A Deep Learning Approach using Convolutional Autoencoders for Image Deblurring

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ABSTRACT
Image de-blurring is a crucial task in computer vision with numerous applications in various fields such as medical imaging, surveillance, and autonomous vehicles. This paper presents a novel approach to image deblurring using convolutional autoencoders (CAEs). The proposed method leverages the power of deep learning and unsupervised learning to automatically learn features and reconstruct sharp images from blurry inputs. By training the CAE on pairs of blurry and corresponding sharp images, the network learns to capture the underlying structure and features essential for deblurring. To evaluate the effectiveness of proposed approach, extensive experiments were conducted on standard datasets consisting of sharp and blurred images.

Keywords
Blur Image, Deblurr, CNN, Auto Encoder

1. INTRODUCTION
The acquisition and transmission of images are often plagued by various forms of degradation, with blurring representing one of the most prevalent and detrimental artifacts. Image blur can stem from several sources including motion blur induced by camera movement, defocus blur resulting from incorrect focus settings, or inherent blur in low-quality imaging systems. Regardless of its origin, image blur severely compromises the interpretability and utility of visual data, impeding subsequent analysis and decision-making processes.

Image deblurring has emerged as a fundamental problem in computer vision research, attracting significant attention over the past decades. The goal of image deblurring is to recover the underlying sharp image from its blurred counterpart, thereby restoring visual fidelity and enabling accurate interpretation and analysis. While traditional approaches to image deblurring[1][2] have relied on handcrafted features and mathematical models, recent advances in deep learning have revolutionized this field, offering unprecedented capabilities for automated feature learning and reconstruction[3][4]. In this paper, we present an effectiveapproach for image deblurring using convolutional neural networks (CNNs) and convolutional autoencoders (CAEs). Following section presents a brief survey of image deblurring methodologies in the literature.

2. LITERATURE REVIEW
In this section, we briefly review existing deblurring methods.

Yang's work et.al. [5]proposed a novel approach to image deblurring by using pairs of blurred and noisy images. The method addressed the challenge of jointly handling blur and noise, demonstrating improved deblurring performance compared to traditional methods. Kim et. al.[6] introduced a deep learning-based approach to image super-resolution, which has applications in image deblurring. The method utilized very deep convolutional neural networks to achieve high-fidelity reconstruction of sharp images from low-resolution inputs, showcasing the potential of deep learning for image restoration tasks.

Jian Sun et.al.[7] presented an enhanced low-rank prior for image deblurring, which leveraged both spatial and spectral information to regularize the deblurring process. The method demonstrated superior performance in handling complex blur patterns and preserving image details compared to traditional regularization techniques.

Yunjin Chen et.al.[8] introduced a deep learning-based approach for low-light image enhancement, which is closely related to image deblurring. The method employed a fully convolutional network trained on pairs of low-light and well-exposed images to learn an end-to-end mapping for enhancing dark images, showcasing the potential of deep learning for challenging imaging conditions.

Chao Dong et.al.[9] proposed a novel deep learning-based approach for motion deblurring that incorporates contextual perceptual networks to handle complex motion blur patterns. The method achieved state-of-the-art performance by effectively capturing motion information and preserving image details in deblurred outputs.

Gong et.al.[10] proposed a learning-based approach for semantic image deblurring that adapts the structured output space to better preserve semantic content during the deblurring process. The method leveraged semantic segmentation information to guide the deblurring process, leading to improved visual quality and semantic consistency in the deblurred images.

Wang et.al.[11]provided a comprehensive review of recent advancements in real-world blind image deblurring, highlighting key challenges and promising directions for future research. The review synthesized insights from both traditional and deep learning-based approaches, offering valuable perspectives on addressing practical issues in image deblurring.

Zhang et.al.[12] proposed a self-attention mechanism for image deblurring that dynamically focuses on informative regions of the image during the deblurring process. The method achieved improved deblurring performance by adaptively allocating attention to relevant image features, leading to enhanced sharpness and detail recovery in the deblurred outputs.

3. METHODOLOGY
In this paper, we propose a deep learning technique to enhance the quality of deblurred images by removing the artifacts restoring visual clarity. The ultimate goal is to achieve significant improvements in image quality, as measured by metrics Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE), and to contribute to the field of image enhancement and computer vision.

We also study the implementation of classical methods, namely, Wiener Deconvolution and Lucy-Richardson Deconvolution and compare it with auto encoder results.

inner Deconvolution operates in the frequency domain, aiming to recover the original image by undoing the effects of blur and noise. It incorporates knowledge of the power spectral densities of the original image and the blur kernel, along with an estimate of the noise level, to compute an optimal deconvolution filter.

On the other hand, Lucy-Richardson Deconvolution is an iterative method based on maximum likelihood estimation. It iteratively refines an estimate of the original image by alternately convolving it with the estimated blur kernel and comparing the result with the observed blurry image.

3.1 Convolutional autoencoder approach

First, relevant libraries are imported for data manipulation, image processing, and deep learning. Clean (sharp) and blurry image frames are loaded from specified directories, resized, and normalized to a standard size of 128x128 pixels with pixel values in the [0, 1] range. The dataset is then divided into training and testing sets to evaluate the model's performance. A random pair of clean and blurry images is visualized for illustrative purposes. The architecture utilized for image deblurring follows an encoder-decoder design, as illustrated in Figure 1

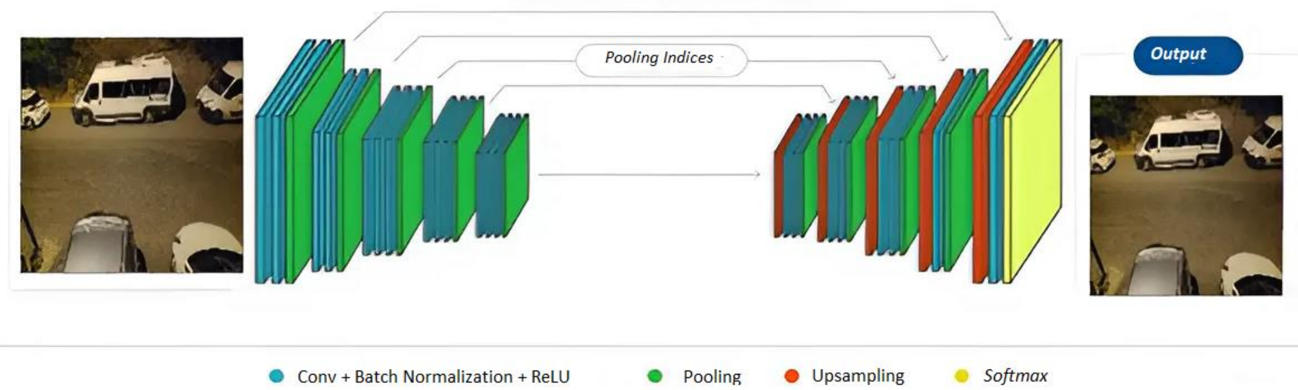

Figure 1. CNN encoder-decoder architecture

The autoencoder model is configured with specific parameters, such as the input shape, batch size, kernel size, and latent dimension. The architecture consists of an encoder that compresses the input images into a lower-dimensional latent space and a decoder that reconstructs the original clean images from this latent representation. The model is compiled with a mean squared error loss function and trained on the blurry images, allowing it to predict clean images. If the training loss stagnates, a learning rate reduction strategy is applied.

To evaluate the model's effectiveness, performance metrics are computed for each image pair, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). These metrics quantify the quality of the predicted clean images compared to the ground truth. The average PSNR, SSIM, and MSE scores are calculated over the entire dataset, providing a comprehensive assessment of the deblurring model's performance. These metrics help determine the model's ability to restore sharpness and reduce blurriness in images, and the average scores offer a summary of its overall effectiveness in the task of image deblurring.

3.2 Wiener Deconvolution approach

The Wiener Deconvolution method assumes that the degradation of an image can be represented as a linear and shift-invariant convolution process. This process is described as:

$$G(x,y)=h(x,y)*f(x,y)+n(x,y) \text{ ---------------------------------(1)}$$

where $g(x,y)$ represents the degraded image, $h(x,y)$ is the degradation operator often denoted as point spread function (PSF). The PSF denotes the degree at which an optical process spreads a point of light. and $f(x,y)$ is the original true image.

Wiener filtering reduces the additive noise as well as deblurring simultaneously. The Wiener Deconvolution is performed in the frequency domain using the Fast Fourier Transform (FFT). The observed image, PSF, and noise are transformed into the frequency domain. The Wiener Deconvolution filter is applied in the frequency domain to estimate the original image:

$$F(u,v)=G(u,v)\cdot H*(u,v)/(|H(u,v)|2+K) \text{ ----------------------(2)}$$

The estimated image is obtained by applying the inverse FFT to the filtered frequency domain representation. Fine-tuning of parameters such as the PSF and K may be required to achieve the desired deblurring effect. The deblurred image is evaluated using metrics PSNR, SSIM, and MSE to assess its quality and accuracy.

3.3 Lucy-Richardson Deconvolution approach

According to [14], given the motion blurred image B, the clear image I is computed by Bayesian estimation Given the motion blurred image B, the clear image I is computed by Bayesian estimation. The algorithm iteratively refines an estimate of the original image by alternately convolving it with the estimated blur kernel and comparing the result with the observed blurry image. By iteratively updating the image estimate to better match the observed data, Lucy-Richardson Deconvolution can effectively mitigate the effects of blur and restore sharper details in the image.

The update formula for each iteration is expressed as:

$$fk+1(x,y)=fk(x,y)\otimes fk(x,y)/[h(x,y)\otimes g(x,y)] \text{ ------------------(3)}$$

where, $f\,k+1(x,y)$ is the updated estimate of the original image at iteration k+1.

$f\,k\,(x,y)$ is the current estimate of the original image at iteration k.

$g(x,y)$ is the observed blurred image., $H(x,y)$ is the estimated blur kernel, $\otimes$ denotes the convolution operation.

The formula iteratively refines the estimate of the original image by comparing the observed blurred image with the convolution of the current estimate and the estimated blur kernel, adjusting the image estimate to better match the observed data. The process continues until convergence or a predefined stopping criterion is met

4. EXPERIMENTAL RESULTS

Experiments are performed on image dataset [13] consisting of 1050 blurred and sharp images. The average values of metrics are presented in Table 1 for the methods studied in this paper.

Table 1. Result comparison of methods in terms of PSNR, SSIM and MSE

Metric	Auto encoder	Wiener Deconvolution	Lucy-Richardson Algorithm
Average PSNR (dB)	26.28	13.88	14.02
Average SSIM	0.87	0.812	0.82
Average MSE	0.0027	0.042	0.002

Figure 2. Results of proposed methods for sample images, Column 1: Motion blur images Column 2: Clean Images (Ground Truth) Column 3: Predicted images

Figure 2. Represents the proposed output results for sample images from the dataset [13]. First column depicts the sample motion blur images, Second column shows ground truth images and third column shows the images recovered using proposed autoencoder algorithm. The proposed CAEs method produces better deblurred images comparatively other. Proposed method preserves the information from image removing the blur within the image.

5. CONCLUSION

This paper presented an image deblurring technique using an autoencoder approach. The results were benchmarked against traditional methods. The autoencoder achieved the highest average PSNR (26.28 dB) and SSIM (0.87), demonstrating superior image quality and structural similarity to the original images. Additionally, it had the lowest average MSE (0.0027), indicating minimal pixel-level discrepancies. Among the three methods evaluated, the autoencoder proved to be the most effective in terms of image quality and accuracy. Nevertheless, selecting the appropriate deblurring method should be guided by the specific application needs, as Weiner Deconvolution and the Lucy-Richardson algorithm may be more suitable for scenarios with lower computational requirements and less emphasis on image quality. Fine-tuning and application-specific testing can help enhance the deblurring performance further.

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