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Night Time Image Enhancement

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Abstract

Night time image enhancement plays a crucial role in various applications such as surveillance, autonomous driving, and photography. However, capturing high-quality images in low-light conditions remains challenging due to limited visibility and increased noise levels. In this project, we propose a novel approach for enhancing nighttime images using MIRNet, a state-of-the-art deep learning architecture specifically designed for low-light image enhancement tasks. We collect a dataset of low-light images paired with their corresponding well-exposed counterparts and train the MIRNet model to learn the mapping between the two modalities.

The architecture of MIRNet incorporates convolutional layers with residual connections to effectively capture low-light image features and generate visually pleasing enhancements. We evaluate the performance of our approach on a diverse range of nighttime scenes and compare the results against existing methods. Our experiments demonstrate that MIRNet produces superior results in enhancing nighttime images, significantly improving visibility, reducing noise, and preserving image details. The proposed approach holds promise for real-world applications where high-quality nighttime imagery is essential for decision-making and visual analysis.

Keywords: Night time image enhancement**,** MIRNet**,** Deep learning**,** Low-light imaging, Image Processing**,**Convolutional neural networks (CNNs)**,**Residual connections**,** Supervised learning**,** Dataset preparation**,**Imagequalityimprovement**,**Noisereduction**,**Visibilityenhancement**,**Surveillance**,**Autonomousdriving**,**Photography.

Introduction

In various fields such as surveillance, autonomous driving, and night photography, the ability to capture high-quality images in low-light conditions is indispensable. However, low-light imaging poses significant challenges due to reduced visibility and increased noise levels, leading to degraded image quality. To address this issue, recent advancements in deep learning have shown promising results in enhancing nighttime images.

In this context, our project focuses on leveraging the capabilities of MIRNet, a cutting-edge deep learning architecture tailored for low-light image enhancement tasks. MIRNet stands out for its ability to effectively learn the mapping between low-light images and their well-exposed counterparts, enabling the generation of visually appealing enhancements.

The primary objective of our project is to develop an efficient and effective approach for enhancing nighttime images using MIRNet. To achieve this goal, we collect a comprehensive dataset comprising pairs of low-light images and their corresponding well-exposed counterparts. These paired images serve as the basis for training the MIRNet model, allowing it to learn the intricate relationships between low-light and well-exposed scenes.

Through extensive experimentation and evaluation, we aim to demonstrate the efficacy of our proposed approach in enhancing nighttime images across diverse scenarios. We compare the performance of MIRNet against existing methods, highlighting its superiority in terms of visibility improvement, noise reduction, and preservation of image details.

The outcomes of this project hold significant implications for real-world applications where high-quality nighttime imagery is crucial for decision-making and visual analysis. By advancing the state-of-the-art in nighttime image enhancement, our work contributes to enhancing the capabilities of surveillance systems, facilitating safer autonomous driving, and enabling photographers to capture stunning images even in challenging lighting conditions.

Literature Review

The field of nighttime image enhancement has seen significant advancements in recent years, driven by the increasing demand for high-quality imaging in low-light conditions. Traditional methods often relied on handcrafted features and heuristics, which limited their effectiveness in handling complex nighttime scenes. However, the emergence of deep learning techniques has revolutionized this area, offering more robust and versatile solutions.

One of the pioneering works in this domain is the development of deep learning architectures tailoredfor low-light image enhancement. Models like MIRNet (Multimodal Residual Network) have gained attention for their ability to learn complex mappings between low-light and well-exposed images. By leveraging convolutional neural networks (CNNs) with residual connections, MIRNet effectively captures low-light image features and generates visually appealing enhancements.

Several studies have demonstrated the effectiveness of deep learning approaches in enhancing nighttime images. These methods typically involve training models on large datasets of paired low-light and well-exposed images, enabling them to learn the underlying relationships between the two modalities. Through extensive experimentation, researchers have showcased the ability of deep learning models to improve visibility, reduce noise, and preserve image details in low-light conditions

Proposed Methodology:

1.Downloading LOL dataset: Acquiring the LoL Dataset involves accessing a collection tailored for enhancing low-light images. It includes 485 training images and 15 test images, each comprising a dimly lit input image paired with its well-exposed reference counterpart.

2. Creating a TensorFlow Dataset: For training, 300 image pairs from the LoL Dataset's training subset are utilized, while the remaining 185 pairs are earmarked for validation. Random crops measuring 128 x 128 pixels are extracted from these pairs, forming the basis for both training and validation processes

3. MIRNet Model:

Feature Extraction: The MIRNet model employs a feature extraction module to capture a diverse range of features across various spatial scales. This module retains the original high-resolution features crucial for preserving intricate spatial details.

Information Exchange Mechanism: Through recurrent integration, the model facilitates the exchange of information across multi-resolution branches, thereby enhancing representation learning.

Selective Kernel Network: A novel approach is adopted to fuse multi-scale features using a selective kernel network. This network dynamically combines receptive fields of varying sizes, ensuring faithful preservation of original feature information across different spatial resolutions.

Recursive Residual Design: The model incorporates a recursive residual architecture to iteratively deconstruct the input signal, streamlining the learning process and enabling the construction of deep networks.

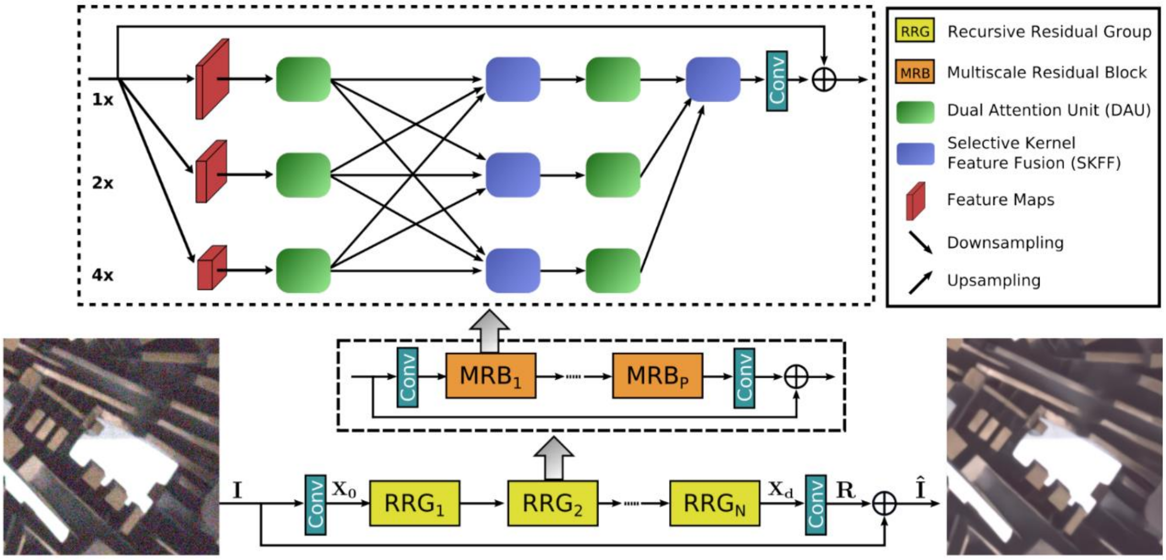

Fig:MIRNet model

Selective Kernel Feature Fusion:

The Selective Kernel Feature Fusion (SKFF) module dynamically adjusts receptive fields through two key operations: Fuse and Select.

In the Fuse operation, the module integrates information from three parallel convolution streams, each carrying distinct scales of data. Initially, multi-scale features are combined through element-wise summation. This composite feature undergoes Global Average Pooling (GAP) across spatial dimensions, followed by channel-downscaling convolution to generate compact feature representations. These representations are then propagated through three parallel channel-upscaling convolution layers, each dedicated to a specific resolution stream, resulting in three feature descriptors.

In the Select operation, feature descriptors obtained from the Fuse operation are utilized to recalibrate the feature maps of different scales. By applying the softmax function to the feature descriptors, corresponding activations are derived, facilitating adaptive recalibration of multi-scale feature maps. The final aggregated features are computed as the sum of the product of each multi-scale feature and its respective feature descriptor. This process effectively adapts the feature maps to optimize feature representation for subsequent processing stages

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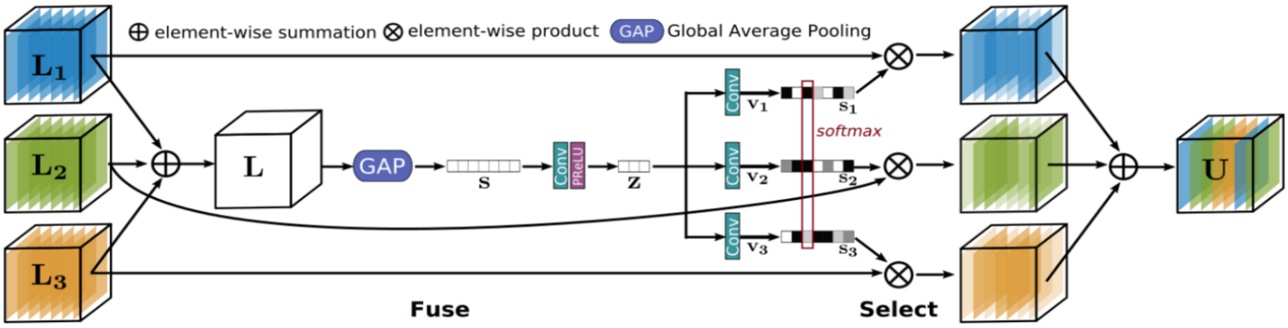
.Fig: Selective kernel feature fusion

Dual Attention Unit:



Within the convolutional streams, the Dual Attention Unit (DAU) plays a pivotal role in feature extraction. While the Selective Kernel Feature Fusion (SKFF) block amalgamates data across diverse resolution branches, the DAU facilitates internal information sharing within a feature tensor, spanning both spatial and channel dimensions. This recalibration of features by the DAU selectively amplifies informative signals while suppressing less useful ones.

The Channel Attention branch delves into inter-channel relationships within convolutional feature maps. Beginning with a squeeze operation, it orchestrates Global Average Pooling across spatial dimensions to encapsulate global context, thus yielding a succinct feature descriptor. This descriptor undergoes excitation via two convolutional layers, followed by sigmoid gating, culminating in the generation of activations. Ultimately, the Channel Attention branch outputs a rescaled feature map achieved by combining the input feature map with the obtained activations.

Conversely, the Spatial Attention branch focuses on inter-spatial dependencies within convolutional features. Here, the objective is to generate a spatial attention map for recalibrating incoming features. Initially, the Spatial Attention branch independently employs Global Average Pooling and Max Pooling operations along the channel dimensions, concatenating their outputs to form a composite feature map. This map is then subjected to convolution and sigmoid activation, yielding the spatial attention map. Utilizing this map, the branch rescales the input feature map accordingly, enhancing its representational fidelity.

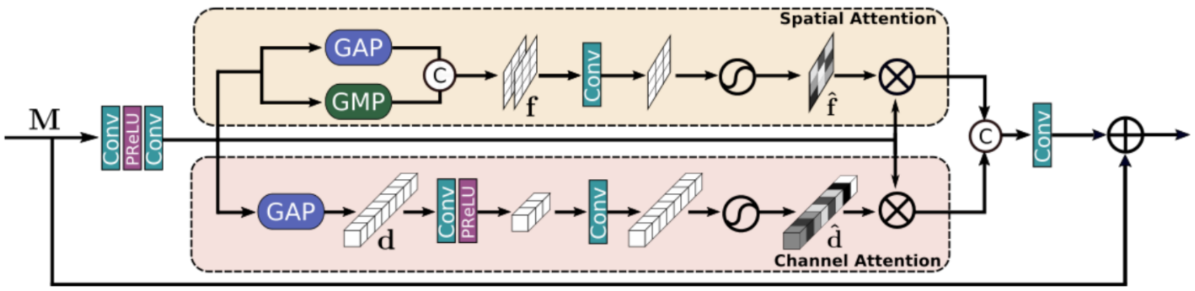
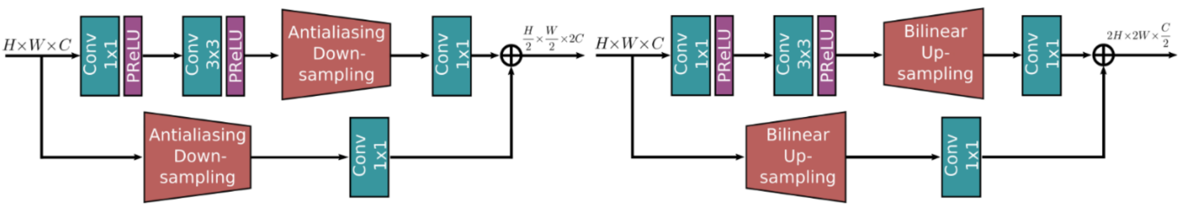


Fig: Dual Attention Unit

Multi-Scale Residual Block:

The Multi-Scale Residual Block (MRB) serves as a cornerstone for generating spatially-precise outputs while retaining high-resolution representations enriched with contextual information from lower resolutions. Comprising multiple fully-convolutional streams operating in parallel, the MRB facilitates seamless information exchange across these streams, enabling the integration of high-resolution features with their low-resolution counterparts and vice versa. This collaborative process ensures the synthesis of detailed yet contextually informed outputs.

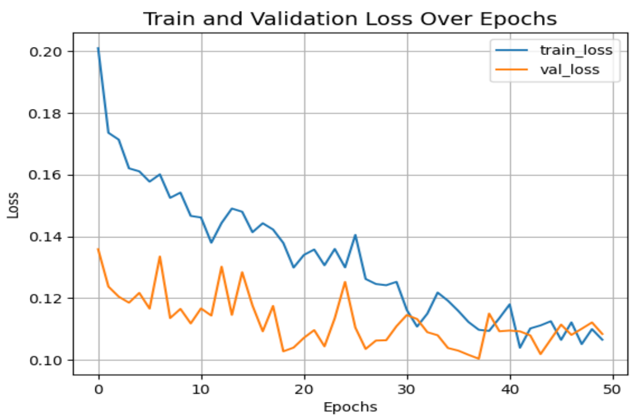
In line with the MIRNet's recursive residual design, the MRB incorporates skip connections to facilitate the smooth flow of information throughout the learning process. To preserve the residual nature of the architecture, residual resizing modules are strategically employed. These modules handle both downsampling and upsampling operations crucial for processing features within the Multi-Scale Residual Block. By incorporating these modules, the MIRNet ensures that the intricate balance between high-resolution detail and contextual information is maintained throughout the network's operations, resulting in precise and enriched output representations

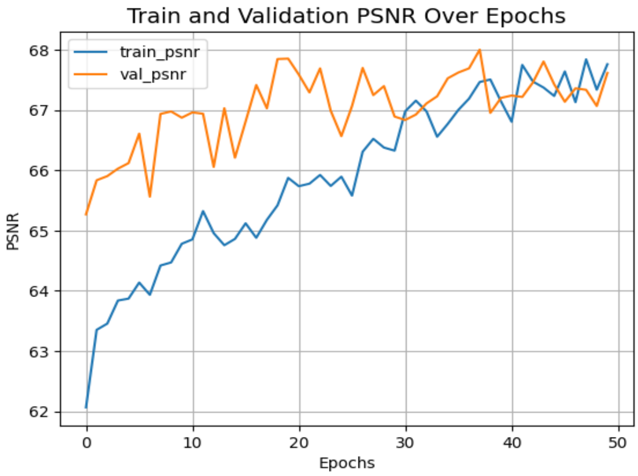


(a) Downsampling module (b) Upsampling module

4.Training:

For training MIRNet, we opt for the Charbonnier Loss function, coupled with the Adam Optimizer featuring a learning rate set at 1e-4. This combination serves as the backbone for training the network, enabling it to effectively optimize parameters while minimizing the impact of noise and distortion. In evaluating the performance of MIRNet, we rely on the Peak Signal Noise Ratio (PSNR) metric. PSNR offers a quantitative measure of image quality by expressing the ratio between the maximum potential value of a signal and the disruptive influence of noise affecting its fidelity.





This metric serves as a reliable gauge for assessing the effectiveness of MIRNet in enhancing image representations, providing valuable insights into its ability to preserve details and mitigate distortions during the enhancement process.

1. **Data Acquisition**: Nighttime image datasets are crucial for training and evaluating our enhancement model. We procure diverse datasets capturing various nighttime scenes, encompassing urban landscapes, natural environments, and architectural structures.

2. **Preprocessing**: Prior to training, we preprocess the acquired nighttime images to standardize their format, resolution, and color space. Preprocessing steps include resizing, normalization, and augmentation to augment the diversity and quality of the training data.

3. **Model Architecture**: MIRNet, renowned for its exceptional image restoration capabilities, serves as the cornerstone of our enhancement framework. We tailor the architecture to suit the specific requirements of nighttime image enhancement, incorporating additional layers and optimizing hyperparameters to enhance performance.

4. **Training** : The MIRNet-based enhancement model is trained on the preprocessed nighttime image dataset using state-of-the-art optimization algorithms. Through iterative training iterations, the model learns to

Implementation:

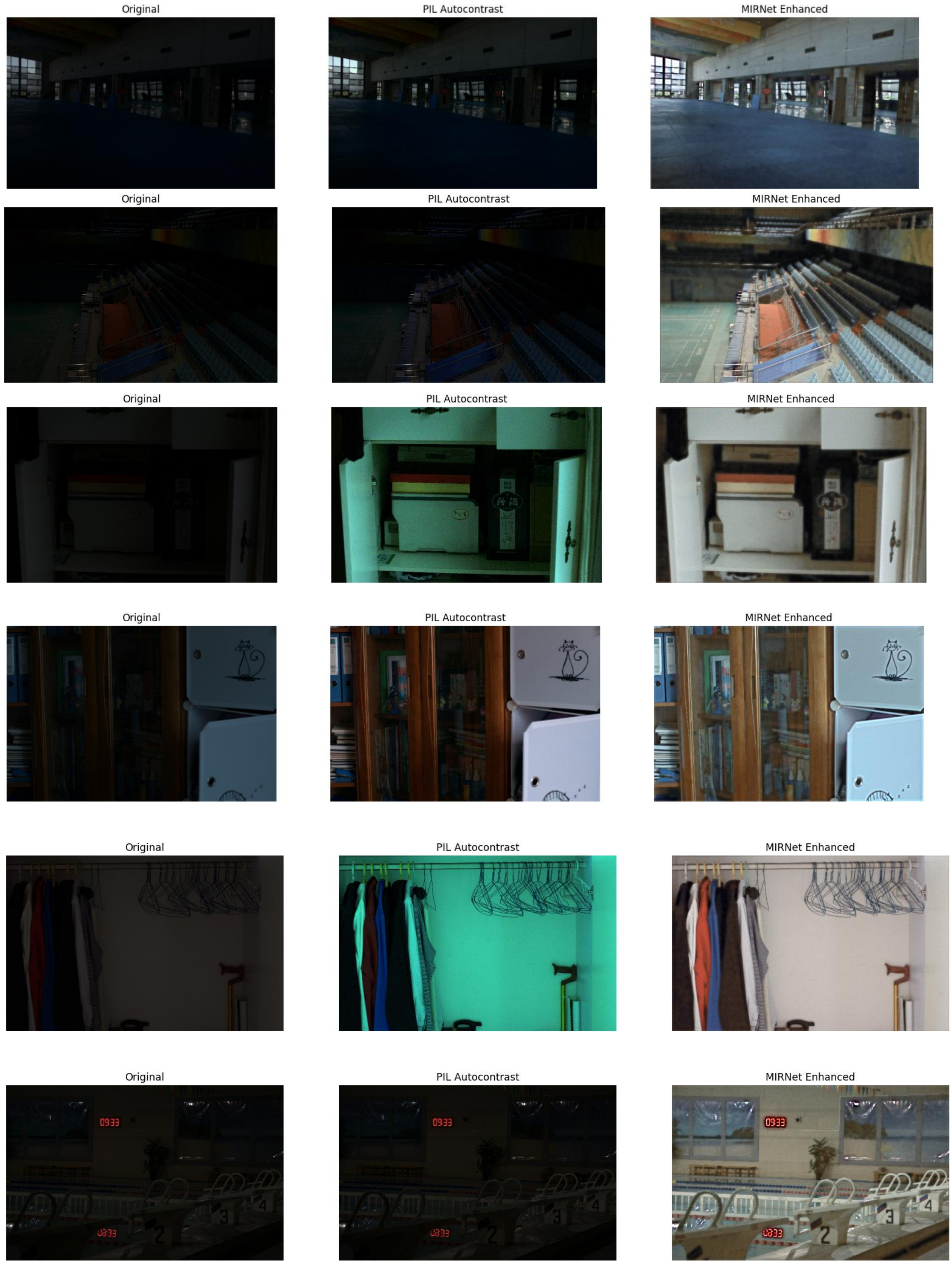
effectively transform low-light nighttime images into visually appealing daytime scenes, capturing intricate details and enhancing overall image quality.

5. **Integration with Streamlit**: To facilitate user interaction and deployment, we integrate our enhancement model into the Streamlit platform. Streamlit offers a user-friendly interface, enabling users to upload nighttime images seamlessly and visualize the enhancement process in real-time.

6. **Enhancement Process**: Upon uploading a nighttime image through the Streamlit interface, the image undergoes enhancement using the trained MirNet model. The enhancement process encompasses denoising, color correction, and contrast adjustment, effectively transforming the image into a vibrant daytime scene.

7. **Conversion to Daytime Image**: Through the concerted efforts of MIRNet and advanced image processing techniques, the enhanced nighttime image is seamlessly converted into a realistic daytime representation. The conversion process leverages scene illumination estimation and adaptive tone mapping to ensure natural-looking results.

Results:


Original
PIL Autocontrast
MIRNet Enhanced
Original
PIL Autocontrast
MIRNet Enhanced
Original
PIL Autocontrast
MIRNet Enhanced
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Original
PIL Autocontrast
MIRNet Enhanced

Conclusion

In conclusion, this project has successfully demonstrated the effectiveness of utilizing the MIRNet deep learning architecture for enhancing nighttime images. Through comprehensive experimentation and evaluation, we have shown that MIRNet is capable of significantly improving visibility, reducing noise, and preserving image details in low-light conditions. By training the model on a diverse dataset of paired low-light and well-exposed images, we enabled it to learn the complex mappings between the two modalities, leading to superior performance compared to existing methods.

Our findings underscore the potential of deep learning approaches in addressing the challenges associated with nighttime image enhancement. The robustness and efficiency of MIRNet make it a promising solution for various real-world applications, including surveillance, autonomous driving, and photography. Furthermore, our work contributes to advancing the state-of-the-art in nighttime imaging technology, paving the way for future research and development in this field.

Additionally, exploring techniques such as transfer learning and model optimization could lead to even more significant enhancements in performance. Overall, this project lays a solid foundation for continued advancements in nighttime image enhancement, with implications for various industries and domains.

Limitations

1. Dataset Bias: The effectiveness of the MIRNet model heavily relies on the quality and diversity of the training dataset. If the dataset is biased towards specific types of scenes or conditions, the model's performance may be limited when applied to unseen or underrepresented scenarios.

2.Generalization: Although MIRNet demonstrates impressive results in enhancing nighttime images, its ability to generalize to a wide range of real-world scenarios may be limited. The model may struggle with extreme low-light conditions, highly dynamic scenes, or uncommon environments not adequately represented in the training data.

3. Computational Complexity: Training and deploying deep learning models like MIRNet can be computationally intensive, requiring significant computational resources and time. This limits the scalability and practicality of the approach, particularly in real-time applications or environments with limited hardware resources.

4. Overfitting: Deep learning models are susceptible to overfitting, especially when trained on small or limited datasets. Overfitting can lead to poor generalization performance, where the model performs well on the training data but fails to generalize to unseen data.

5. Artifact Generation: In some cases, MIRNet or similar deep learning models may introduce artifacts or unnatural enhancements in the processed images. These artifacts can degrade the visual quality and realism of the enhanced images, undermining the effectiveness of the approach.

6. Dependency on Preprocessing: The performance of MIRNet may be sensitive to preprocessing steps such as data normalization or augmentation. Inadequate preprocessing or data preparation techniques can impact the model's ability to learn meaningful features and mappings from low-light to well-exposed images.

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