Automatic Chromatic Aberration Correction Using Convolutional Neural Networks with a U-Net Architecture

Corrección automática de la aberración cromática mediante redes neuronales convolucionales con arquitectura U-Net

Luis Alberto Torres Muñoz[1], Natalia de Jesús Gaeta Verdín[1], David Ignacio Serrano Garíca[1], Francisco Joel Cervantes Lozano[1]

[1]Universidad de Guadalajara, Centro Universitario de Ciencias Exactas e Ingenierías, Departamento de Ingeniería Electro-Fotónica. Guadalajara, Jalisco México. luis.torres4350@alumnos.udg.mx

Abstract

Chromatic aberration is a common optical defect in simple lens systems that degrades image quality by causing unwanted color fringes and reduced sharpness. In this paper, we propose a method based on a convolutional neural network with a U-Net architecture to automatically correct chromatic aberration. We generated a synthetic dataset of 80,000 images from Google Open Images by simulating aberration using per-channel Gaussian blur and lateral chromatic shift. Trained for 100 epochs with a combined loss function (MSE + 0.1·L1), the network achieved a PSNR of 30.4 dB and an SSIM of 0.9418 on the test set. The results demonstrate the feasibility of this approach for restoring degraded images.

Keywords: chromatic aberration, image correction, deep learning, U-Net, convolutional neural networks.

Introduction

Chromatic aberration is an optical phenomenon caused by light dispersion, in which different wavelengths focus at different points, creating unwanted color fringes and reduced image sharpness (Hecht, 2017; Hu et al., 2023). This defect is particularly critical in low-cost optical systems and in applications that require high color fidelity, such as fluorescence microscopy or computational photography (Bian et al., 2021; Dong et al., 2024).

Traditionally, researchers have addressed this through advanced optical design (achromatic doublets) or algorithms based on inverse physical models (Duplov, 2025; Weligampola et al., 2025). However, these approaches are limited by complexity, cost, and performance across scenarios (Qian et al., 2026).

In recent years, deep learning has emerged as a transformative tool in image restoration (Fanous et al., 2024; Nie et al., 2026). Convolutional neural networks (CNNs) have demonstrated an exceptional ability to learn nonlinear mappings directly from the data, often outperforming traditional techniques (Contreras & Bacca, 2025; Guo et al., 2025; Wang et al., 2025). In particular, U-Net architectures, with their encoder-decoder structure and “skip” connections, have proven effective at preserving fine details while correcting pixel-level degradation (Guo et al., 2025; Ronneberger et al., 2015).

In this paper, we propose a U-Net-based method for automatically correcting chromatic aberration in images. We train the model on a synthetic dataset of 80,000 images and evaluate it using objective and subjective metrics. The results demonstrate the feasibility of implementing the proposed method in optical systems.

Methodology

Dataset

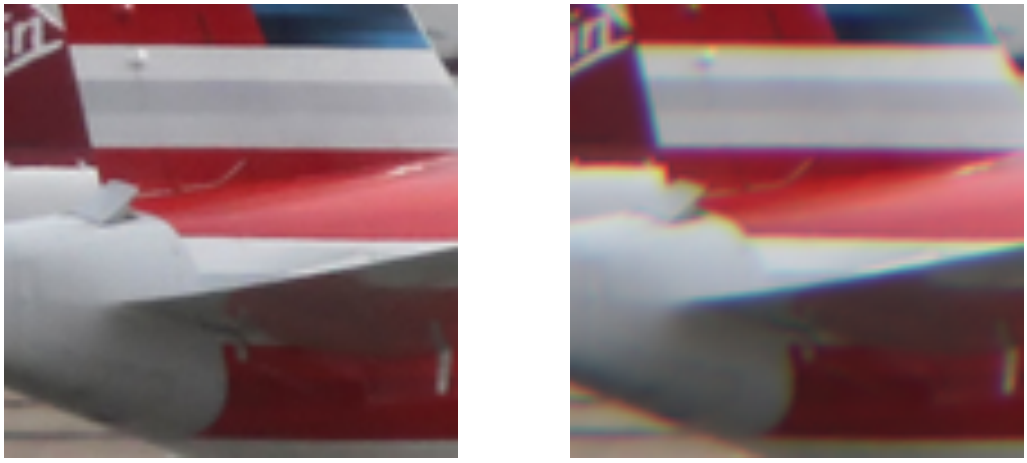
Because no large-scale dataset contains real images with and without chromatic aberration, we generated a synthetic dataset from 80,000 images from Google Open Images. A per-channel degradation model was applied that incorporates wavelength-dependent blurring: Each channel (R, G, B) is convolved with a Gaussian kernel with different standard deviations (σ):

$$\sigma_R \in [\sigma_{\min}, \sigma_{\max}] \quad (1)$$

$$\sigma_G = \sigma_R + \Delta_g, \text{ where } \Delta_g \in [0, \Delta_{g_{max}}] \quad (2)$$

$$\sigma_B = \sigma_G + \Delta_b, \text{ where } \Delta_b \in [0, \Delta_{g_{min}}] \quad (3)$$

and lateral chromatic shift: Random shifts are applied to the red and blue channels in opposite directions.



Ground Truth Blurry

Figure 1. Chromatic aberration in an image left, "Ground Truth" iamge; rigth, "Blurry" image. Source: Own elaboration based on Open images Dataset V7.

Thus, for each original image I, a corresponding input image with chromatic aberration, I_{blur}, is generated, as shown in Figure 1.

The dataset was divided into 70,000 training examples, 5,000 validation examples, and 5,000 test examples.

Model Architecture

We implemented a modified U-Net in PyTorch 2.0 with approximately 7.8 million parameters.

The architecture consists of:

- **Encoder:** 4 convolutional blocks (3×3, BatchNorm, ReLU) with 2×2 max pooling. Channels: 64 → 128 → 256 → 512.

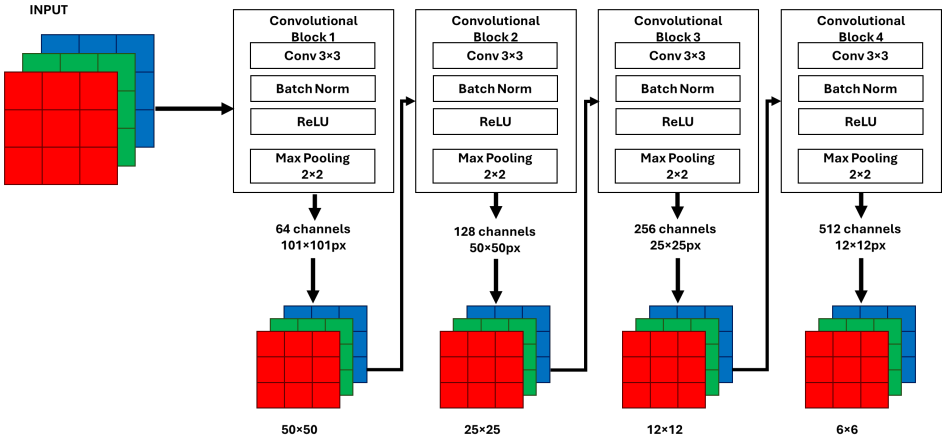


Figura 2. Encoder architecture: convolutional blocks with ther respective channel dimensions and spatial resolution. Source: Own elaboration.

- **Bottleneck:** 1,024 channels at 6×6 pixels.
- **Decoder:** 4 deconvolution blocks (ConvTranspose2d) with “skip” connections.

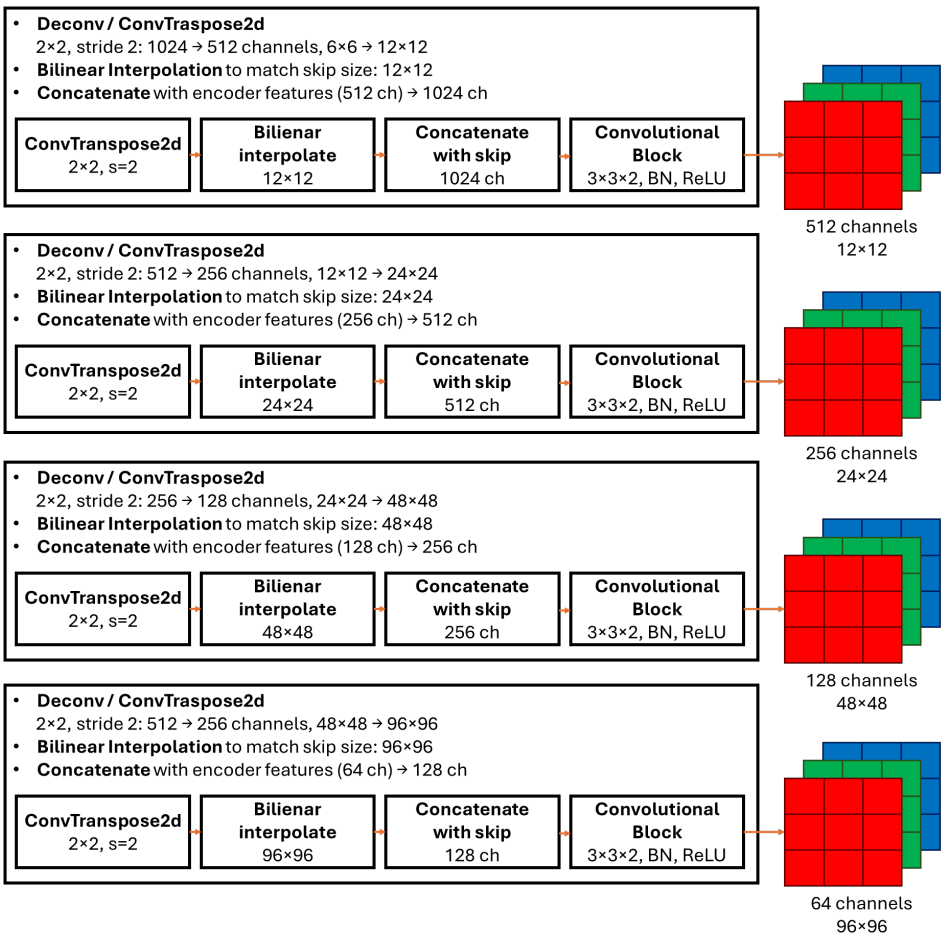


Figure 3. Decoder architecture: deconvolution blocks with their respective channel dimensions and spatial resolution. Source: Own elaboration.

- **Final layers:** 3×3 convolution, 1×1 convolution (3 channels), bilinear upsampling to 101×101 pixels.

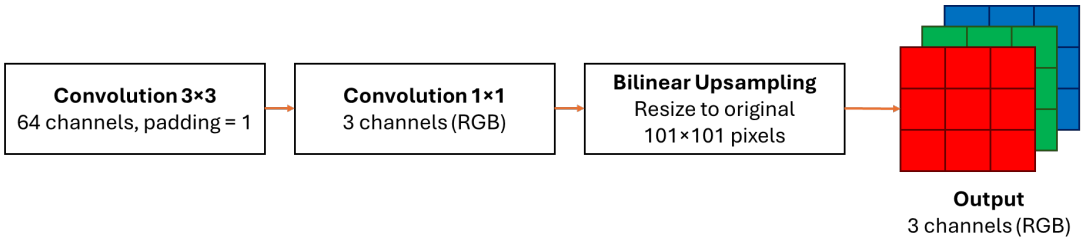


Figure 4. Architecture of the final layers: convolution, channel reduction, and resolution adjustment.
Fuente: Own elaboration.

Training

The model was trained for 100 epochs using:

- **Optimizer:** Adam, learning rate 0.001
- **Scheduler:** StepLR (factor of 0.5 every 30 epochs)
- **Batch size**: 32
- **Loss function:** L = MSE + 0.1·L1

The MSE + L1 combination balances overall fidelity with preserving edges and textures.

Results

Training Progress

The initial loss of 0.0684 decreased rapidly over the first 20 epochs, stabilizing at ~0.0065 after 80 epochs. The curve shows a smooth convergence with no evidence of overfitting. Figure 5 shows the evolution of the training loss over 100 epochs

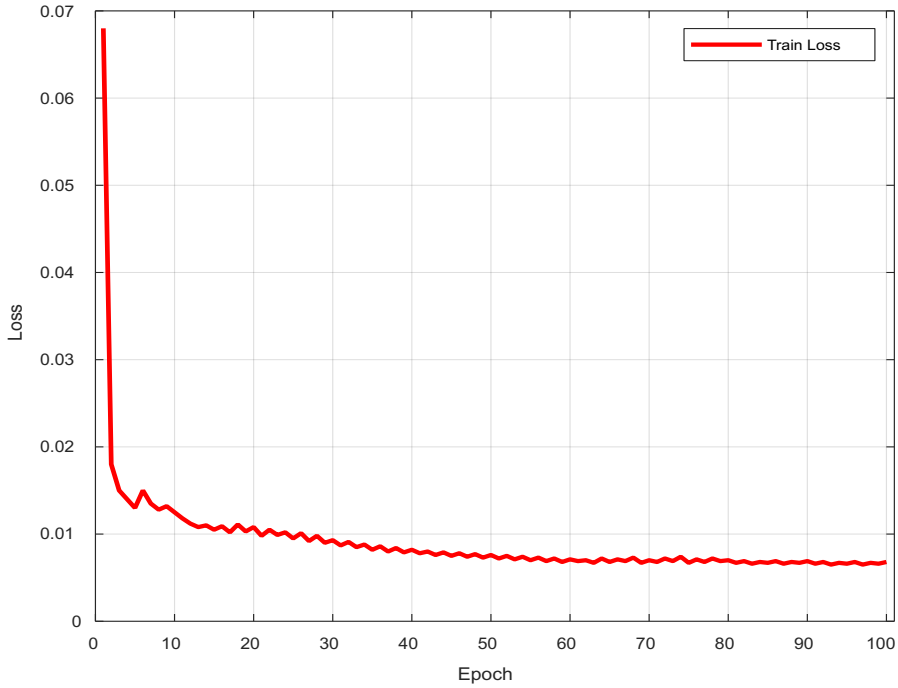


Figure 5. Evolution of the tarining loss (MSE + 0.1·L1) over the course of 100 epochs.
Fuente: Own elaboration.

Qualitative Assessment

The corrected images gradually eliminate color fringing along high-contrast edges while preserving textures and fine details. Starting epoch 60, the visual differences are minimal. Figure 6 shows an example of corrections applied to a static test image captured at the beginning, during, and at the end of training.



Epoch 1 Epoch 50 Epoch 100

Figure 6. Evolution of the correction in a test image during training.
Source: Own elaboration based on Open images Dataset V7.

Figure 7 shows a direct comparison between the input image with aberration, the corrected image at the end of training, and the reference image (ground truth), clearly demonstrating reduced chromatic artifacts.



Input Output Ground Truth

Figure 7. Side-by-side compatision of a test image before and after correction.
Source: Own elaboration based on Open images Dataset V7.

Quantitative Assessment

The model was evaluated on 100 test images using the following metrics:

Table 1. Model Performance.

Metrics	Value
PSNR	30.4 dB
SSIM	0.9418

These results indicate high reconstruction accuracy and excellent structural preservation.

Conclusions

This work demonstrates that a U-Net architecture can effectively learn chromatic aberration correction from synthetic data, achieving consistent restoration with a PSNR of 30.4 dB and an SSIM of 0.9418. The results show that the model not only removes chromatic fringing in high-contrast regions but also preserves fine details and the perceptual structure of the images, confirming that convolutional networks can approximate complex optical degradation processes without explicit physical modeling.

The stability observed during training suggests that the combination of the loss function (MSE + 0.1·L1) and the StepLR scheduler is well-suited to this type of problem. The loss curve showed a smooth decline with no signs of overfitting, indicating that the model generalizes well to unseen data. Automatic learning-rate reductions enabled finer convergence in the final stages of training, achieving an optimal balance between convergence speed and accuracy.

However, the model was trained exclusively on synthetic data; therefore, its real-world performance will depend on how closely the simulation matches actual physical optical conditions. This inherent limitation suggests several avenues for future research. First, the model must be validated on real, low-cost optical systems to assess performance under real-world conditions and adjust training parameters as needed. Second, the model must be adapted to different aberration conditions including variations in intensity, lens type, and lighting to improve its robustness and applicability across scenarios. Third, the architecture must be optimized to enable real-time inference, which is essential for practical applications such as computational photography or embedded computer vision systems. Finally, we propose extending the model to higher-resolution images, enabling its application in fields such as high-resolution microscopy or medical imaging.

The practical implications of this work are significant for low-cost optical systems where advanced optical design is not economically feasible, for real-time processing on devices capable of neural network inference, and for improving image quality in computational photography, microscopy, and computer vision applications.

In conclusion, this work lays the groundwork for implementing deep learning-based chromatic aberration correction systems, offering a practical and effective alternative to traditional approaches based on advanced optical design or inverse physical modeling, with a clear path toward real-world application.

References

Bian, Y., Jiang, Y., Huang, Y., Yang, X., Deng, W., Shen, H., Shen, R., & Kuang, C. (2021). Deep learning virtual colorization overcoming chromatic aberrations in singlet lens microscopy. *APL Photonics*, 6(3), 031301.https://doi.org/10.1063/5.0039206

Contreras, K., & Bacca, J. (2025). Computational Correction of Eye Aberrations:: A Physical Modeling Approach with Zernike Polynomials and Deep Learning. *2025 XXV Symposium of Image, Signal Processing, and Artificial Vision (STSIVA)*, 1-5, 10.1109/STSIVA66383.2025.11156245

Dong, Y., Zheng, B., Li, H., Tang, H., Zhao, H., Huang, Y., An, S., & Zhang, H. (2024). Achromatic single metalens imaging via deep neural network. *ACS Photonics*, 11(4), 1645–1656. https://doi.org/10.1021/acsphotonics.3c01870

Duplov, R. (2025). Secondary spectrum correction in lens systems with large air spaces. *Optical Engineering*, 64(04).https://doi.org/10.1117/1.OE.64.4.045103

Fanous, M. J., Costa, P. C., Işıl, Ç., Huang, L., & Ozcan, A. (2024). Neural network-based processing of compromised biophotonic image data. *Light: Science & Applications*, 13(1). https://doi.org/10.1038/s41377-024-01544-9

Guo, M., Wu, Y., Hobson, C. M., Su, Y., Qian, S., Krueger, E., Christensen, R., Kroeschell, G., Bui, J., Chaw, M., Zhang, L., Liu, J., Hou, X., Han, X., Lu, Z., Ma, X., Zhovmer, A., Combs, C., Moyle, M., Yemini, E., Liu, H., Liu, Z., Benedetto, A., La Riviere, P., & Shroff, H. (2025). Deep learning-based aberration compensation improves contrast and resolution in fluorescence microscopy. *Nature Communications*, *6(1). https://doi.org/10.1038/s41467-024-55267-x

Guo, Z., An, Q., Yang, C., Hu, J., Li, X., & Wang, L. ((2025). Roadmap for exoplanet high-contrast imaging. *Photonics*, *12*(10), 1030. https://doi.org/10.3390/photonics12101030

Hecht, E. (2017). *Optics* (5th ed.). Pearson.

Hu, S., Xiao, X., Ye, X., Yu, R., Chu, Y., Chen, J., Zhu, S., & Li, T. (2023). Deep learning enhanced achromatic imaging with a singlet flat lens. *Optics Express*, *31*(21), 33873. https://doi.org/10.1364/OE.501872

Nie, Y., Su, R., Thibault, S., Christoph, M., Van Erps, J., Thienpont, H., & Ottevaere, H. (2026). Deep learning across optical system workflow. *Journal of Physics: Photonics*.10.1088/2515-7647/ae3f6b

Qian, X., Jiang, Q., Gao, Y., Sun, L., Yi, Z., Yang, K., Van Gool, L., & Wang, K. (2026). Towards universal computational aberration correction (arXiv:2603.12083). *arXiv*. https://doi.org/10.48550/arXiv.2603.12083

Ronneberger, O., Fischer, P., Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab, N., Hornegger, J., Wells, W., Frangi, A. (eds) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. 9351. Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28

Wang, Z., Shi, R., Zhou, Y., & Bai, J. (2025). Enhanced aberration correction with the deep attention Wiener network. *Applied Optics*, 64(8), 1924. https://doi.org/10.1364/AO.547094

Weligampola, H., et al. (2025). Diffusion algorithm for metalens optical aberration correction (arXiv:2511.12689). *arXiv.* https://doi.org/10.48550/arXiv.2511.12689