University of Science and Technology of Hanoi
Information and Communication Technology Department

# IMAGE DEBLURRING USING GAN AND AUTOENCODER

Group 22

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# 1.INTRODUCTION

## Context and Motivation:

- Image deblurring is essential in computer vision.
- Crucial for fields: photography, surveillance, autonomous driving, medical imaging.
- Blurry images degrade performance in vision-based applications.
- Common causes: camera shake, defocus, fast-moving objects.

(a)

(b)

(c)


(a) camera shake
(b) defocus scene
(c) moving objects.

# 1.INTRODUCTION

## Objectives:

- Investigate GAN and Autoencoder for single-image motion deblurring.
- Train models on the GoPro dataset.
- Evaluate models with PSNR and SSIM.
- Compare performance with baseline models.

## Expected outcomes:

- Develop GAN and Autoencoder-based deblurring systems.
- Evaluate image restoration performance.
- Identify strengths and limitations of each model.
- Demonstrate practical potential for real-world applications.

# 2.DATASET

- **GoPro Dataset:** High-quality dataset for motion deblurring.
- Captured using GoPro Hero4 Black camera at 240 fps.
- 3,214 image pairs: blurry and sharp ground truth.
- Resolution: 1280 × 720 pixels.
- Used for training and benchmarking deblurring models.

# 3. DATA PREPROCESSING

**GAN Models:**

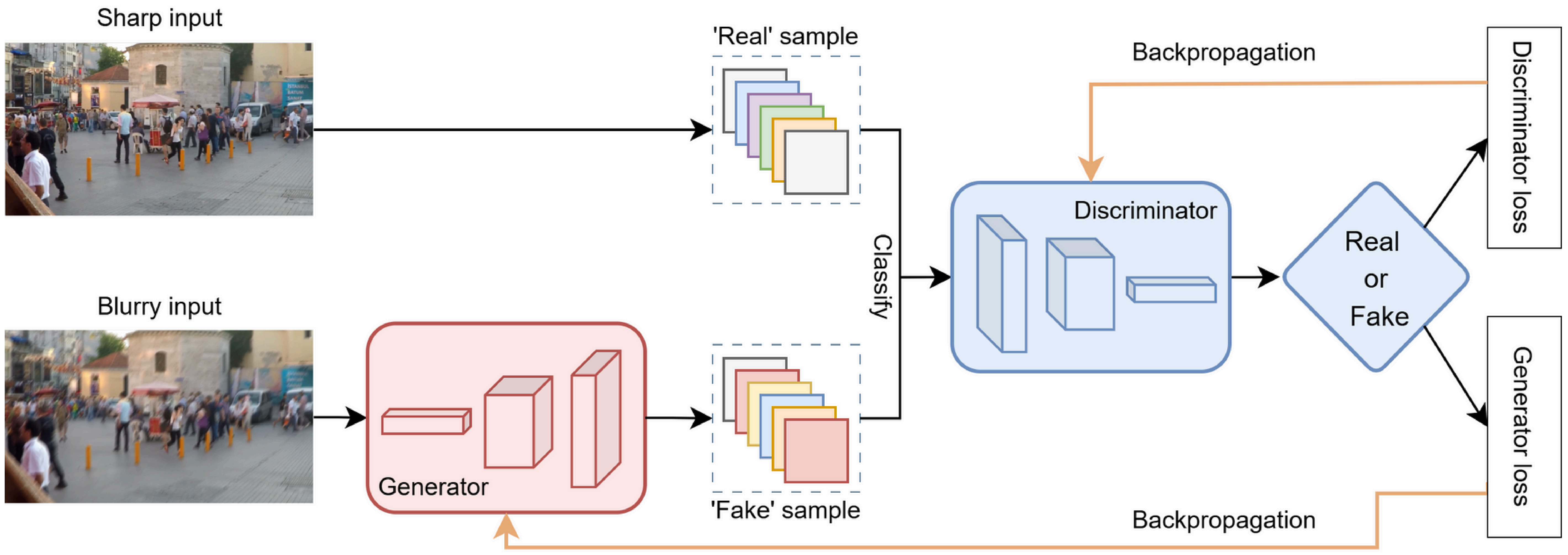
- Resize images to 448 × 448 pixels.
- Convert to tensor format for PyTorch.

**Autoencoder Model:**

- Resize images to 224 × 224 pixels.
- Normalize pixel values to range [0, 1].

# 4. GAN ARCHITECTURE

## Generator Architecture:



# 4. GAN ARCHITECTURE

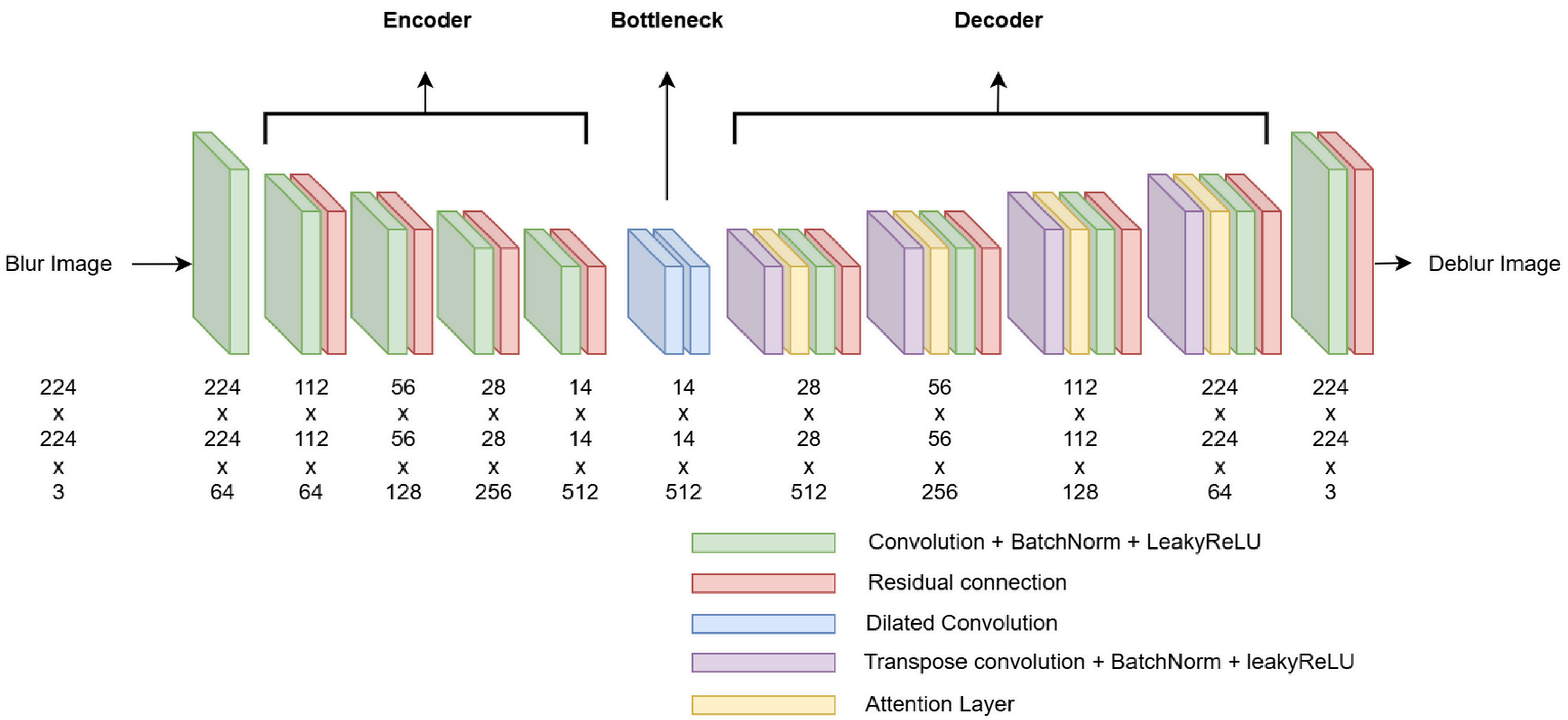
**Generator:**

- Encoder-decoder architecture.
- Extracts features from blurred images and reconstructs sharp images.
- Uses residual blocks for better feature propagation.

**Discriminator:**

- Classifies images as "real" (sharp) or "fake" (generated).
- Uses convolutional layers with batch normalization and LeakyReLU activation.
- Final layer: Sigmoid activation for real/fake probability.

# 5. AUTOENCODER ARCHITECTURE



# 5. AUTOENCODER ARCHITECTURE

**Encoder:**

- Progressive downsampling with increasing feature depth.
- Captures blur patterns at various resolutions.

**Bottleneck:**

- Dilated convolutions for a larger receptive field.
- Captures wide contextual information for accurate blur estimation.

**Decoder:**

- Upsamples to reconstruct sharp images.
- Uses residual connections and attention mechanisms to focus on important regions.

# 6. EVALUATION METRICS

## PSNR (Peak Signal-to-Noise Ratio):

$$\text{MSE} = \frac{1}{M \cdot N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [I(i,j) - K(i,j)]^2$$

$$\text{PSNR} = 10 \cdot \log_{10} \left( \frac{\text{MAX}_I^2}{\text{MSE}} \right)$$

- Higher PSNR indicates better image quality.

## SSIM (Structural Similarity Index Measure):

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

- Closer to 1 means higher perceptual quality.

# 7. EXPERIMENTAL RESULTS

| MODEL | Parameters | PSNR | SSIM |
|---|---|---|---|
| Kupyn et al | - | 28.7 | 0.958 |
| Nah et al | - | 28.93 | 0.91 |
| Ji et al | - | 31.15 | 0.96 |
| Li et al | 11.4M | 29.3 | 0.72 |
| GAN (ours) | 8.1M | 27.24 | 0.8568 |
| Autoencoder (ours) | 10.3M | 26.95 | 0.839 |

# 7. EXPERIMENTAL RESULTS


**Autoencoder:**

- From left to right: Input blur image, Ground truth sharp image, autoencoder output.

# 7. EXPERIMENTAL RESULTS

**GAN architecture:**

- From left to right: Input blur image, GAN output, Ground truth sharp image.

# 8. CHALLENGES AND LIMITATIONS

## Challenges:

- Difficulty in restoring fine details in images.
- GAN architecture lacked advanced techniques like attention mechanisms and Wasserstein loss.
- Performance gap due to simplicity of models.

## Limitations:

- Low PSNR and SSIM scores indicate challenges in fine detail restoration.
- Simple architectures in GAN and Autoencoder hinder performance on complex blur patterns.
- Lack of advanced regularization techniques.

# 9. CONCLUSION AND FUTURE WORK

## Conclusions:

- Developed GAN and Autoencoder models for image deblurring.
- GAN performed slightly better, but both models showed potential.
- Integrated techniques like residual connections and attention for improved performance.

## Future work:

- Improve sharpness and finer details for better deblurring.
- Capture more nuanced textures and structures in the blur.
- Expand the models' capabilities to handle diverse blur scenarios.
- Develop an application to demonstrate real-world model performance.

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# THANK YOU FOR YOUR ATTENTION!