET [13]. (h) Our proposed RFormer. (i) Ground-truth HQ fundus image. Our RFormer reconstructs more detailed contents and structural textures.

Figure 6. Restored fundus image comparisons of Scene 2 on our RF. Six SOTA methods and our RFormer are included. (a) LQ fundus image. (b) Bicubic+RL [61]. (c) GLCAE [62]. (d) Cofe-Net [58]. (e) ESRGAN [65]. (f) RealSR [33]. (g) I-SECRET [13]. (h) Our proposed RFormer. (i) Ground-truth HQ fundus image. Our RFormer yields more visually pleasant results and restores more edge details.

Table 1. Quantitative comparisons with SOTA algorithms on our RF. PSNR, SSIM, Params, and FLOPS are reported.

| Method            | PSNR  | SSIM  | Params(M) | FLOPS(G) |
|-------------------|-------|-------|-----------|----------|
| Cofe-Net [58]    | 17.26 | 0.789 | 39.31     | 22.48    |
| GLCAE [62]       | 21.37 | 0.570 | –         | –        |
| I-SECRET [13]    | 24.57 | 0.854 | 10.85     | 14.21    |
| Bicubic+RL [61]  | 25.34 | 0.824 | –         | –        |
| ESRGAN [65]      | 26.73 | 0.823 | 15.95     | 18.41    |
| RealSR [33]      | 27.99 | 0.850 | 15.92     | 29.42    |
| RFormer (Ours)   | 28.32 | 0.873 | 21.11     | 11.36    |

4.2.2 Domain Discrepancy

To validate the huge domain discrepancy between the synthetic and real clinical datasets, we adopt two CNN-based fundus image restoration methods, I-SECRET [13] and Cofe-Net [58], to conduct ablation study. We train them with the synthetic data and then test them on our RF. As shown in Fig. 1 (d), the two models fail to reconstruct the real clinical LQ fundus images. They either yield over-smooth results sacrificing detailed contents, or introduce visually unpleasant artifacts. Since the synthetic data can not be applied to real fundus image restoration, it still remains a severe data-hungry issue. To meet with this research requirement, we establish a large scale clinical dataset, RF. To the best of our knowledge, this is the first work contributing a real clinical fundus image restoration benchmark.

5. Experiments

5.1 Implementation Details

During the training procedure, fundus images are first cropped into the patches with the size of 128×128. Then the patches are fed into our proposed RFormer. The Adam [36] optimizer ($\beta_1=0.9$, $\beta_2=0.999$) is adopted. The initial learning rate is set to $1 \times 10^{-4}$ and linearly decreased to $1 \times 10^{-6}$. 

5.2 Ablation Study

Table 1. Quantitative comparisons with SOTA algorithms on our RF.
### Table 2. Ablation Studies

We train and test all the models on our RF. PSNR, SSIM, Params and FLOPS are reported.

| Patch Size | 22 × 22 | 40 × 40 | 46 × 46 | 62 × 62 | 128 × 128 |
|------------|---------|---------|---------|---------|-----------|
| PSNR       | 28.23   | 28.32   | 28.12   | 28.02   | 28.03     |
| SSIM       | 0.866   | 0.873   | 0.827   | 0.862   | 0.796     |

(a) Ablation study of the patch size of our discriminator.

| Discriminator | PatchGAN | PixelGAN | Pixel and Patch | Ours   |
|---------------|----------|----------|-----------------|--------|
| PSNR          | 27.52    | 28.00    | 27.70           | 28.32  |
| SSIM          | 0.822    | 0.790    | 0.839           | 0.873  |

(b) CNN-based vs. our Transformer-based discriminators.

| Window Size | w/o WSAB | 4 × 4 | 8 × 8 | 16 × 16 | 32 × 32 |
|-------------|----------|------|------|--------|--------|
| PSNR        | 14.27    | 28.23| 28.32| 27.82  | 27.63  |
| SSIM        | 0.601    | 0.873| 0.873| 0.819  | 0.812  |
| Params(M)   | 34.53    | 20.67| 21.11| 27.54  | 47.21  |
| FLOPS(G)    | 16.38    | 10.83| 11.36| 13.46  | 18.59  |

(c) Ablation study of the window size of our proposed WSAB.

(b) Ablation study of our FQPLoss. (a) The LQ fundus image. (b) and (c) depict the images restored by RFormers without and with using FQPLoss, respectively. (d) The ground-truth HQ fundus image. Using our FQPLoss, the model restores more detailed anatomical structure contents and high-frequency textures.

ESRGAN [65], I-SECRET [13], and Cofe-Net [58]). The quantitative comparisons on our RF are shown in Table 1, the proposed RFormer outperforms other competitors in terms of PSNR and SSIM. More specifically, RFormer achieves 0.33 and 1.59 dB improvement in PSNR when compared to RealSR [33] and ESRGAN [65].

Fig. 5 and 6 depict the qualitative comparisons on RF. It can be observed that Bicubic+RL [61], GLCAE [62], I-SECRET [13], and Cofe-Net [58] yield over-smooth results and fail to restore the LQ blurry fundus images. Although ESRGAN [65] and RealSR [33] can reconstruct more high-frequency edge details, they do not maintain the authenticity and anatomical structure of the original fundus. Some undesired artifacts are introduced to the restored images, which may severely mislead the clinical diagnosis. In contrast, our RFormer is capable of restoring more fine-grained contents and structural details without introducing artifacts. Thus, the fundus anatomical structure can be well preserved.

### 5.3. Ablation Study

#### 5.3.1 FQPLoss

We adopt RFormer as the restoration model to conduct an ablation study to validate the effect of our FQPLoss. As listed in Table 2 (c), when the FQPLoss is applied, the PSNR and SSIM are increased by 1.07 dB and 0.129, re-

Our RFormer is implemented by PyTorch. It takes about 12h using an NVIDIA RTX 3090 GPU to train our RFormer for 100 epochs. The mini-batch size is set to 4. Random flipping and rotation are used for data augmentation. We adopt peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) [66] as the metrics to evaluate the performance of fundus image reconstruction.

### 5.2. Comparisons with State-of-the-Art Methods

We provide qualitative and quantitative comparisons between our RFormer with six SOTA methods including two model-based methods (GLCAE [62] and Bicubic+RL [61]) and four CNN-based methods (RealSR [33],
5.3.2 Discriminator

We conduct an ablation study to compare our Transformer-based discriminator with Traditional CNN-based discriminators. The Transformer-based generator remains unchanged. The results are reported in Table 2(b). Compared with the discriminators in CNN-based PatchGAN [32], PixelGAN [32], etc, our Transformer-based discriminator yields the best performance. We provide qualitative comparisons in Fig. 7. It can be observed that our Transformer-based discriminator significantly outperforms CNN-based discriminators in terms of recovering detailed contents and preserving the anatomical structure consistency.

5.3.3 Patch Size

We experimentally analyze the effect of the patch size set in the Transformer-based discriminator. The results are shown in Table 2 (a). Our RFormer achieves the best restoration result with the patch size of 40×40.

5.3.4 Window Size

We change the window size of W-MSA and conduct experiments to study its effect. The results are reported in Table 2 (d). It can be observed that our RFormer yields the best result when the window size is set to 8×8.

5.4. Clinical Image Analysis and Applications

The ultimate goal of restoring and enhancing fundus images is to serve the real clinical tasks better and improve the accuracy of clinical diagnosis. To validate the effectiveness of our proposed RFormer, we use it as a pre-processing technique for downstream clinical image analysis tasks, including vessel segmentation and optic disc/cup detection. LadderNet [83] and M-Net [19] are employed as the segmentation baselines.

5.4.1 User Study

Since the restored fundus images should meet the requirements of ophthalmologists, we invite three experienced ophthalmologists to evaluate the quality of images restored by our RFormer and other algorithms [13,33,58,61,62,65]. They agree that our method is superior to other compared
restoration methods in LQ fundus image restoration and auxiliary diagnosis of ophthalmic diseases.

### 5.4.2 Vessel Segmentation

We test LadderNet [83] pre-trained on DRIVE [60] dataset for vessel segmentation on our collected RF. Please note that the vessel segmentation maps of real HQ fundus images serve as the references for comparison due to the lack of segmentation labels on our RF. The vessel segmentation results are shown in the third row of Fig. 9 and 10. As can be seen that LadderNet fails in segmenting the blood vessels of clinical LQ fundus images. In contrast, LadderNet extracts obvious vessel structure of the fundus images restored by our RFormer, which is closest to the segmentation results of real HQ fundus images. These results clearly suggest the effectiveness of our proposed method.

### 5.4.3 Optic Disc/Cup Detection

We also evaluate the effect of our RFormer for the downstream disc/cup detection task. We test M-Net [19] pre-trained on ORIGA [77] dataset for optic disc/cup detection on our collected RF. Similar to the vessel segmentation task, the optic disc/cup detection results of real HQ fundus images function as the references due to the lack of segmentation labels. The qualitative comparisons of different fundus image restoration methods are depicted in Fig. 9 and 10. The fourth line is the optic disc/cup detection map and the fifth line depicts the zoom-in patches of the fourth line. It can be observed that M-Net fails to detect the disc/cup on clinical LQ fundus images. On the contrary, M-Net detects the optic cup and disc more accurately on the fundus images reconstructed by our RFormer. This evidence verifies that our method benefits the optic disc/cup detection task.

### 6. Conclusion

In this paper, we establish the first real clinical fundus image restoration benchmark, Real Fundus, which contains LQ and HQ fundus image pairs to alleviate the data-hungry issue. Our dataset can help better evaluate restoration algorithms in clinical scenes. Based on this dataset, we propose a novel Transformer-based method, RFormer, for clinical fundus image restoration. To the best of our knowledge, it is the first attempt to explore the potential of Transformer in this task. Comprehensive qualitative and quantitative results demonstrate that our RFormer significantly outperforms a series of SOTA methods. Extensive experiments verify that the proposed RFormer serving as a data pre-processing technique can boost the performance of different downstream tasks, such as vessel segmentation and

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**Figure 10. Vessel segmentation and optic disc/cup detection of Scene 4 on our RF.** From top to bottom are fundus images, optic disc/cup patches, vessel segmentation maps, optic disc/cup detection maps, and the zoom-in patches of the optic disc/cup detection maps. (a) LQ fundus image. (b) Bicubic+RL [61]. (c) GLCAE [62]. (d) Cofe-Net [58]. (e) ESRGAN [65]. (f) RealSR [33]. (g) I-SECRET [13]. (h) Our RFormer. (i) HQ fundus image. Our method can improve the performance of vessel segmentation and optic disc/cup detection.
optic disc/cup detection. We hope this work can serve as a baseline for real clinical fundus image restoration and benefit the community of medical imaging.

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