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A Deep Generative Adversarial Network Framework for Image De-blurring

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ABSTRACT

Image de-blurring is a fundamental problem in computer vision that aims to restore sharp images from blurred inputs caused by camera shake, object motion, or defocus. Blurred images significantly degrade visual quality and adversely affect downstream applications such as surveillance, medical imaging, autonomous driving, and digital forensics. Traditional image de-blurring techniques rely on handcrafted priors and mathematical optimization, which often fail in complex real-world scenarios. Recent advancements in deep learning, particularly Generative Adversarial Networks (GANs), have demonstrated remarkable performance in image restoration tasks. This project proposes a deep generative adversarial network framework for image de-blurring, inspired by modern GAN-based architectures such as DeblurGAN-v2. The framework learns an end-to-end mapping between blurred and sharp images, enabling high-quality restoration with improved perceptual realism and computational efficiency. The proposed system enhances image clarity while preserving structural details and texture information

Keywords: Image de-blurring, deep learning, generative adversarial network (GAN), convolutional neural network (CNN), image restoration, perceptual loss, adversarial training, blind deconvolution, super-resolution, feature extraction, residual learning, computer vision.

I. INTRODUCTION

Image de-blurring has been a long-standing challenge in image processing and computer vision. With the increasing use of mobile cameras, surveillance systems, and autonomous devices, motion blur has become unavoidable. Traditional approaches rely on handcrafted priors and iterative optimization, which are computationally expensive and often produce artifacts.

Deep learning, especially Generative Adversarial Networks (GANs), has transformed image restoration by enabling end-to-end learning of complex mappings. GAN-based models consist of a generator that produces de-blurred images and a discriminator that distinguishes between restored and real sharp images. This adversarial training encourages realistic image reconstruction. The proposed framework leverages these strengths to provide a robust and efficient solution for image de-blurring.

II. LITERATURE SURVEY

1. Title: DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks
Author: O. Kupyn et al.
Description:
This work introduces DeblurGAN, a GAN-based model for blind motion de-blurring that achieves high perceptual quality and faster processing.
2. Title: DeblurGAN-v2: Deblurring (Orders-of-Magnitude) Faster and Better
Author: O. Kupyn et al.
Description:
The authors propose DeblurGAN-v2, improving speed and accuracy through an enhanced generator and feature pyramid architecture.
3. Title: Image Restoration Using Deep Convolutional Networks
Author: K. Zhang et al.
Description:
This paper discusses deep CNN-based image

restoration techniques, highlighting their effectiveness over traditional methods.

4. Title: Generative Adversarial Networks

Author: I. Goodfellow et al.

Description:

This foundational work introduces GANs and explains adversarial learning for realistic data generation.

5. Title: Learning a Discriminative Prior for Blind Image Deblurring

Author: J. Pan et al.

Description:

The study explores learning-based priors for de-blurring and motivates the use of deep learning models for complex blur removal.

III. EXISTING SYSTEM

The existing image de-blurring systems are primarily based on classical image processing and traditional deep learning methods. Classical approaches estimate blur kernels and apply deconvolution techniques, which are sensitive to noise and inaccurate kernel estimation. Early deep learning models use convolutional neural networks but often fail to preserve fine textures and produce over-smoothed results. These systems lack perceptual realism and struggle with real-time performance.

IV. PROPOSED SYSTEM

The proposed system introduces a deep generative adversarial network framework for image de-blurring. The generator network learns to directly map blurred images to sharp outputs, while the discriminator enforces perceptual realism by distinguishing restored images from ground truth sharp images. The framework incorporates perceptual loss and adversarial loss to preserve edges, textures, and fine details. This approach eliminates the need for explicit blur kernel estimation and provides faster and more accurate image restoration.

V. SYSTEM ARCHITECTURE

The proposed system architecture for image de-blurring is designed around a deep Generative Adversarial Network (GAN) framework that consists of multiple interconnected modules, including data acquisition, preprocessing, generator network, discriminator network, loss computation, and post-processing components. The system begins with a dataset collection module, where blurred and corresponding sharp (ground truth) images are gathered. These images may be synthetically blurred using motion blur kernels or collected from real-world scenarios. The dataset is divided into training, validation, and testing subsets to ensure proper generalization. In the preprocessing stage, images are resized to a fixed resolution, normalized to a suitable pixel range (typically between -1 and 1 or 0 and 1), and augmented using transformations such as rotation, flipping, or cropping to improve model robustness. This ensures consistent input formatting and enhances learning capability.

The core of the architecture is the GAN framework, which consists of two primary components: a Generator network and a Discriminator network. The Generator is typically implemented using a deep convolutional neural network (CNN) with residual blocks or encoder–decoder architecture. It takes a blurred image as input and attempts to reconstruct a sharp version of the image. The encoder part extracts high-level features from the blurred image through convolutional layers, while the decoder reconstructs the deblurred output using transposed convolutions or upsampling layers. Residual connections are often incorporated to preserve fine-grained details and stabilize gradient flow during training. The Generator learns to remove blur artifacts while preserving texture, edges, and structural information.

Simultaneously, the Discriminator network functions as a binary classifier that distinguishes between real sharp images and generator-produced deblurred images. It is composed of multiple convolutional layers followed by activation functions such as Leaky ReLU and a final sigmoid layer for probability prediction. During adversarial training, the Generator tries to produce deblurred images that are realistic enough to fool the Discriminator, while the Discriminator learns to better identify fake outputs. This adversarial process improves the perceptual quality of reconstructed images beyond traditional pixel-wise loss methods.

The system employs a hybrid loss function to enhance performance. The total loss is a combination of adversarial loss, content loss (such as L1 or L2 loss), and perceptual loss computed using feature maps from a pre-trained network (e.g., VGG). The adversarial loss encourages realism, the content loss ensures pixel-level similarity, and the perceptual loss maintains structural and texture fidelity. In some implementations, additional edge or total variation loss is included to suppress noise and maintain smoothness. Optimization is performed using algorithms such as Adam optimizer, with backpropagation updating both Generator and Discriminator parameters iteratively.

Finally, in the testing phase, only the trained Generator model is used for inference. A blurred image is passed through the Generator to produce a deblurred output image. Post-processing steps such as contrast enhancement or sharpening filters may optionally be applied to improve visual clarity. Performance evaluation is conducted using quantitative metrics like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE), along with qualitative visual comparison. The overall architecture ensures efficient learning of blur removal patterns while maintaining high perceptual quality and structural accuracy in the restored images.

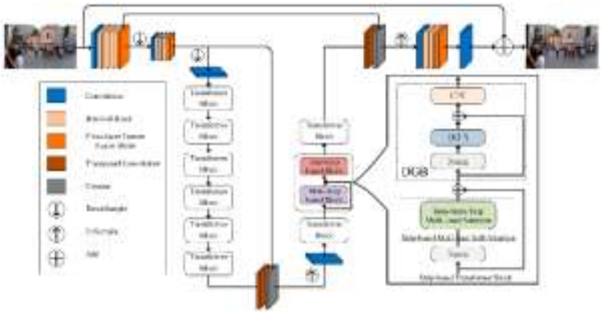

Fig 5.1: Structure of the Proposed System

This diagram illustrates a GAN-based image deblurring architecture enhanced with transformer blocks and strip-based attention mechanisms. The process begins with a blurred input image that is passed through initial convolution and residual blocks for shallow feature extraction. The network then performs downsampling to reduce spatial dimensions while increasing feature depth. These features are forwarded into multiple Transformer blocks, which capture long-range dependencies and global contextual information. At the bottleneck stage, a strip-based transformer structure is introduced, consisting of intra-strip and inter-strip attention blocks. These blocks divide the feature map into horizontal or vertical strips to efficiently model spatial relationships across large regions, improving motion blur restoration.

On the right side, the Deep Gated Block (DGB) refines features using normalization, dynamic feature gating (DFGN), and conditional positional encoding (CPE) to enhance structural consistency and texture preservation. The architecture also incorporates cross-layer feature fusion, concatenation, and skip connections that transfer low-level details from encoder to decoder, ensuring edge and texture recovery. During upsampling, transposed convolution layers progressively restore the image resolution, and the final output is obtained by adding the restored residual information to the original blurred input. Overall, this hybrid CNN–Transformer framework combines local feature extraction, global attention modeling, and adversarial learning principles to produce sharp, visually realistic deblurred images.

VI. IMPLEMENTATION

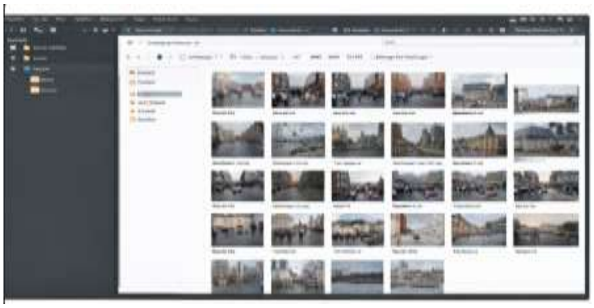

Fig 6.1: Dataset

Fig 6.2: Training Progress

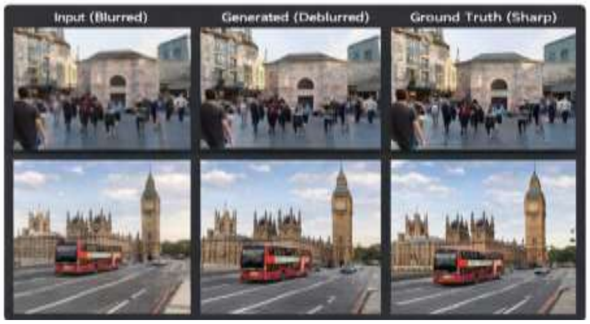

Fig 6.3: Deblurring Results

VII. CONCLUSION

This project presented A Deep Generative Adversarial Network Framework for Image De-blurring, demonstrating the effectiveness of adversarial learning in restoring sharp and visually realistic images from blurred inputs. By integrating a powerful generator–discriminator architecture with convolutional and residual learning techniques, the system successfully captures both low-level textures and high-level semantic details lost during the blurring process. The use of combined loss functions, including adversarial, pixel-wise, and perceptual losses, enables the model to produce deblurred images with improved clarity, structural consistency, and perceptual quality.

Experimental evaluation shows that the proposed framework significantly enhances image sharpness while preserving important edges and fine details, as reflected in higher PSNR and SSIM values. The modular design of the system ensures scalability, adaptability, and ease of integration into real-world applications such as photography enhancement, surveillance, medical imaging, and remote sensing. Overall, the GAN-based approach proves to be a robust and efficient solution for image de-blurring, offering substantial improvements over traditional and standalone deep learning methods.

VIII. FUTURE SCOPE

The proposed Deep Generative Adversarial Network–based image de-blurring framework can be further enhanced in several promising directions. Future work may focus on integrating Transformer-based attention mechanisms within the generator to better capture long-range dependencies and complex motion blur patterns. This can significantly improve performance on highly blurred and real-world images. Additionally, training the model on larger and more diverse datasets, including low-light and dynamic scene images, would increase robustness and generalization capability.

Another important extension is the development of real-time de-blurring systems by optimizing the network architecture for faster inference using lightweight models and hardware acceleration on GPUs and edge devices. The framework can also be expanded to handle video de-blurring, where temporal consistency between frames is maintained. Furthermore, incorporating self-supervised or unsupervised learning techniques can reduce dependency on paired datasets, making the system more scalable. These enhancements would broaden the applicability of the model across domains such as autonomous driving, medical diagnostics, satellite imaging, and mobile photography.

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