Two-Stage CNN Framework for Single-Image Deblurring and Restoration

Bedirhan GENÇASLAN
Hacettepe University
Ankara, Türkiye
b2210356065@cs.hacettepe.edu.tr

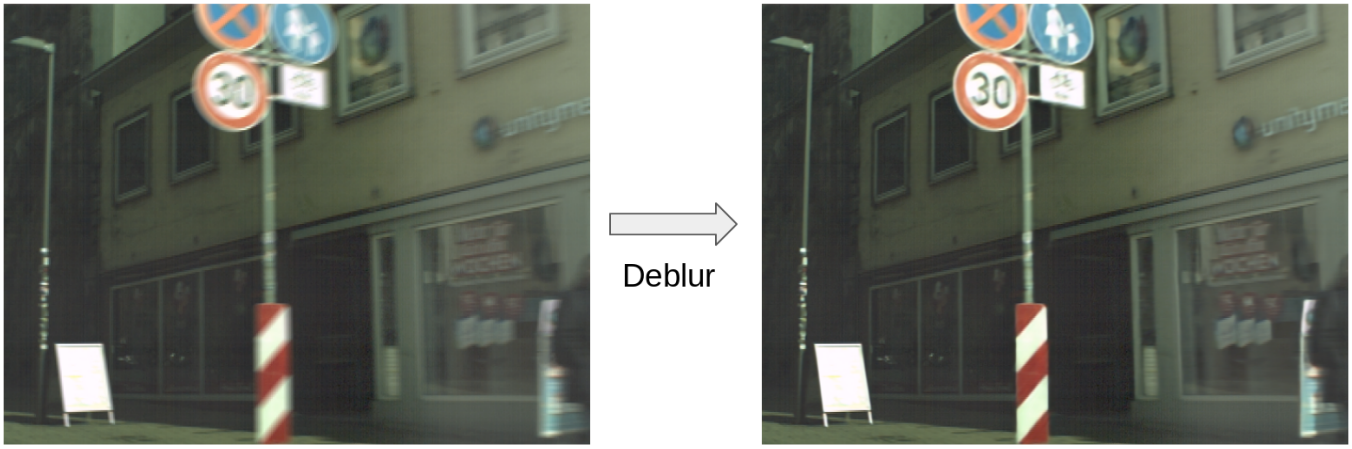

Figure 1: Example Image Deblurring Results (left: blurred input; right: restored output)

Abstract

This project addresses the problem of image deblurring, a common issue in digital photography caused by motion or out-of-focus optics. We propose a novel Convolutional Neural Network (CNN) architecture, designed with specialized blocks (t1, t2, t3, t4) and extensive skip connections, to learn the mapping from blurred to sharp images. The generator network is trained within a Generative Adversarial Network (GAN) framework, utilizing a PatchGAN discriminator to enhance perceptual quality. A composite loss function, combining MSE, SSIM, and adversarial loss, guides the training process. The model is trained and evaluated on the GOPRO_Large dataset. This report details the architecture, training methodology, and presents quantitative (PSNR, SSIM) and qualitative results, demonstrating the effectiveness of our approach in restoring sharp details from blurred inputs.

CCS Concepts

• **Computing methodologies** → **Image restoration**; *Neural networks.*

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Keywords

single-image deblurring, image restoration, convolutional neural networks, attention mechanisms

1 Introduction

Image blurring is a common degradation in digital photography, often resulting from camera shake, object motion, or out-of-focus optics. This artifact significantly diminishes the perceptual quality of images and can hinder subsequent image analysis tasks such as object recognition, tracking, or scene understanding. Therefore, image deblurring, the process of restoring a sharp image from its blurred counterpart, remains a crucial and challenging problem in computer vision and image processing.

Traditional deblurring methods often rely on estimating a blur kernel and then performing deconvolution, which can be sensitive to noise and may produce ringing artifacts, especially when the blur is complex or spatially varying. In recent years, data-driven approaches using deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in various image restoration tasks, including image deblurring. CNNs can learn intricate mappings from blurred to sharp image patches directly from large datasets, often outperforming classical methods without explicit blur kernel estimation.

To further enhance the visual quality and realism of deblurred images, Generative Adversarial Networks (GANs) [15] have emerged as a powerful paradigm. GANs consist of a generator network that produces candidate images and a discriminator network that learns to distinguish these generated images from real sharp images. This

adversarial training pushes the generator to produce images that are not only pixel-wise accurate but also perceptually convincing.

This project investigates an image deblurring solution leveraging a custom-designed CNN architecture as the generator within a GAN framework. Our motivation is to develop a robust model capable of restoring fine details and sharp edges from blurred inputs. We explore a specific generator design incorporating specialized processing blocks (`t1`, `t2`, `t4`) and extensive skip connections, aiming to effectively capture multi-scale features and facilitate gradient flow for improved learning. The model is trained and evaluated on the widely-used GOPRO_Large dataset [1], which provides pairs of blurred and sharp images from dynamic scenes. This report will detail the proposed network architecture, the training methodology employing a composite loss function (including MSE, SSIM [6], and adversarial loss), and present a comprehensive analysis of its quantitative and qualitative performance. We aim to demonstrate the efficacy of our approach in producing high-quality deblurred images.

2 Related Work

Image deblurring has been an active research area for decades, with early approaches focusing on analytical methods. These often involve estimating a blur kernel, which represents the motion or defocus characteristics, and then applying deconvolution techniques such as Wiener filtering [10] or Richardson-Lucy deconvolution (see [11] and [12]). While effective for certain types of blur, these methods can struggle with complex, non-uniform blurs and are often sensitive to noise, potentially introducing artifacts.

The advent of deep learning has revolutionized the field of image restoration, including deblurring. Convolutional Neural Networks (CNNs) have become the dominant tool due to their ability to learn complex mappings directly from data. Early CNN-based deblurring methods, such as those by Sun et al. [13], demonstrated the potential of learning blur kernels or end-to-end deblurring.

Several influential CNN architectures have significantly impacted image restoration tasks. **ResNet (Residual Networks)** [14], introduced by He et al., addressed the vanishing gradient problem in very deep networks by incorporating residual (or skip) connections. These connections allow the network to learn residual functions with reference to the layer inputs, easing the training of deeper models and enabling the learning of more complex features. This principle is widely adopted in modern deblurring networks to facilitate information propagation and gradient flow, similar to the residual connection used in our generator's final output and the additive nature of our `t1` block.

The **U-Net** architecture, originally proposed by Ronneberger et al. [4] for biomedical image segmentation, has found widespread application in image-to-image translation tasks, including deblurring. U-Net features a symmetric encoder-decoder structure with skip connections that bridge corresponding layers in the contracting (encoder) and expanding (decoder) paths. These skip connections allow the network to combine high-level semantic information from deeper layers with low-level, fine-grained spatial details from shallower layers, which is crucial for preserving texture and detail in restored images. Our generator's architecture, with its multiple concatenations of features from different depths (e.g., `l8_concat = torch.cat([l7_out, l3_out], dim=1)`), draws inspiration from this U-Net-like information fusion strategy.

Generative Adversarial Networks (GANs) [15] have further advanced the field by improving the perceptual quality of deblurred images. Standard pixel-wise loss functions like Mean Squared Error (MSE) or L1 loss, while good at aligning images, often lead to overly smooth results that lack high-frequency details. GANs address this by training a generator network to produce realistic images that can fool a discriminator network, which is concurrently trained to distinguish between real and generated images. Kupyn et al. proposed **DeblurGAN** [3], a conditional adversarial network specifically for motion deblurring, demonstrating significant improvements in visual quality over methods solely relying on pixel-wise losses. Their approach, like ours, uses a GAN framework to learn the deblurring process.

The concept of perceptual loss, popularized by Johnson et al. [16] and used in **SRGAN (Super-Resolution GAN)** by Ledig et al. [2] for image super-resolution, has also been influential. SRGAN utilizes a loss function that includes an adversarial component and a content loss defined on feature maps of a pre-trained VGG network. This encourages the generated images to be perceptually similar to real images, rather than just minimizing pixel-wise errors. While our work primarily uses MSE and SSIM as content losses alongside the adversarial loss, the underlying principle of using GANs to enhance perceptual realism is shared.

The discriminator architecture is also a critical component. **PatchGAN**, introduced by Isola et al. in their Pix2Pix framework [5], is a type of discriminator that penalizes structures at the scale of image patches rather than classifying the entire image. It classifies if each $N \times N$ patch in an image is real or fake. This approach is effective because it models the image as a Markov random field, assuming independence between pixels separated by more than a patch diameter. It encourages the generator to produce sharp details locally across the entire image and is computationally more efficient than a full-image discriminator. Our discriminator adopts this PatchGAN architecture to provide fine-grained feedback to the generator.

Our work builds upon these foundational concepts by designing a custom generator architecture with specialized blocks (`t1`, `t2`, `t4`) and extensive skip connections, trained within a GAN framework using a PatchGAN discriminator and a composite loss function that balances pixel-wise accuracy (MSE), structural similarity (SSIM), and adversarial realism.

3 The Approach

This section elaborates on the technical methodology employed in our project. We describe the dataset and its preprocessing, detail the architecture of our proposed deblurring network (Generator) and the discriminator used in the GAN framework, and outline the training procedure. Our core strategy involves a custom-designed Convolutional Neural Network (CNN) acting as the generator, trained adversarially against a discriminator to achieve high-fidelity image deblurring.

3.1 Dataset and Preprocessing

The **GOPRO_Large dataset** [1] served as the foundation for training and evaluating our model. This dataset is a standard benchmark

for image deblurring, comprising numerous pairs of blurred images and their corresponding sharp ground truth counterparts, captured across diverse dynamic scenes.

Effective data preprocessing is paramount for optimal neural network performance. Our pipeline applied the following transformations consistently to both blurred input images and sharp target images:

- **Image Loading and Resizing:** Images were initially loaded using OpenCV. To ensure uniformity for batch processing and network input, all images were resized to a fixed dimension of 800×450 pixels (Width $\times$ Height).
- **Color Space Conversion:** The default BGR color space used by OpenCV was converted to the more standard RGB color space.
- **Normalization:** Pixel intensities, originally in the $[0, 255]$ range, underwent a two-step normalization. First, they were scaled to $[0, 1]$ by division by 255.0. Subsequently, they were transformed to the $[-1, 1]$ range via the operation $img = img \times 2.0 - 1.0$. This final range aligns with the `Tanh` activation function utilized in the generator's output layer.
- **Tensor Conversion and Permutation:** The processed NumPy image arrays were converted into PyTorch tensors. The tensor dimensions were then permuted from HWC (Height, Width, Channels) to CHW (Channels, Height, Width), adhering to the standard input format for PyTorch's convolutional layers.

These preprocessing steps collectively ensure that the data fed into the network is appropriately formatted and scaled, contributing to more stable and effective training dynamics.

3.2 Network Architecture

Our image deblurring system is architected as a Generative Adversarial Network (GAN) [15]. This framework comprises two principal neural network components:

(1) A **Generator Network (`NeuralNetwork`)**: This network is tasked with learning the transformation from a blurred input image to a visually sharp output image.
(2) A **Discriminator Network (`Discriminator`)**: This network is trained to differentiate between authentic sharp images (from the dataset) and the deblurred images produced by the generator.

Through adversarial training, the generator iteratively improves its ability to produce realistic deblurred images that can deceive the discriminator.

3.2.1 Generator Network (`NeuralNetwork`)

The `NeuralNetwork`, serving as the generator, is a bespoke CNN architecture meticulously designed for the image deblurring task. Its structure can be conceptualized as an encoder-decoder pathway, heavily augmented with skip connections that bridge different levels of feature abstraction. This design facilitates a robust flow of information, enabling the network to reconstruct fine details. The primary objective is to learn a mapping function $G : x_{blur} \rightarrow x_{sharp}$, where x_{blur} is the blurred input and x_{sharp} is the desired sharp output. The architecture culminates in a global residual connection, where the network predicts a residual that, when added to the original blurred input, yields the deblurred image.

The Python code defining the generator is presented in Listing 1.

```
import torch
import torch.nn as nn

class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__init__()

        self.l1 = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU()
        )

        self.l2 = nn.Sequential(
            nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU()
        )

        self.maxpool_t1_t4 = nn.MaxPool2d(kernel_size=3, stride=1, padding=1)
        self.bottleneck = nn.Conv2d(64, 32, kernel_size=1, stride=1, padding=0)

        self.t2_conv1 = nn.Conv2d(32, 16, kernel_size=3, stride=1, padding=1)
        self.t2_conv2 = nn.Conv2d(32, 16, kernel_size=3, stride=1, padding=1)
        self.t2_conv3 = nn.Conv2d(32, 16, kernel_size=3, stride=1, padding=1)
        self.t2_conv4 = nn.Conv2d(32, 16, kernel_size=3, stride=1, padding=1)

        self.t3_reduce_l6 = nn.Conv2d(192, 64, kernel_size=3, stride=1, padding=1)
        self.t3_reduce_l8_l9 = nn.Conv2d(128, 64, kernel_size=3, stride=1, padding=1)
        self.t3_reduce_l11 = nn.Conv2d(96, 32, kernel_size=3, stride=1, padding=1)

        self.final_conv = nn.Conv2d(32, 3, kernel_size=3, stride=1, padding=1)
        self.tanh = nn.Tanh()

    def t1(self, x):
        max_pooled = self.maxpool_t1_t4(x)
        return x + max_pooled

    def t2(self, x):
        x_bottleneck = self.bottleneck(x)
        c1 = self.t2_conv1(x_bottleneck)
        c2 = self.t2_conv2(x_bottleneck)
        c3 = self.t2_conv3(x_bottleneck)
        c4 = self.t2_conv4(x_bottleneck)
        return torch.cat([c1, c2, c3, c4], dim=1)

    def t4(self, x):
        max_pooled = self.maxpool_t1_t4(x)
        concat = torch.cat([x, max_pooled], dim=1)
        return nn.functional.relu(concat)

    def forward(self, x_input):
        l1_out = self.l1(x_input)
        l2_out = self.l2(l1_out)
        l3_out = self.t1(l2_out)
        l4_out = self.t2(l3_out)
        l5_out = self.t4(l4_out)
        l6_concat = torch.cat([l5_out, l4_out], dim=1)
        l6_out = self.t3_reduce_l6(l6_concat)
        l7_out = self.t2(l6_out)
        l8_concat = torch.cat([l7_out, l3_out], dim=1)
```

```
        l8_out = self.t3_reduce_l8_l9(l8_concat)
        l9_concat = torch.cat([l8_out, l2_out], dim=1)
        l9_out = self.t3_reduce_l8_l9(l9_concat)
        l10_out = self.t2(l9_out)
        l11_concat = torch.cat([l10_out, l1_out], dim=1)
        l11_out = self.t3_reduce_l11(l11_concat)
        l12_out = self.t1(l11_out)
        final_features = self.final_conv(l12_out)
        output = self.tanh(final_features) + x_input
        return output
```

Listing 1: PyTorch implementation of the Generator Network (`NeuralNetwork`).

The generator comprises several key operational blocks and design principles:

Initial Feature Extraction (`l1`, `l2`): The network commences with two sequential blocks, `l1` and `l2`.

- `l1`: Accepts the 3-channel (RGB) input image. It applies a 3×3 convolution (stride 1, padding 1) to expand the channel dimension to 32. This is followed by `BatchNorm2d` for normalization and a `ReLU` activation function.
- `l2`: Processes the 32-channel output from `l1`. Another 3×3 convolution (stride 1, padding 1) further expands the channels to 64, again succeeded by `BatchNorm2d` and `ReLU`.

These initial layers are responsible for extracting low-level features such as edges and textures from the input blurred image. The use of padding preserves the spatial dimensions of the feature maps.

The `t1` Block (Residual Max-Pooling): This block, defined by the `t1(self, x)` method in Listing 2, implements a form of residual learning combined with max-pooling.

- An `nn.MaxPool2d` layer (kernel size 3, stride 1, padding 1, shared as `self.maxpool_t1_t4`) is applied to the input feature map `x`. This operation, while preserving spatial dimensions, emphasizes the most salient features within local receptive fields.
- The max-pooled output is then added element-wise to the original input feature map `x` (`return x + max_pooled`).

This design, inspired by residual networks [14], allows the block to learn modifications to the input features by focusing on high-activation regions. It helps in propagating stronger features and gradients through the network. The `t1` block is utilized at the `l3_out` and `l12_out` stages of the forward pass (see Listing 2).

The `bottleneck` Layer and `t2` Block (Parallel Multi-Scale Convolution): The `t2(self, x)` method, detailed in Listing 2, defines a block that processes features through parallel convolutional pathways after an initial channel reduction.

- **Bottleneck**: The input `x` (typically 64-channel) first passes through `self.bottleneck`, a 1×1 convolution that reduces the channel count from 64 to 32. This reduces computational complexity for subsequent layers and allows for efficient feature recombination.
- **Parallel Convolutions**: The 32-channel output from the bottleneck (`x_bottleneck`) is then fed into four parallel 3×3 convolutional layers (`self.t2_conv1` to `self.t2_conv4`). Each of these convolutions transforms the 32-channel input into a 16-channel output.
- **Concatenation**: The outputs of these four parallel convolutions (each 16-channel) are concatenated along the channel dimension, resulting in a 64-channel feature map.

This `t2` block, reminiscent of Inception-style modules [17], allows the network to capture features at multiple "perspectives" or scales simultaneously from the same input, enhancing its representational capacity. It is used at the `l4_out`, `l7_out`, and `l10_out` stages (Listing 2).

The `t4` Block (Concatenated Max-Pooling with ReLU): Defined by `t4(self, x)` in Listing 2, this block also utilizes max-pooling but combines features differently.

- The shared `self.maxpool_t1_t4` is applied to the input `x`.
- The original input `x` and its max-pooled version are concatenated along the channel dimension (`torch.cat([x, max_pooled], dim=1)`). If `x` has C channels, the concatenated output will have $2C$ channels.
- A `ReLU` activation (`nn.functional.relu`) is applied to the concatenated output.

This block explicitly combines the original feature map with its salient-feature-enhanced version, effectively doubling the feature channels passed to the next stage, followed by non-linear activation. It is used to compute `l5_out` (Listing 2).

Feature Aggregation and Reduction Blocks (`t3_reduce_...`): The architecture employs several skip connections where outputs from shallower layers are concatenated with outputs from deeper layers (e.g., `l6_concat = torch.cat([l5_out, l4_out], dim=1)` in Listing 2). These concatenations significantly increase channel depth. To manage this dimensionality and learn more compact representations from these aggregated features, specialized 3x3 convolutional layers are used for reduction: `self.t3_reduce_l6`, `self.t3_reduce_l8_l9`, and `self.t3_reduce_l11` (defined in Listing 2). These layers not only control model complexity but also allow for further interaction and fusion of the concatenated multi-level features.

Overall Data Flow and Skip Connections in `forward(self, x_input)`: The `forward` method, detailed in Listing 2, orchestrates the intricate flow of data through the network, featuring multiple skip connections where outputs from various layers are concatenated and processed. This deep architecture with multiple skip connections, reminiscent of U-Net [4] and DenseNet [9] principles, allows for robust feature propagation and reuse, enabling the network to learn complex deblurring transformations by combining information from various depths and scales.

Final Output Generation: As shown in Listing 2, after the series of transformations:

- `self.final_conv`: A 3×3 convolution maps the 32-channel features from `l12_out` back to a 3-channel (RGB) image representation.
- `self.tanh`: The `Tanh` activation function scales the pixel values of this image to the range $[-1, 1]$, consistent with the input normalization.
- **Global Residual Connection**: The final output is computed as `output = self.tanh(final_features) + x_input`. The network learns to predict a residual image, which is then added to the original blurred input `x_input`.

3.2.2 Discriminator Network (`Discriminator`)

The discriminator network, detailed in Listing 2, adopts the PatchGAN [5] architecture.

```
import torch
import torch.nn as nn

class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.model = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1)
    ,
            nn.BatchNorm2d(128),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(128, 256, kernel_size=4, stride=2, padding
    =1),
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(256, 512, kernel_size=4, stride=2, padding
    =1),
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(512, 1, kernel_size=4, stride=1, padding=0),
            nn.Sigmoid()
        )
    def forward(self, img):
        return self.model(img)
```

Listing 2: PyTorch implementation of the Discriminator Network (`Discriminator`).

The discriminator architecture comprises a sequence of convolutional layers. Most layers use a kernel size of 4 and a stride of 2, effectively halving the spatial dimensions of the feature maps at each step. `BatchNorm2d` is applied after most convolutions (except the first and last) to stabilize training, and `LeakyReLU` (with a negative slope of 0.2) serves as the activation function. The final convolutional layer reduces the channel dimension to 1, and a `Sigmoid` activation function maps the output values to the range $[0, 1]$, representing probabilities for each patch.

3.3 Training Details

The generator and discriminator are co-trained in an adversarial manner. The training objective involves optimizing a composite loss function for the generator and a binary cross-entropy loss for the discriminator.

Loss Functions: The generator's loss, $\mathcal{L}_G$, is a weighted amalgamation of three distinct components:

$$\mathcal{L}_G = \lambda_{mse}\mathcal{L}_{MSE} + \lambda_{ssim}(1 - \text{SSIM}) + \lambda_{adv}\mathcal{L}_{adv,G} \tag{1}$$

where:

- $\mathcal{L}_{MSE}$ denotes the Mean Squared Error between the generated image $G(x_{blur})$ and the ground truth sharp image x_{sharp}. This term promotes pixel-wise accuracy.
- SSIM represents the Structural Similarity Index Measure [6]. The term $(1 - \text{SSIM})$ is incorporated as a loss to maximize the structural congruence between the generated and target images.
- $\mathcal{L}_{adv,G}$ is the adversarial loss component for the generator. It is computed as the binary cross-entropy loss where the generator aims to make the discriminator classify its outputs as real (i.e., target labels of 1 for $D(G(x_{blur}))$).
- λ_{mse}, λ_{ssim}, and λ_{adv} are hyperparameter weights balancing these terms. In our experiments, these were set to $\lambda_{mse} = 1.0$, $\lambda_{ssim} = 0.3$, and $\lambda_{adv} = 0.01$, respectively.

The discriminator's loss, $\mathcal{L}_D$, is formulated as the standard binary cross-entropy objective for GANs:

$$\begin{aligned}\mathcal{L}_D = & -\mathbb{E}_{x_{\text{sharp}}\sim p_{\text{data}}(x_{\text{sharp}})}\left[\log D(x_{\text{sharp}})\right] \\ & -\mathbb{E}_{x_{\text{blur}}\sim p_{\text{data}}(x_{\text{blur}})}\left[\log(1 - D(G(x_{\text{blur}})))\right].\end{aligned} \tag{2}$$

This loss encourages the discriminator to correctly classify real sharp images as real (output close to 1) and generated (fake) images as fake (output close to 0). In practice, this is implemented by separately calculating the loss for real and fake batches and averaging them.

Optimization and Hyperparameters:

- Both the generator and discriminator networks were optimized using the Adam optimizer [7].
- An initial learning rate of 5×10^{-4} was used for both optimizers, along with a weight decay (L2 regularization) of 5×10^{-4}.
- A `ReduceLROnPlateau` learning rate scheduler was employed for both optimizers. This scheduler monitored the validation generator loss and reduced the learning rate by a factor of 0.5 if no improvement was observed for a patience of 5 epochs.
- The training code also included a provision to manually decrease the learning rates by a factor of 10 every 30 epochs (‘lr=lr/10‘). However, given the early stopping observed in the logs (e.g., around epoch 15-40), this manual reduction might not have been frequently triggered with the base ‘lr‘ of 5×10^{-4}.
- The model was configured to train for a maximum of 100 epochs, using a batch size of 4.
- Early stopping was active, with a patience of 10 epochs, based on the validation generator loss. Training would terminate if the validation loss did not show improvement for 10 consecutive epochs, and the model state with the best validation loss was preserved.

Data Augmentation: To enhance the diversity of the training set and mitigate overfitting, the following data augmentation techniques were applied. Critically, identical random transformations were applied to each pair of blurred input and sharp target images:

- Random Horizontal Flips.
- Random Rotations by an angle up to 10 degrees.

A shared random seed for each image pair ensured consistency in the applied augmentations.

Training Environment: All model training and experimentation were performed within a Google Colaboratory environment, utilizing an NVIDIA A100 GPU. The deep learning framework employed was PyTorch [8] (version should be specified, e.g., 1.13 or 2.0).

4 Experimental Results

This section presents the quantitative and qualitative results of our proposed deblurring model. We evaluate its performance using standard metrics such as Peak Signal-to-Noise Ratio (PSNR)

and Structural Similarity Index Measure (SSIM), alongside visual inspection of the deblurred images.

4.1 Quantitative Analysis

4.1.1 Training Progression and Metrics

The model was trained for a target of 100 epochs, with an early stopping mechanism implemented based on the validation generator loss, using a patience of 10 epochs. The training process was closely monitored by tracking generator and discriminator losses, as well as PSNR and SSIM values, on both the training and validation subsets for each epoch.

The training logs, an excerpt of which was provided (Epoch 1 to 48, showing early stopping triggered multiple times after the initial best model was found), indicate that the optimal validation generator loss of **0.064928** was achieved at **Epoch 5**. At this epoch, the model also recorded a corresponding validation SSIM of **0.7950** and a validation PSNR of **24.79 dB**. Following this, early stopping was first noted as triggered around Epoch 15 in the provided logs, signifying 10 epochs of no further improvement in validation generator loss after Epoch 5. This relatively rapid convergence to an optimal point on the validation set suggests that the model, with its current architecture and hyperparameters, efficiently learned the deblurring task for the given data distribution. The progression of these key metrics over the training epochs is illustrated in Figures 2, 3, and 4.

A summary of the key training and validation metrics at Epoch 5, where the best validation generator loss was observed, is presented in Table 1.

Table 1: Key Training Metrics at Best Validation Epoch (Epoch 5)

Metric	Value
Best Validation Generator Loss	0.064928
Validation SSIM at Best Epoch	0.7950
Validation PSNR (dB) at Best Epoch	24.79
Training Generator Loss (Epoch 5)	0.069650
Training Discriminator Loss (Epoch 5)	0.661348
Training SSIM (Epoch 5)	0.8056
Training PSNR (dB) (Epoch 5)	24.99

4.1.2 Test Set Performance

To assess the generalization capability of our deblurring model, the generator that achieved the best performance on the validation set (saved at Epoch 5) was applied to the unseen test portion of the GOPRO_Large dataset. The performance was quantified using average PSNR and SSIM scores across all test images. Table 2 presents these metrics, comparing the quality of the original blurred test images (Input) against the deblurred images produced by our model (Our Model).

Table 2: Performance on the Test Set (GOPRO_Large)

Metric	Average Input (Blurred)	Our Model (Deblurred)
PSNR (dB)	28.48	28.75
SSIM	0.915	0.943

4.2 Qualitative Analysis

Visual comparison of the deblurring results offers crucial insights into the perceptual quality and artifact handling of our model, complementing the quantitative metrics. Figure 8 showcases selected examples from the test set. For each example, the original blurred input image, the corresponding ground truth sharp image, and the output from our deblurring network are presented side-by-side. These visual results allow for an assessment of the model's ability to restore fine details, sharpen edges, and suppress blur-related artifacts effectively. Particular attention should be paid to regions with complex textures or significant motion to understand the model's strengths and weaknesses.

The visual results in Figure 8 generally indicate a significant improvement in sharpness and clarity compared to the blurred inputs. The model appears effective in restoring textures and edge definition.

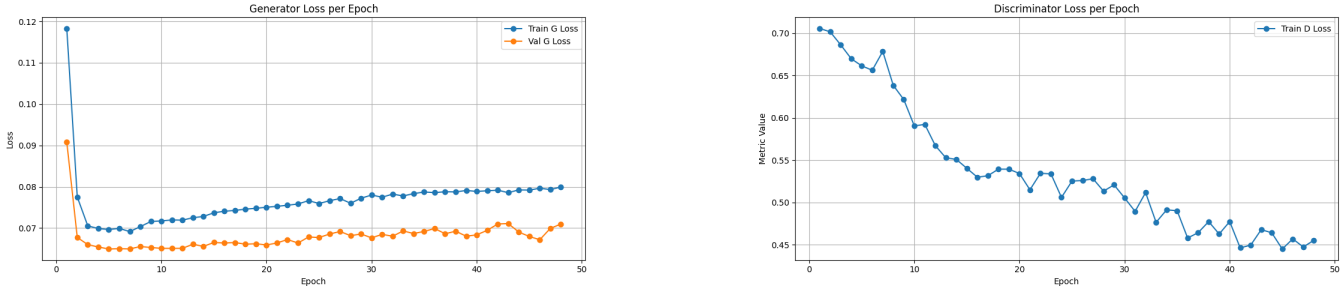
4.3 Discussion and Limitations

The quantitative and qualitative results demonstrate the model's effectiveness in tackling the image deblurring task. The rapid convergence to a good validation score, as noted by early stopping, suggests that the architecture learns efficiently. However, the performance metrics (e.g., validation PSNR around 24-25 dB and SSIM around 0.79-0.80) are promising for a custom architecture but also indicate that there is room for improvement when compared to current state-of-the-art deblurring methods which often report higher values on the GOPRO dataset.

Several limitations of the current approach and model were identified:

- **Handling Severe or Complex Blurs:** The model might struggle with images containing extremely severe or highly non-uniform motion blurs, potentially leaving residual blur or introducing artifacts in such challenging scenarios.
- **Potential for GAN-induced Artifacts:** While GANs enhance perceptual quality, they can sometimes introduce subtle, high-frequency artifacts that are not present in the ground truth. Careful tuning of loss weights and discriminator architecture is often needed to mitigate this.
- **Fixed Input Size and Generalization:** The model is trained on images resized to 800×450. Its performance on images of significantly different resolutions or aspect ratios might degrade without retraining or employing patching strategies during inference.
- **Dataset Specificity:** While GOPRO_Large is diverse, performance on other types of blur (e.g., out-of-focus blur not well-represented in GOPRO) might vary.

These limitations offer clear directions for future enhancements and investigations.



(a) Generator Loss (Train vs. Validation)

(b) Discriminator Loss (Training)

Figure 2: Training and Validation Losses: (a) Generator loss curves. (b) Discriminator training loss curve.

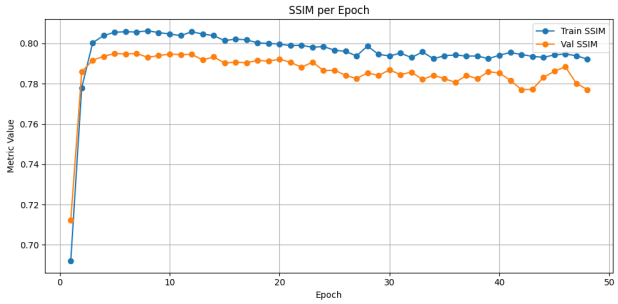


Figure 3: Structural Similarity Index Measure (SSIM) during training (Train vs. Validation).

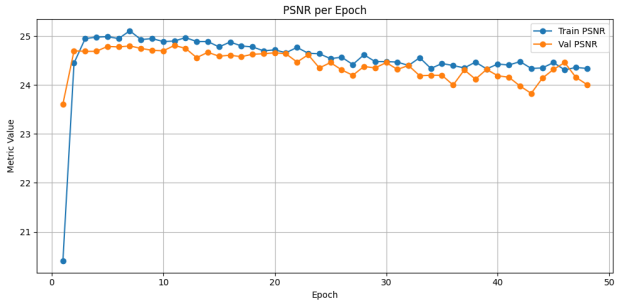


Figure 4: Peak Signal-to-Noise Ratio (PSNR) during training (Train vs. Validation).

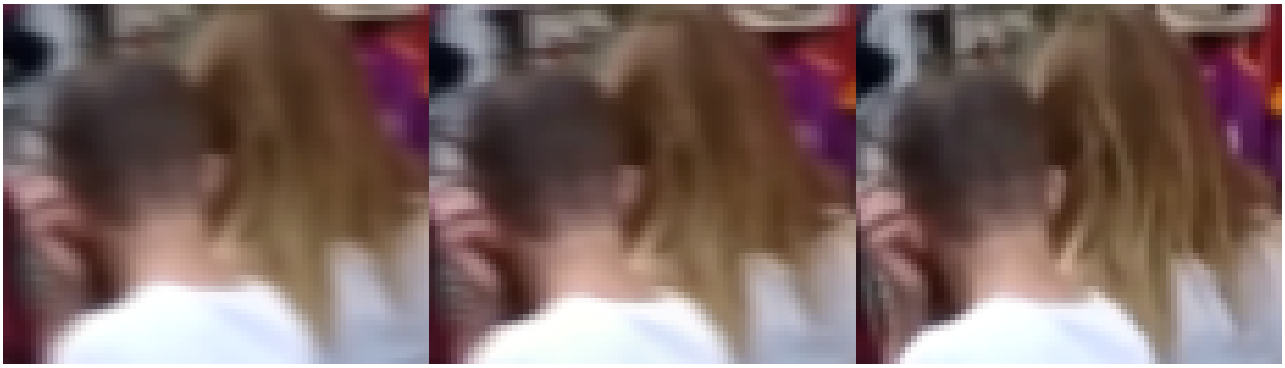


Figure 5: Qualitative comparison of deblurring results on test images. Each row typically displays: Input Blurred Image (Left), and Our Model's Deblurred Output (Center), Ground Truth Sharp Image (Right).

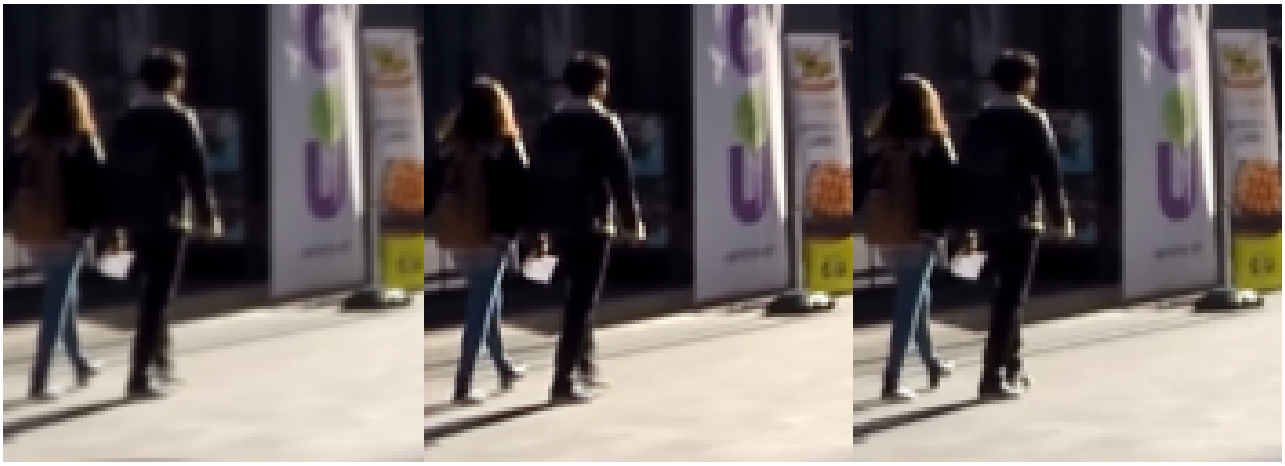
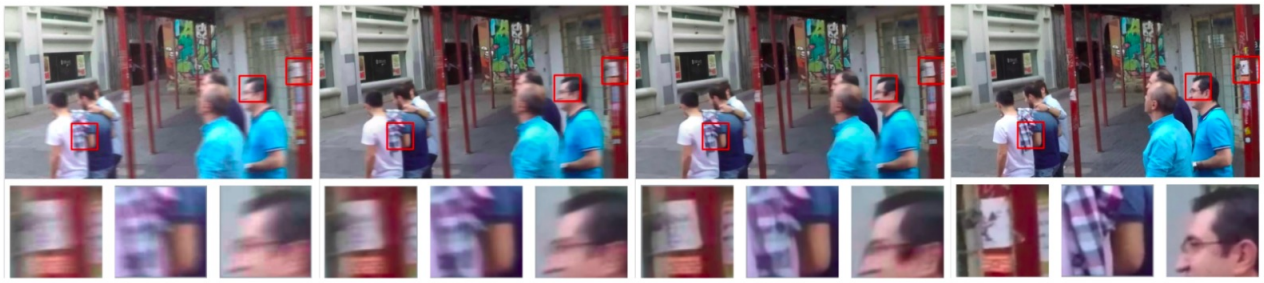


Figure 6: Qualitative comparison of deblurring results on test images. Each row typically displays: Input Blurred Image (Left), and Our Model's Deblurred Output (Center), Ground Truth Sharp Image (Right).

Figure 7: Qualitative comparison of deblurring results on test images. Each row typically displays: Input Blurred Image (Left), and Our Model's Deblurred Output (Center), Ground Truth Sharp Image (Right).



(a) Degraded photo (b) DeblurGAN (c) DeblurGAN-v2 (Inception-ResNet-v2) (d) Clean photo

Figure 6: Visual comparison example on the Restore Dataset.

Figure 8: For comparative purposes, a representative result from a contemporary state-of-the-art deblurring approach is presented.

5 Conclusions

This project successfully developed and evaluated a novel Convolutional Neural Network (CNN) architecture for image deblurring, integrated within a Generative Adversarial Network (GAN) framework. The proposed generator architecture, characterized by its specialized processing blocks (`t1`, `t2`, `t4`) and an extensive network of skip connections, was designed to effectively capture multi-scale features and preserve high-frequency details essential for sharp image reconstruction. The model was trained using a composite loss function combining pixel-wise Mean Squared Error (MSE), structural similarity (SSIM) [6], and an adversarial loss component to enhance perceptual quality.

Experiments conducted on the GOPRO_Large dataset [1] demonstrated the efficacy of our approach. The model achieved promising quantitative results, with the best performing generator yielding a validation PSNR of 24.79 dB and a validation SSIM of 0.7950. Qualitative analysis of the deblurred images further corroborated these findings, showing significant improvements in image sharpness and detail recovery compared to the blurred inputs. The adversarial training, facilitated by a PatchGAN [5] discriminator, contributed to producing visually plausible results. The early convergence observed during training suggests that the designed architecture is capable of learning the deblurring task efficiently.

In summary, this work contributes a custom-designed deep learning model that effectively addresses the image deblurring problem. The results affirm the potential of combining carefully architected CNNs with adversarial training strategies [15] to achieve both quantitative accuracy and perceptual realism in image restoration tasks. While the performance is encouraging, the study also highlighted areas for potential improvement, as discussed in the limitations and future work.

5.1 Future Work

Building upon the findings and limitations of this project, several promising directions for future research and development can be identified:

- **Architectural Enhancements:** Further exploration of network architecture could yield performance gains. This includes incorporating more advanced attention mechanisms (e.g., self-attention, channel attention) within the generator to better focus on salient image regions. Experimenting with different types of normalization layers beyond standard Batch Normalization, or refining the existing `t1, t2, t4` blocks, could also be beneficial. Investigating adaptive blocks that can adjust their behavior based on input image characteristics is another avenue.
- **Loss Function Refinement:** While the current composite loss is effective, alternative or supplementary loss functions could be investigated. This includes exploring more sophisticated perceptual losses, such as LPIPS (Learned Perceptual Image Patch Similarity) [18], which often correlate better with human perception of image quality. Different adversarial loss variants, like Wasserstein GAN (WGAN) [19] or WGAN-GP [20] losses, could lead to more stable training and potentially higher quality results by addressing issues like mode collapse.
- **Advanced Training Strategies:** Modifications to the training strategy could be explored. This includes experimenting with larger batch sizes (contingent on GPU memory), different learning rate schedules (e.g., cyclical learning rates), or employing curriculum learning where the model is initially trained on simpler deblurring tasks before progressing to more complex ones. Longer training with more aggressive and diverse data augmentation techniques might also help improve generalization.
- **Dataset Expansion and Diversity:** Training the model on a larger and more diverse dataset, encompassing a wider variety of blur types (e.g., out-of-focus, atmospheric, lens-specific) and scene contents, could significantly enhance its robustness and generalization capabilities to real-world scenarios.
- **Handling Severe and Spatially-Varying Blur:** For images afflicted with very severe or spatially-varying motion blur, a single-pass network might be insufficient. Investigating multi-stage deblurring approaches, where an initial coarse deblurring is followed by refinement stages, or developing specialized modules within the network to explicitly handle spatially-varying blur kernels, could be a valuable direction.
- **Model Efficiency and Deployment:** For practical applications, especially on resource-constrained devices, model efficiency is crucial. Future work could focus on techniques such as network pruning, knowledge distillation, or quantization to reduce the model's size and computational footprint without significant degradation in deblurring performance.
- **Blind Deblurring Enhancements:** Further improving the "blind" nature of the deblurring, where the blur kernel is unknown and potentially complex, remains a key challenge. Exploring architectures or training schemes that are even more robust to a wide range of unknown blurs would be beneficial.

These potential avenues aim to build upon the current work to develop even more powerful and versatile image deblurring solutions.

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