2D Reconstruction of Optical Diffracted Red Blood Cell Specimens Using Deep Learning Techniques

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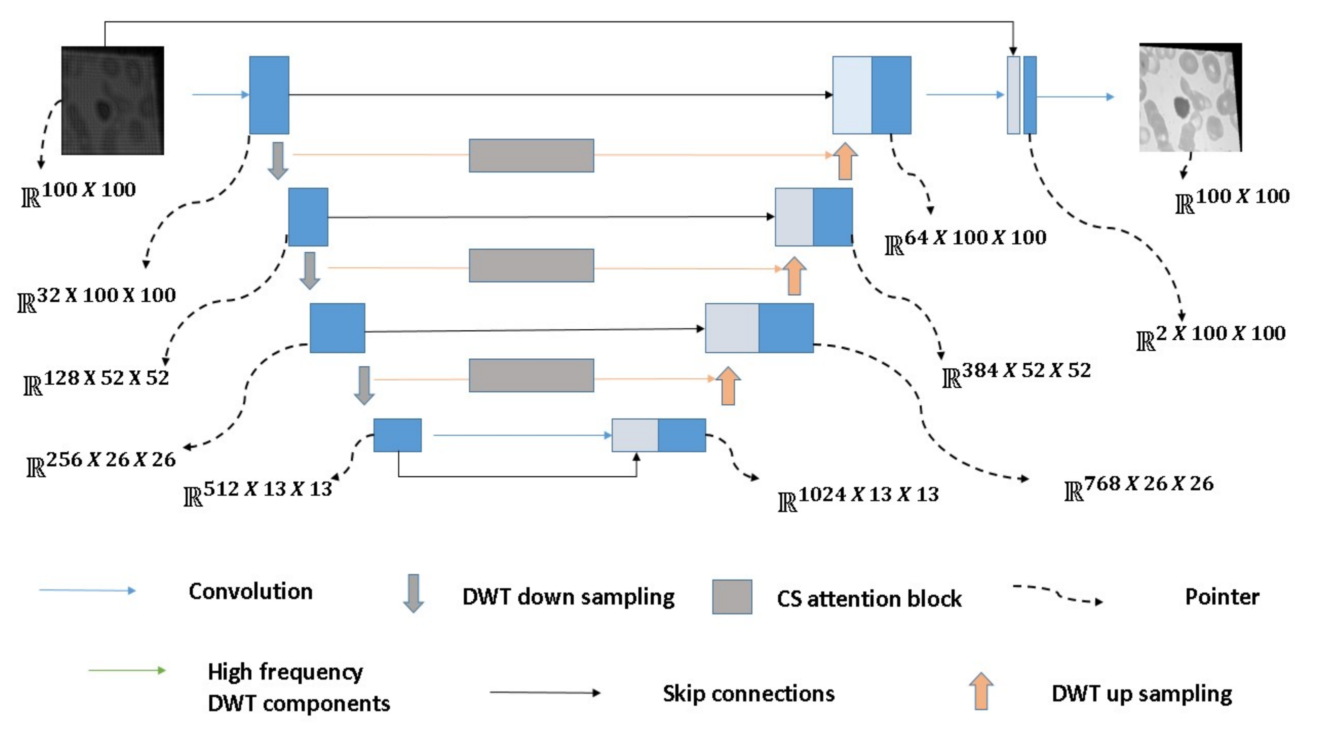
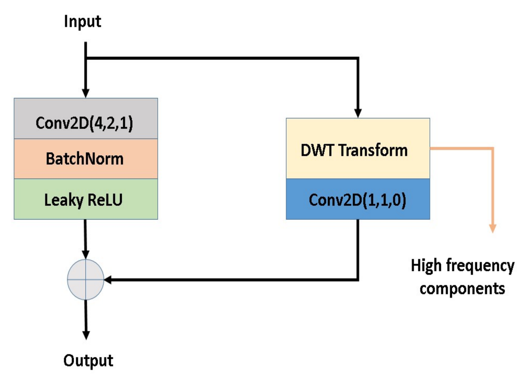
Introduction

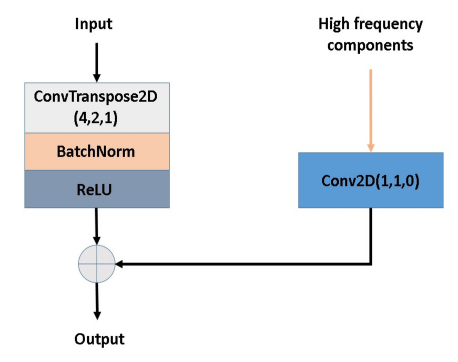
Optical diffractive imaging techniques can achieve high-resolution imaging of RBCs, allowing for the visualization of fine structural details and subcellular features. Unlike some other imaging method, it is typically label-free, meaning it does not require the use of contrast agents or dyes. This preserves the natural state of RBCs and eliminates potential artifacts introduced by labeling. It has applications in biomedical research, including the study of diseases related to Red Blood Cells (RBCs), such as malaria and sickle cell anemia. The primary approach is to reconstruct the image of red blood cells from their diffracted patterns using deep learning techniques. which yield superior results and significantly reduce processing time when compared to traditional iterative methods. Deep learning models can be adapted to different imaging setups and modalities with relatively minor adjustments to the network architecture or training data.
This adaptability allows for greater flexibility and versatility in optical diffracted image reconstruction.



Detailing of network architecture with attentionmechanism connected to high frequency component



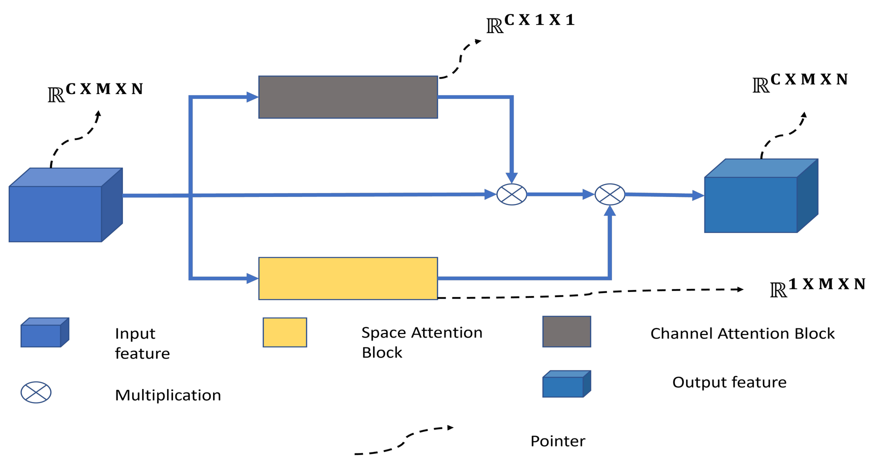
Block diagram of DWT down sampling module



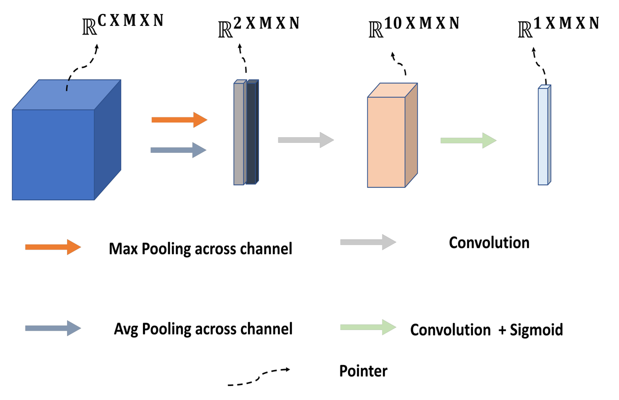
Block diagram of DWT up sampling module

Method

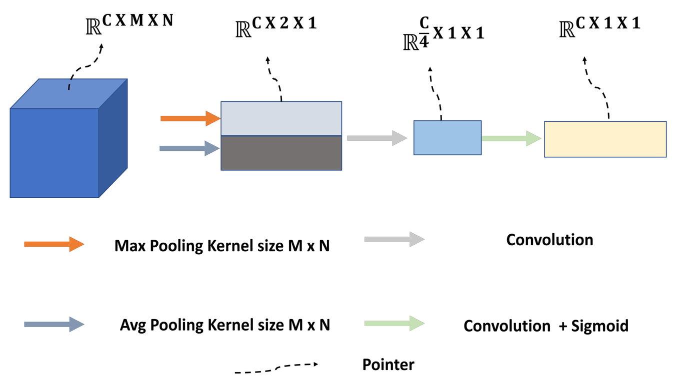
The U-Net design, which is frequently used in a variety of image reconstruction applications. The model incorporates frequency domain learning on top of the original U-Net. Additionally, it incorporates an outside skip link between the inputs and the output, which gives the model residual learning. Using picture frequency domain information can greatly improve the efficiency of the approaches for image reconstruction. To guarantee that texture features are preserved in the rebuilt images, we advise applying the discrete wavelet transform (DWT) during the feature extraction stage. The network can learn from both frequency domains by splitting the input feature maps into low-frequency and high frequency components and to improve the outputs of the network space and channel attention mechanism is used. It is applied to high frequency components to preserve the edges information of the blood cells.
Forward model is formulated for generating the synthetic diffraction patterns using physics principles involved in optical diffraction. Blood cell count and detection (BCCD) dataset is used for diffraction pattern images.



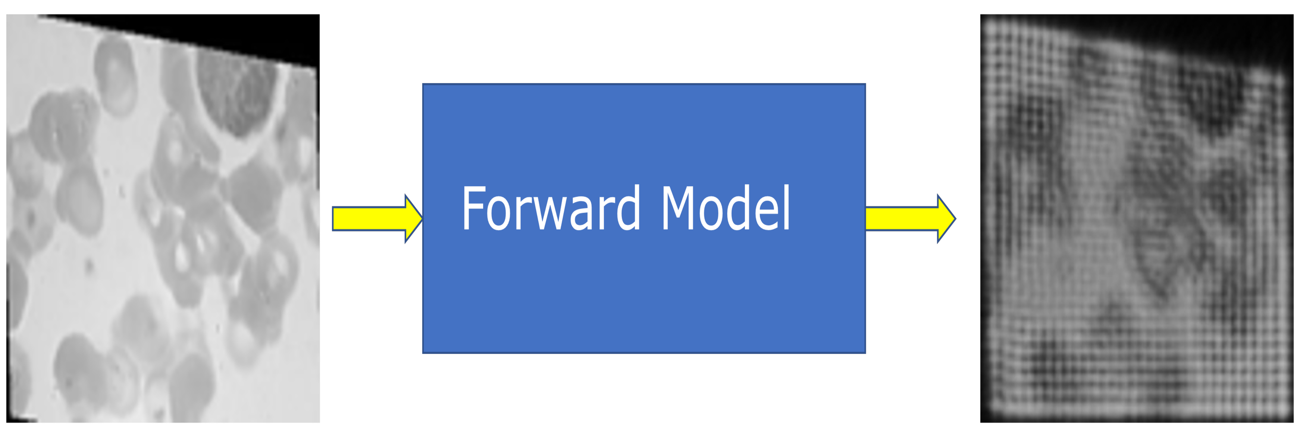
Block diagram of space and channel attention mechanism



Block diagram of space attention block



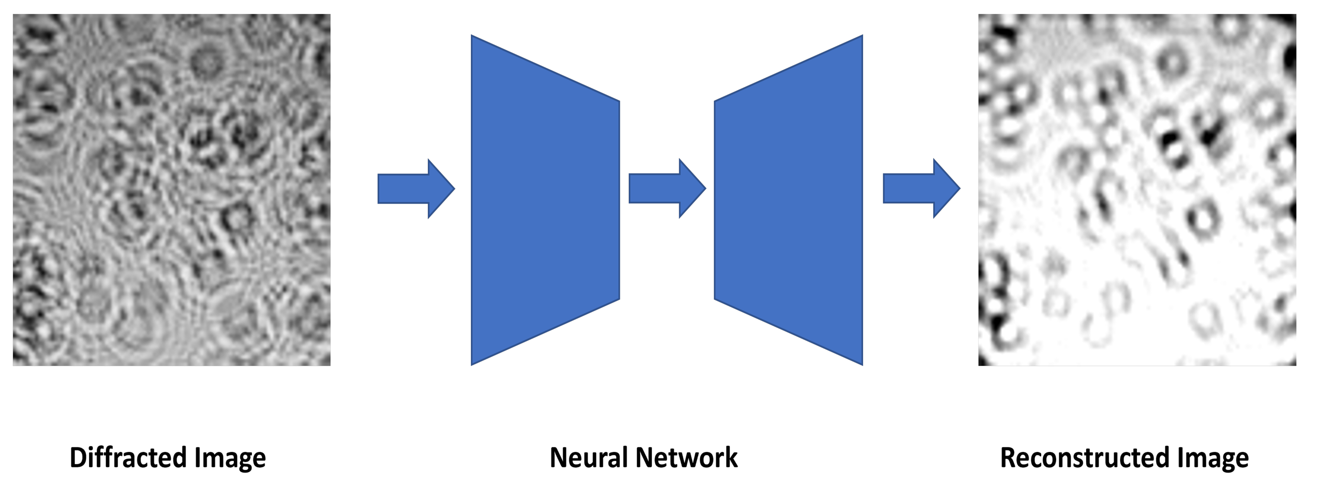
Block diagram of channel attention block



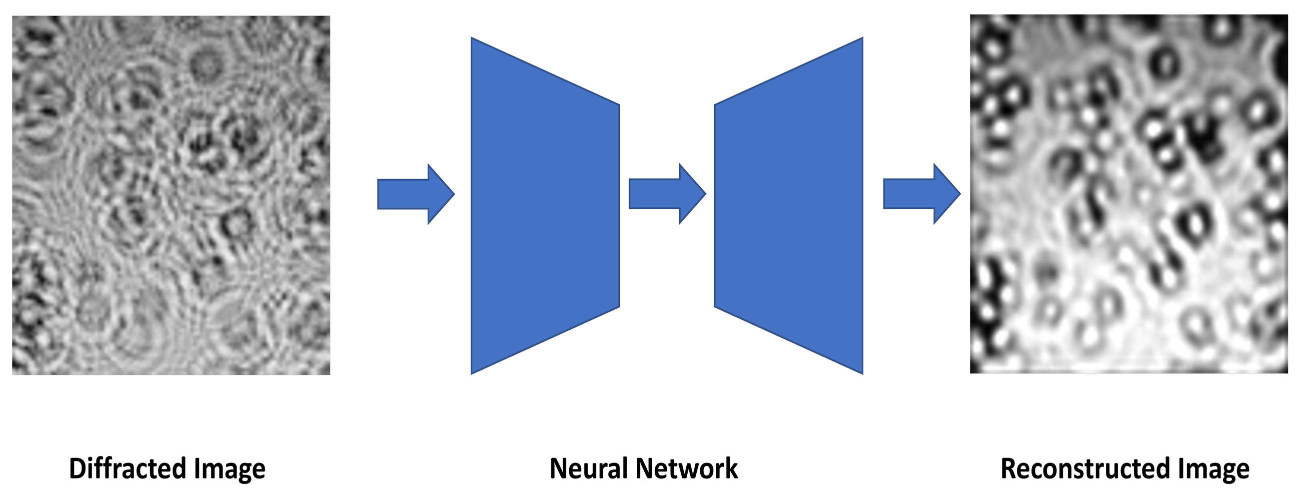
Block diagram of synthetic diffracted image generation

Channel Attention Block: In this block we focus the channel that has high importance and giving less importance to remaining channel. the method for doing this is to find the maximum value and average value of the every channel by performing the maxpooling operation and average pooling operation respectively with kernel size is same as size of channel such that you get maximum value and average value of the channel .concatenate this values form a feature tensor of size $C \times 2 \times 1$. This tensor goes to convolutional layer gives output size $C/4 \times 1 \times 1$ followed by convolutional layer, BatchNormalization and Sigmoid function gives output having attention gains for each channel.
Space Attention Block: In this block we calculate mean and maximum values at each spatial position across the channel axis . we concatenate this two features and it forms two channel spatial block having the size of the image.This features pass through the convolutional block gives the ten channel output. This output goes to the convolutional block foloowed by Batch Normalization and Sigmoid ends with output having spatial attention gains

Output Images

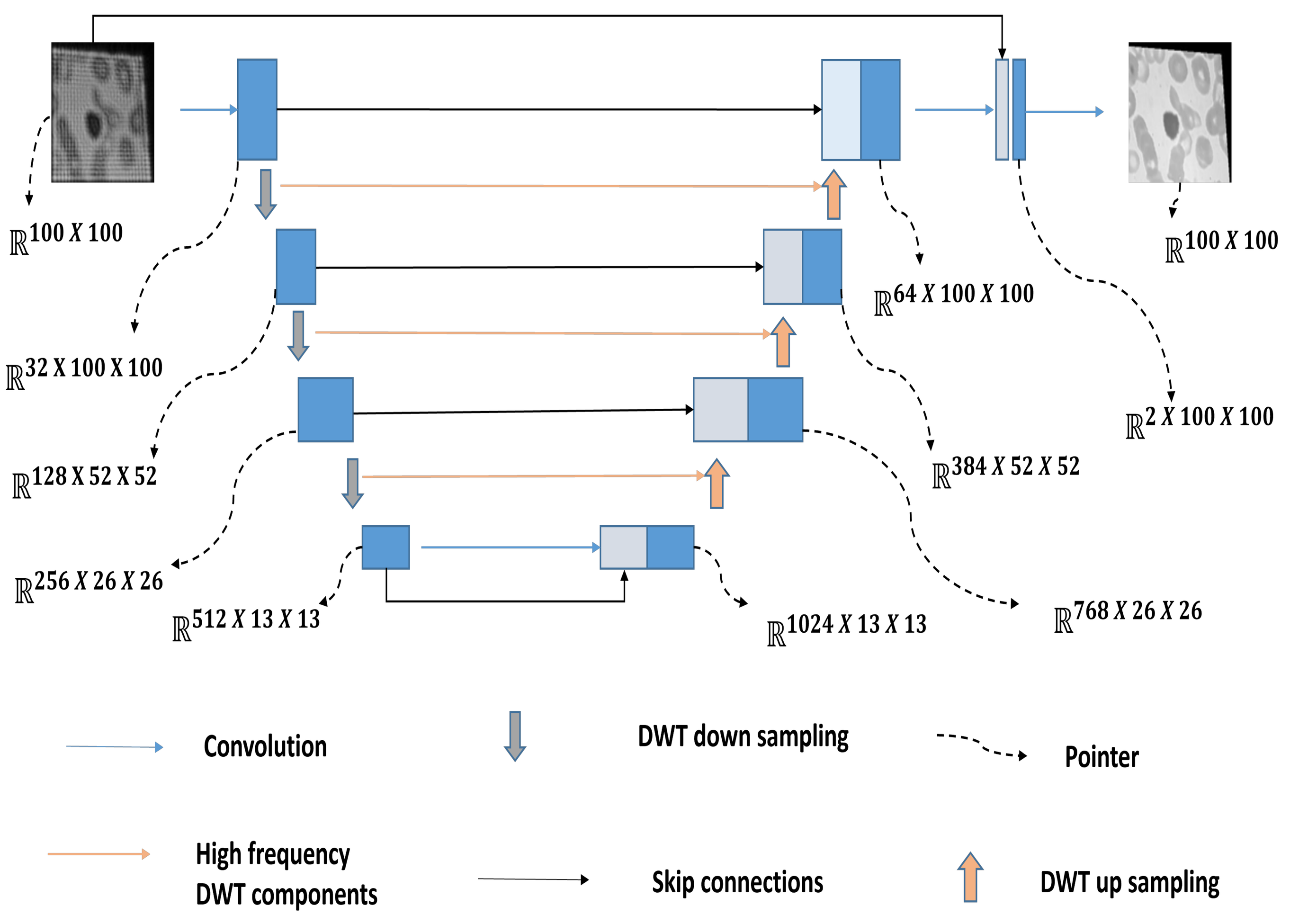


Performance of network on real diffracted RBC mage



Performance of network with attention blocks on real diffracted RBC image

Model



Detailing of network architecture

Conclusion

In our method, we trained the network on a BCCD dataset consisting of 4200 images. During training, we observed an overall PSNR of 35.3 and SSIM of 0.88 for the network without an attention mechanism. Additionally, for the network with an attention mechanism, we observed an overall PSNR of 28.47 and SSIM of 0.85. However, when we evaluated the network using the leukemia dataset, it produced notably good results. Specifically, for this dataset, we observed an overall PSNR of 25.8 and SSIM of 0.845 for the network with an attention mechanism, and an overall PSNR of 26.77 and SSIM of 0.877 for the network without an attention mechanism.

References

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[3] Fu, M., Liu, H., Yu, Y., Chen, J. and Wang, K. [2021], Dwgan: A discrete wavelet transform gan for nonhomogeneous dehazing,in 'Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition' , pp. 203–212.