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CSE 681

Low-Light Enhancement (GAN vs. UNet)

Proposal: Enhancing Low-Light Image Enhancement using GAN and U-Net

1. Title

"GAN-based Low-Light Image Enhancement: A Deep Learning Approach for Improved Image Quality in Challenging Lighting Conditions"

2. Introduction

Low-light image enhancement is a critical challenge in computer vision, impacting applications from photography to autonomous driving. Traditional techniques often suffer from noise amplification and loss of detail. This proposal explores a GAN-based approach to enhance low-light images, focusing on generating high-quality, realistic outputs by leveraging adversarial training.

3. Research Problem and Objectives

- **Research Problem**: Existing low-light enhancement techniques often result in poor-quality reconstructions with amplified noise. This project aims to address these issues by employing GANs to improve image quality.
- **Objectives**:
  1. Develop a GAN architecture tailored for low-light image enhancement.
  2. Enhance visual quality, noise reduction, and color accuracy.
  3. Compare the proposed GAN model with state-of-the-art techniques for performance evaluation.

4. Literature Review

Low-light image enhancement is an essential area in computer vision, targeting applications ranging from photography to autonomous systems. Enhancing images captured under suboptimal lighting conditions is challenging, as it involves addressing noise, color distortion, and the loss of fine details. The literature on light enhancement can be broadly classified into traditional approaches, deep learning-based techniques, and the emerging use of Generative Adversarial Networks (GANs).

1. Traditional Techniques

Traditional methods for enhancing low-light images often rely on histogram equalization, Retinex theory, and contrast enhancement. Gonzalez and Woods' *Digital Image Processing* offers a comprehensive overview of these techniques, providing fundamental methods like

- **Histogram Equalization**: A widely used method to improve image contrast by redistributing pixel intensity values.

- **Retinex Algorithms**: Based on human visual perception, these algorithms decompose an image into reflectance and illumination layers to enhance visibility. They are effective in preserving color balance while adjusting brightness.

These approaches have limitations, particularly in handling severe noise, color fidelity, and preserving structural details in extremely low-light conditions. These challenges prompted the exploration of machine learning and deep learning solutions.

2. Deep Learning-based Approaches

Deep learning has significantly advanced the field of image enhancement. CNN-based models excel in learning complex patterns and have become the backbone of many modern enhancement techniques. Key contributions in this domain include:

- **LLNet: A Deep Autoencoder Approach to Natural Low-Light Image Enhancement (Lore et al., 2017)**: This research presents a deep autoencoder architecture tailored for enhancing low-light images. The model addresses both visibility improvement and noise reduction by using a dual-layer network, effectively balancing detail preservation with brightness adjustments.
- **Learning to See in the Dark (Chen et al., 2018)**: A landmark study that employs a deep CNN to process raw sensor data from extremely dark images. The method leverages the Sony Image Dataset (SID) and demonstrates how deep learning can achieve exceptional quality in challenging lighting. However, while CNNs perform well, they may introduce artifacts or fail to generalize across diverse lighting conditions, making GANs an attractive alternative.

3. GAN-based Techniques

Generative Adversarial Networks (GANs) have recently become a popular choice for low-light image enhancement, leveraging the ability to generate high-quality images that resemble real-world scenes. The literature reveals several innovative approaches:

- **EnlightenGAN: Deep Light Enhancement without Paired Supervision (Chen et al., 2020)**: This study introduces EnlightenGAN, a model that enhances low-light images without relying on paired datasets. The GAN framework consists of a generator, which learns to produce realistic, well-lit images, and a discriminator, which assesses image quality. This adversarial training significantly improves the generalization of the model to various lighting conditions and offers more realistic outputs compared to traditional CNNs.
- **Kindling the Darkness: A Practical Low-Light Image Enhancer (Zhang et al., 2019)**: This research employs a lightweight CNN for mobile applications, but it highlights the limitations of traditional CNN-based methods, such as struggles with noise and color consistency. GAN-based approaches, by contrast, effectively maintain color accuracy and handle noise through adversarial training.

- **LIME: Low-Light Image Enhancement via Illumination Map Estimation (Guo et al., 2020)**: Although not GAN-based, this study presents a hybrid approach that uses deep learning to estimate illumination maps for low-light images, which helps in fine-tuning GAN models to focus on lighting adjustments while preserving fine details.

4. Evaluation Metrics and Perceptual Metrics

Evaluating the performance of enhancement techniques requires both objective and subjective metrics. Zhang et al.'s work on perceptual metrics highlights the use of deep learning models to assess the visual quality of images, an important aspect for GAN-based approaches where traditional metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) may not fully capture perceptual quality.

5. Gaps and Future Directions

While GAN-based models have demonstrated superiority in enhancing low-light images, several challenges remain:

- **Generalization**: GANs can sometimes overfit to specific datasets, struggling with diverse lighting scenarios.
- **Training Stability**: Adversarial training can be unstable, leading to mode collapse or vanishing gradients.
- **Complexity and Computation**: GAN models often require significant computational resources, which limits their application in real-time or resource-constrained environments
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5. Methodology

- **Model Architecture**:
  - Use a GAN framework, consisting of a generator and discriminator.
  - The generator aims to enhance low-light images, while the discriminator evaluates the realism of the output.
  - Explore the effect of using a Unet as a generator.
  - Explore using advanced variants like StyleGAN or conditional GANs to improve output quality.
- **Loss Functions**:
  - Combination of adversarial loss, perceptual loss, and L1/L2 loss to balance realism and fidelity.
- **Modifications**:
  - Introduce noise reduction layers within the generator.
  - Implement attention mechanisms for localized enhancement.

6. Data Collection and Preprocessing

- **Datasets**: Utilize publicly available datasets like LOL (Low-Light), SID (Sony Image Dataset), or similar for training.
- Generate a Training dataset using carla or Unreal Engine.
- **Preprocessing**:
  - Data augmentation (rotation, flipping, noise addition).
  - Normalization of pixel values.
  - Creation of paired data for training (low-light input with corresponding well-lit target).

7. Experimental Design

- Use standard metrics like PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and perceptual quality measures to evaluate performance.
- Comparison with baseline methods:
  - Histogram Equalization
  - CNN-based methods
  - Non-GAN deep learning techniques
  - GAN deep learning techniques
- Benchmarking using computational resources to assess training time and model efficiency.

8. Expected Results and Analysis

- Improved image quality with enhanced brightness, better noise reduction, and preservation of color details compared to traditional techniques.
- Analysis of GAN-generated outputs to assess improvements in structural similarity and perceptual quality.
- Visual and statistical comparisons through graphs, charts, and example images.

9. Potential Contributions

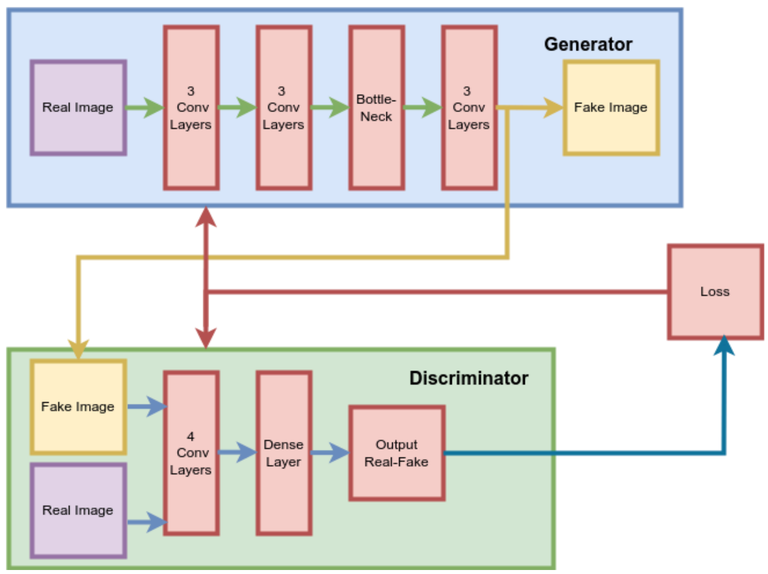
- Introduce a novel GAN architecture optimized for low-light scenarios.
- Scale up the model to handle bad weather scenarios.
- Experiment with different Neural network architectures to act as generators.
- Integrate a GAN network with SLAM techniques achieving better results in bad lighting scenarios.
- Potential applications in photography, security, and autonomous driving for better visibility in challenging conditions.

10. Implementation Details

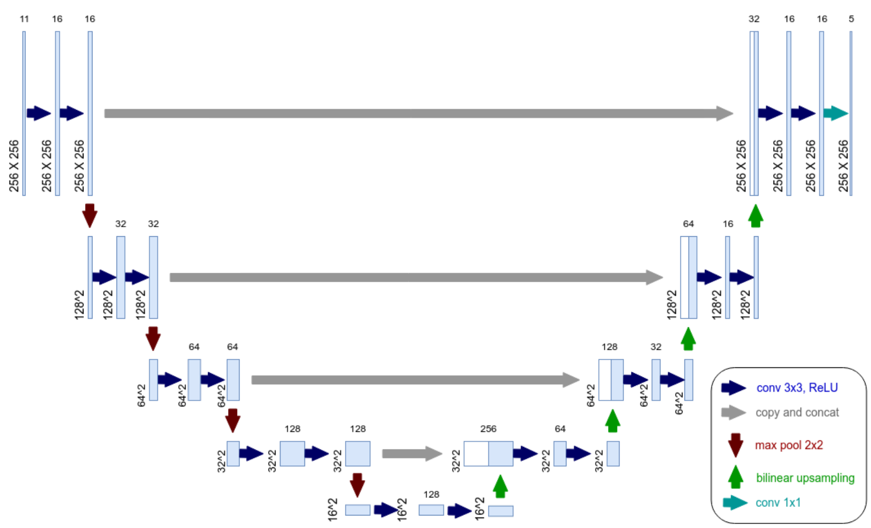
Implementation will include Two models

- Unit
- GAN

Implementation is conducted by using the TensorFlow framework in Python.



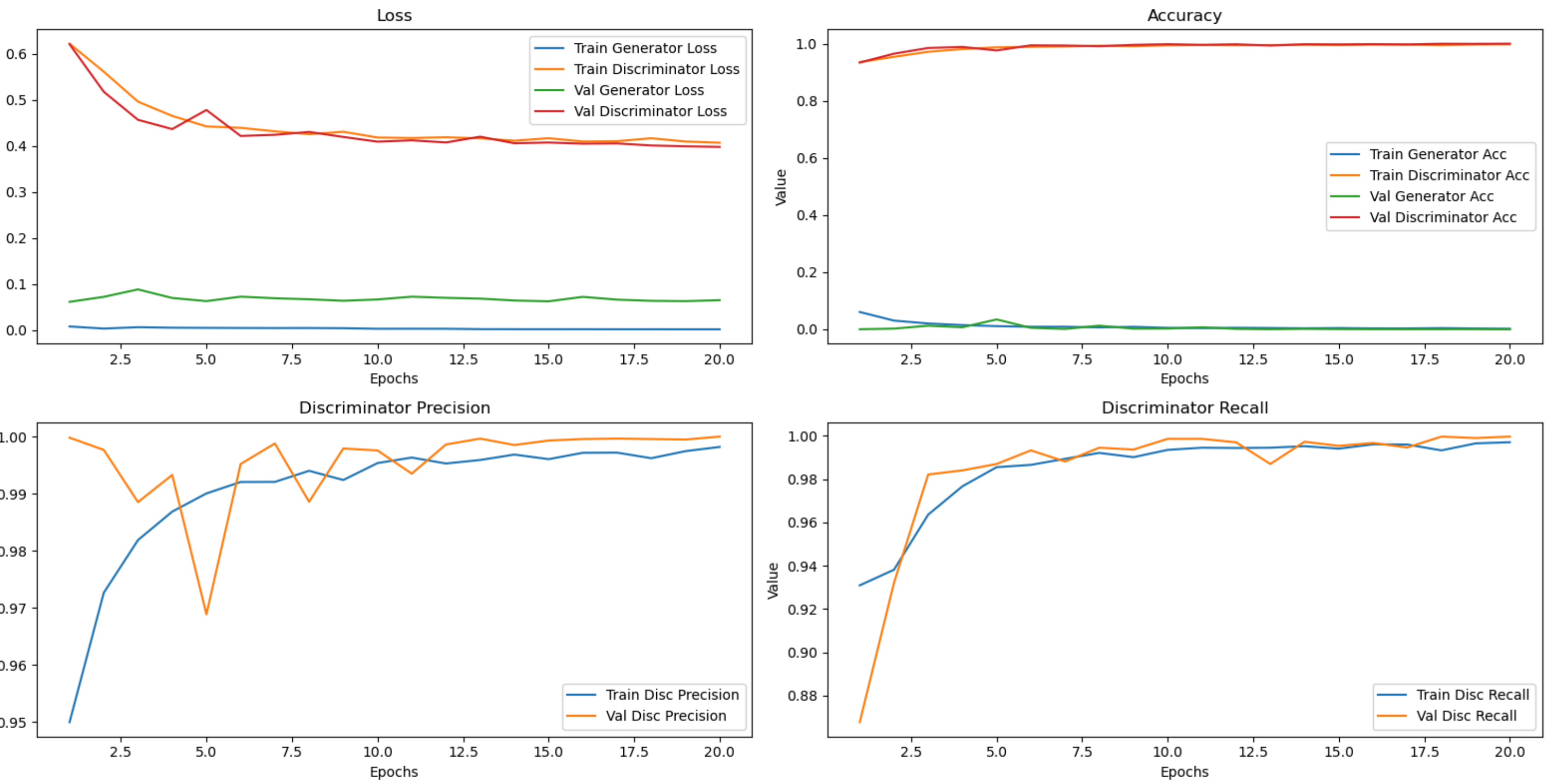
Implemented GAN Network architecture



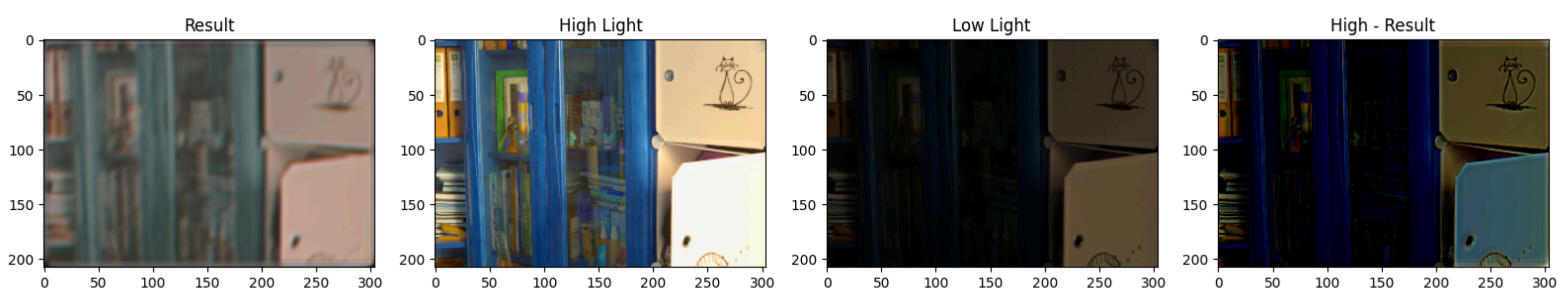
Implemented U-Net architecture

11. Implementation Results

- GAN

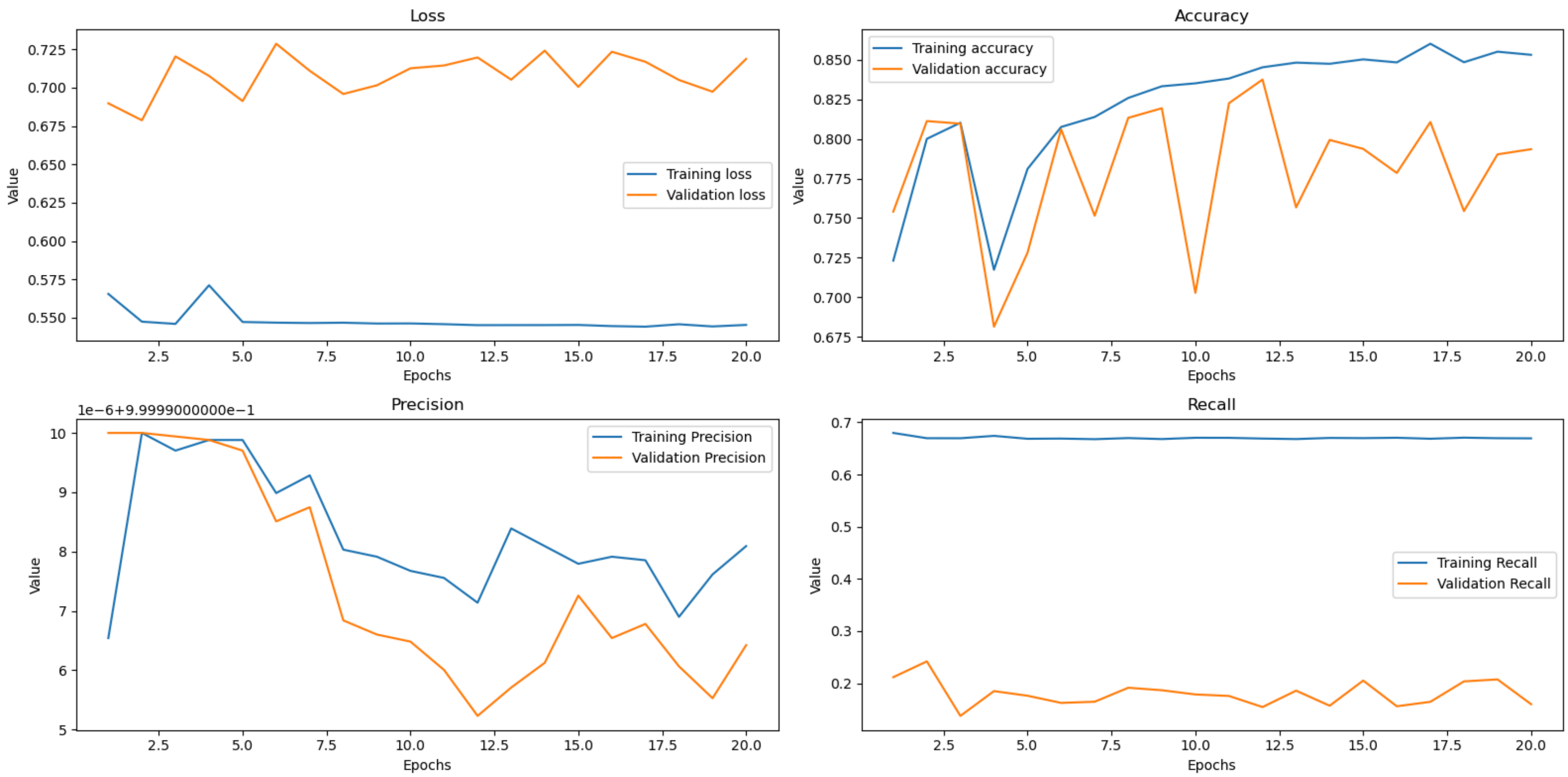


GAN Network Analysis ’20 epochs’

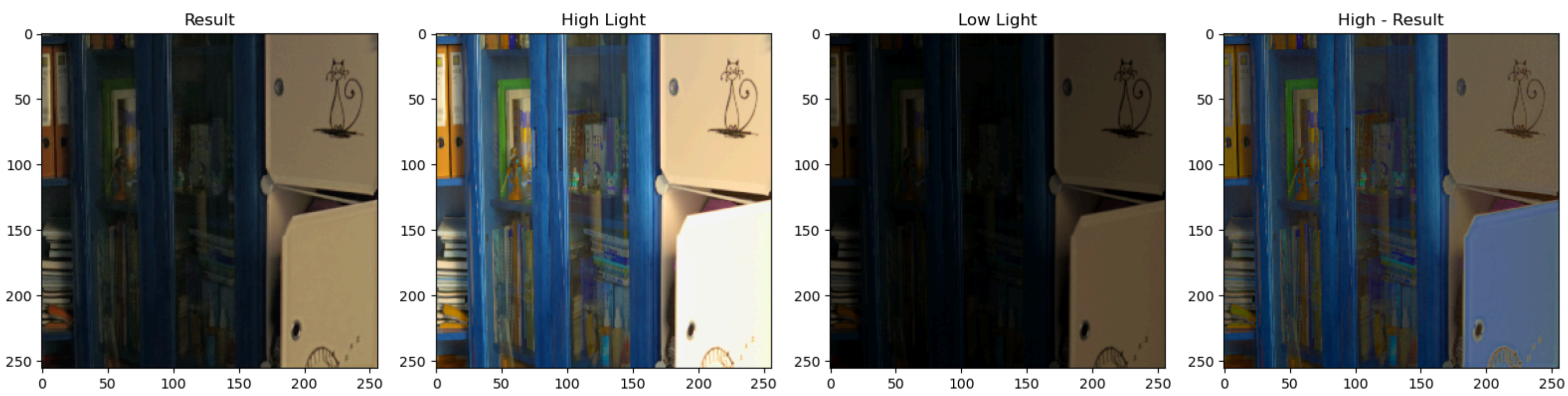


GAN Results

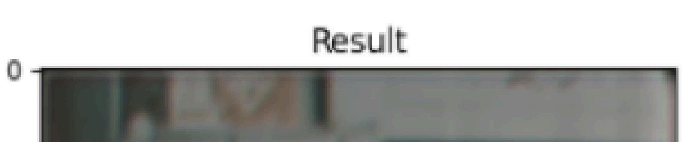
- Unet

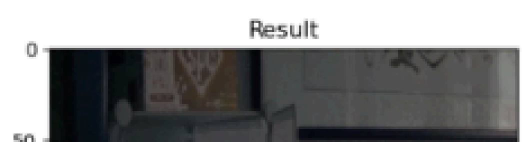


Unet Network Analysis ’20 epochs’



U-Net Results





12. Discussion

- By tracking the two proposed networks, "GAN" and "U-Net," it is clearly noticed that U-Net performs better with fewer resources. By only tracking for 20 epochs, it performed much better, also taking into consideration that the training time for the U-Net is much less than that of the GAN network.
- Implemented Networks
- Presentation Video

12. References

- Learning-to-See-in-the-Dark
- Chen, C., Chen, Q., Xu, J., & Koltun, V. (2018). Learning to See in the Dark.
- Wei, C., Wang, W., Yang, W., & Liu, J. (2018). Deep Retinex Decomposition for Low-Light Enhancement.
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