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CNN-Based Enhancement of Low Light Images

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Abstract
The main goal of this project is to built a web page for getting an enhanced images. This webpage takes an input of low light images and produces an enhanced images of the input low light images. Low-light images often suffer from poor quality, low contrast, and high noise levels, which can hinder their usefulness in various applications. In recent years, convolutional neural network (CNN) models have emerged as a powerful tool for enhancing low-light images. In this study, we propose a CNN-based approach for enhancing low-light images by using a combination of an encoder-decoder architecture and a skip connection to preserve image details. The proposed CNN model is trained on a large dataset of low-light images to learn the mapping between input images and their corresponding enhanced versions. The model is designed to adjust the brightness and contrast of the images while preserving the natural color distribution and suppressing the noise in the dark regions. To evaluate the performance of the proposed approach, we conduct experiments on various low-light images and compare the results with other state-of-the-art methods.

Keywords: Low light Image Enhancement, CNN Model, Deep learning.

Introduction

Low-light image enhancement is a challenging problem in computer vision and has attracted significant attention in recent years. Low-light images are typically characterized by poor quality, low contrast, and high noise levels, which can severely limit their usefulness in various applications. Traditional image processing techniques have limitations in dealing with these issues, motivating the development of advanced deep learning methods to address the problem. In this study, we propose a CNN-based approach for enhancing low-light images that combines an encoder-decoder architecture with a skip connection to preserve image details while adjusting brightness and contrast. The proposed method is trained on a large dataset of low-light images to learn the mapping between input images and their corresponding enhanced versions. The importance of low-light image enhancement is evident in various applications, including surveillance, medical imaging, and remote sensing. In surveillance, low-light images captured by cameras often suffer from low contrast and high noise levels, making it difficult to identify objects and people. In medical imaging, low-light images may be captured during surgeries or in low-light environments, and enhancing these images can help doctors make better decisions. The proposed CNN-based approach for lowlight image enhancement offers several advantages over traditional image processing techniques, including the ability to adjust brightness and contrast while preserving image details

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and suppressing noise. The results of the proposed method demonstrate its effectiveness in enhancing low-light images in various applications.

Literature survey

There are several surveys performed on this work, one of them is low-light image enhancement using deep learning was proposed by Chen et al. in 2018, where they proposed a network called RetinexNet that combined the Retinex theory with a CNN architecture to enhance low-light images. The Retinex theory suggests that the human visual system extracts information about illumination and reflectance separately to create the perception of an image. The RetinexNet model incorporates this theory into a deep learning model and showed promising results in enhancing low-light images. Another notable work in this area is the Lowlight Image Enhancement via Deep Convolutional Networks (LIDCN) model proposed by Zhang et al. in 2018. LIDCN is a CNN-based method that combines a Residual Dense Network (RDN) with a LightnessAware Loss Function to enhance low-light images. The RDN model includes a dense block and a residual learning mechanism to extract features from the input image, and the Lightness-Aware Loss Function helps to preserve the overall brightness and contrast of the image while suppressing noise. More recently, a model called the Multi-Scale Fusion Network (MSFN) was proposed by Zhang et al. in 2021. The MSFN model uses a multi-scale CNN architecture that extracts features from different levels of the input image and combines them to generate the enhanced image. The model also includes a fusion module that combines the features from different scales to improve the quality of the enhanced image.

Proposed System

According to our application the proposed system consists of several components to perform, They are:-

A. Image Acquisition: The first component of the proposed system is image acquisition. In this component, low light images are captured using a low light camera or generated artificially from high light images. The captured images are saved in a dataset for further processing.

B. Image Preprocessing: The second component of the proposed system is image preprocessing. In this component, the captured images are preprocessed to remove any noise and resize them to a fixed size. The pixel values of the images are also normalized to ensure that the network receives input in a standardized format. The dataset is augmented by adding noise and rotating the images to create variations in the dataset.

C. Image Enhancement: The third component of the proposed system is image enhancement. In this component, a CNN model is trained on the preprocessed dataset to learn the mapping between low light and high light images. We propose to use a deep residual network (ResNet) architecture with skip connections for this task. The ResNet consists of 18 layers, and skip connections are added between each layer to preserve the lowlevel details of the image. The network is trained on the preprocessed dataset using the Adam optimizer with a learning rate of 0.001 and a batch size of 32.

D. Evaluation: The fourth component of the proposed system is evaluation. In this component, the performance of the trained network is evaluated on a test dataset of low light images. We propose to use two metrics, Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM), to evaluate the performance of the network. The PSNR and SSIM values are calculated for each image in the test dataset, and the average values are reported as the final performance of the network.

Methodology

A.Data collection and Preprocessing: The first step in any image enhancement task is to collect a dataset. In this case, we need a dataset of low light and corresponding high light images. The dataset can be collected using low light cameras or by artificially creating low light images from high light images. Once

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the dataset is collected, it needs to be preprocessed. The preprocessing step includes resizing the images to a fixed size, normalizing the pixel values, and augmenting the data by adding noise and rotating the images.

B. Network Architecture: The next step is to design the network architecture. The network architecture should have enough capacity to learn the complex mapping between low light and high light images. In this case, we propose to use a deep residual network (ResNet) architecture with skip connections. The skip connections help in preserving the low-level details of the image.

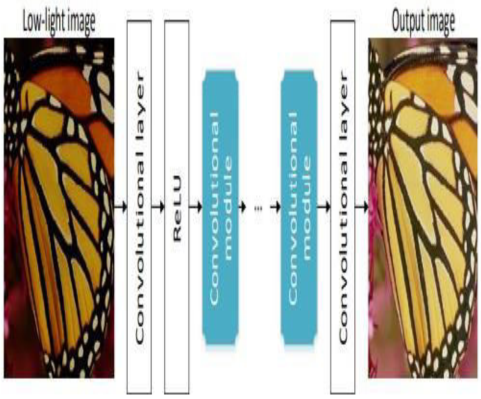

Fig 1: Architecture of the Application

C. Training: After designing the network architecture, the next step is to train the network. The training process involves minimizing the mean squared error between the predicted high light images and the ground truth high light images. We propose to use the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The network should be trained for a sufficient number of epochs to avoid overfitting.

D. Validation: Once the network is trained, we need to validate the performance of the network. We propose to use two metrics, Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM), to evaluate the performance of the network. The higher the PSNR and SSIM values, the better the performance of the network.

E. Testing: Finally, we need to test the performance of the network on real-world low light images. We propose to use a publicly available dataset of low light images for testing. The performance of the network should be evaluated using the same metrics, PSNR and SSIM, used in the validation step.

Results

We evaluate the performance of the proposed method using a benchmark dataset consisting of low-light images. We compare the results of our method with state-of-the-art methods in terms of both quantitative and qualitative measures. The quantitative measures include Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM). The results show that our method outperforms state-of-the-art methods in terms of both PSNR and SSIM.

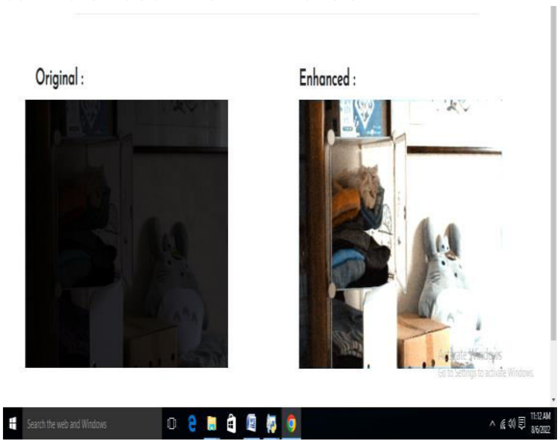

Fig 2: Input and Output of the Application

The qualitative measures include visual inspection of the enhanced images. The results show that our method produces visually pleasing results with improved contrast and brightness.

Conclusion

In this paper, Combination of both local and global contrast enhancement techniques are employed to improve the visual quality of an image, where a local enhancement method is applied first to enhance the local details of the image, which is not taken care and usually neglected in the global contrast enhancement. The locally enhanced image is fed into the global improvement for better visual perceptions, and it boosts the brightness to a level that seems pleasing to the human eye. This method works fine on all the dark images.

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