3.3 Results with simple GANs

From Section 1, GANs are also a popular ML architecture to generate super-resolution images. We verified the DenseED model performance in the GANs generator networks. The GAN architecture includes two networks: generator and discriminator. Optimizing both of these networks simultaneously generates the super-resolution images. A simple block diagram of GAN is shown in Fig. 7 which indicates both generator and discriminator networks.

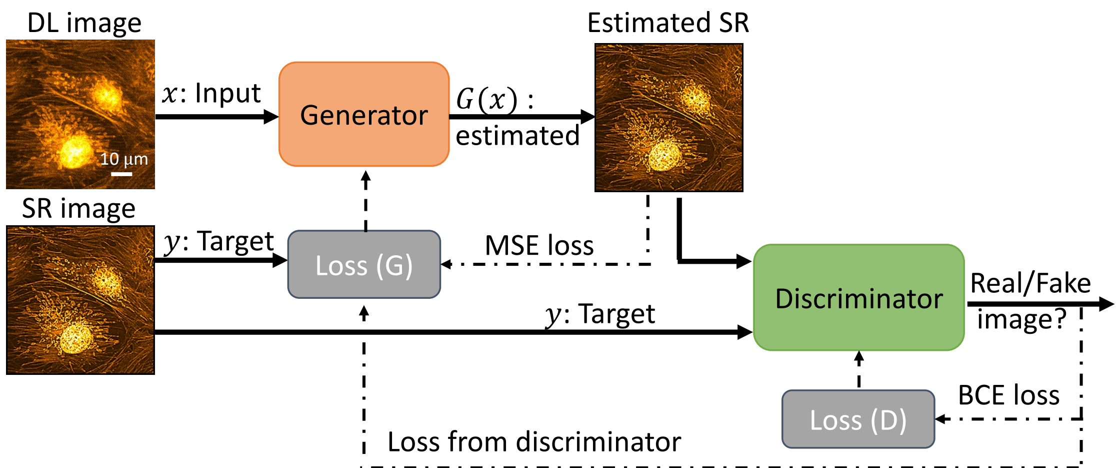

Figure 7: Illustration of simple GAN architecture with generator and discriminator networks. G: generator, D: discriminator, x: DL image as input, and y: target SR image, respectively.

In GANs, the input diffraction-limited image is passed through the generator networks, which contains CNNs similar to FCNs (either AE or U-Net with skip connections or residual connections) to generate the super-resolution image. The discriminator network with a few convolutions followed by the fully connected layers that provides the probability of the generated image is accurate super-resolution or not. In simple terms, the probability value to identify the generator network images as fake image compared to real ground-truth super-resolution image. Discriminator evaluates the binary cross-entropy (BCE) error between the generated and target SR image then updates its network weights. Similarly, the generator network identifies the MSE loss between the estimated and target SR image, including the discriminator network's error. The loss functions used in generator and discriminator networks are given below.

$$\text{Loss}_G = -log(D(G(x))) + \text{MSEloss}(G(x), y) \quad (1)$$

$$\text{Loss}_D = -log(D(y)) - log(1 - D(G(x))) \quad (2)$$

Fig. 7 shows the input diffraction-limited image is indicated as x, the estimated generator network super-resolution output as $G(x)$, target SR image as y, respectively. The discriminator network finds the BCE loss when the estimated SR and target SR images are passed through the discriminator network $(D(.))$. Similarly, the generator network calculates the MSE loss between estimated SR image $G(x)$ and target SR image y, including the loss from discriminator when the estimated SR image $D(G(x))$ passes through the discriminator network. We choose a simple generator as the AE with three encoder and decoder blocks (symmetric structure), respectively.

Similarly, the discriminator network has four convolutional layers (convolution, ReLU, and batch-norm in sequence) and, followed by four fully connected layers, are used to generate a single probability of the generated image looking either real or fake.

An estimated super-resolution image validates the trained GAN architecture accuracy from a diffraction-limited image during the testing phase. Fig. 5(a) shows one of the diffraction-limited images in a testing FOV. Fig. 5(e) shows the super-resolution image estimated by the simple GAN ML model, and Fig. 5(c) is the target SRRF super-resolution image for testing. The PSNR values of the input diffraction-limited image and the estimated SR image by the simple GAN model are 21.24 dB, and 24.08 dB, respectively, with reference to the target super-resolution image. Appendix 4 provides the quantitative metrics (PSNR and SSIM) on the estimated super-resolution result with a simple GAN ML model, including the loss function as the mixed loss to optimize the MSE loss and GAN loss simultaneously. GANs are sensitive to the learning rate values; therefore, it is challenging to get the best results by varying all possible network parameters.

3.4 Results with DenseED in GANs

Simple GAN architectures can produce super-resolution results, but the image quality is not sufficient compared to FCNs with DenseED blocks. Hence we incorporate the DenseED blocks in the GAN architecture in the generator network, and we can get better super-resolution images. Fig. 5(a) shows one of the diffraction-limited images in a testing FOV. Fig. 5(g) shows the estimated super-resolution image with the DenseED (3,6,3) configuration as a generator in the GAN architecture. Fig. 5(c) shows the target super-resolution image. The PSNR values of the input diffraction-limited image and the estimated super-resolution image by the DenseED (3,6,3) in the GAN generator ML model are 21.24 dB, and 24.28 dB, respectively, with reference to the target super-resolution image. The PSNR improvement is due to adding DenseED blocks in the generator network in GANs, and the estimated SR image using DenseED blocks in GANs closely matches the target image. Hence, the DenseED blocks help to provide super-resolution from the diffraction-limited images in the GAN architecture. Appendix 4 provides the quantitative metrics of PSNR and SSIM on the estimated super-resolution with different configurations of the DenseED blocks (DenseED (3,6,3) is the reference model) in the GAN architecture generator network as the trained ML model, including the different dense layer in each dense block, learning rate, loss function as the mixed loss of MSE loss, GANs loss and SSIM loss to optimize all the three losses simultaneously. GANs are sensitive to the learning rate values and challenging to get the best results by varying all possible network parameters.

Finally, the DenseED block in both FCN and GAN architectures helps to generate super-resolution images when the ML model is trained with an ultra-small dataset. The performance improvement depends on optimizing other hyper-parameters and parameters of the network, including learning rate, non-linear activation, loss function, and weight decay to regularize the over-fitting. For the DenseED model, the number of dense blocks and dense layers are also important in each dense block.

3.5 Transfer learning of the trained model

This subsection shows the efficiency of our trained ML model with DenseED (3,6,3) configuration in the FCN architecture on a completely different sample collected using our custom-built two-photon microscopy. The new test sample is the mouse kidney (FluoCells prepared slide #3 (F-