Low Light Image Enhancement (Denoising of Images)

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Abstract

Denoising of images is crucial in a wide array of applications, from medical imaging and remote sensing to photography and digital art. Noise, which can be introduced through various sources such as sensor imperfections, environmental conditions, or transmission errors, degrades the quality of images and thus reduces overall clarity. Denoising improves visibility and helps improve image recognition systems. The method discussed in this report makes use of convolutional neural networks and custom keras models with custom loss functions.

Data Preprocessing

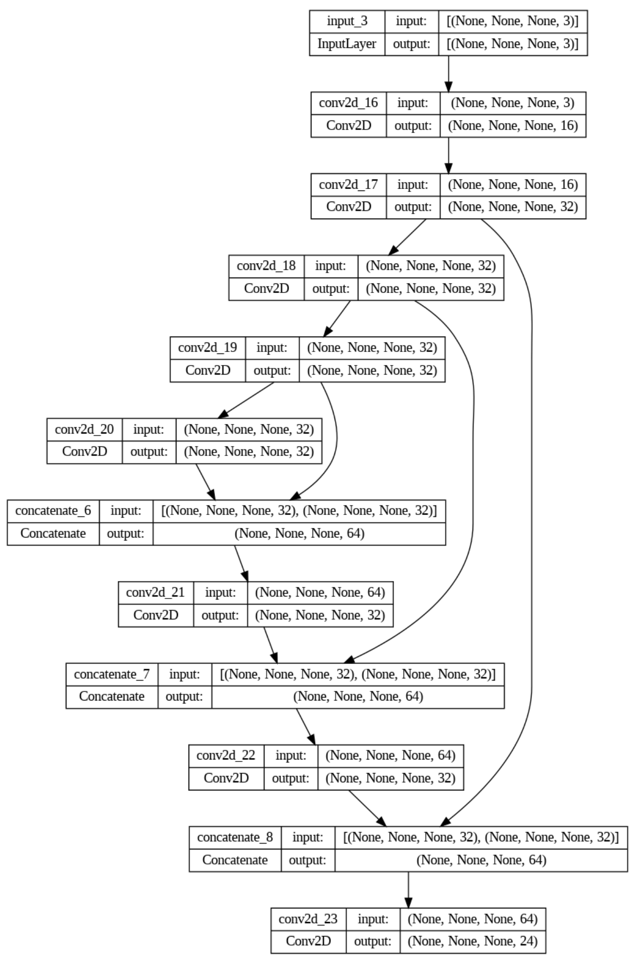
The dataset used is LOL dataset which consists of 500 images, 485 of which are part of the training set and 15 are part of the evaluation set. The training set is split into training and validation set. The final training set has 420 images. Each image is resized to 350x350 pixels from 400x600 pixels. Then the value of each pixel is scaled down between 0-1.

Model Architecture

The architecture of the neural network implemented is shown below. It consists of 8 convolutional layers in total. All the layers consist of 32 filters except the first one and all have the activation function relu except the laast one which has tanh.

This model works by finding the best light-enhancement curves for a given image. These curves are then used to adjust the brightness of all the pixels in the image's RGB channels to create the final enhanced image.

A light-enhancement curve is a type of curve that automatically brightens a dark image. The curve adjusts itself based on the specific details of the image to improve its appearance.



Different Loss Functions

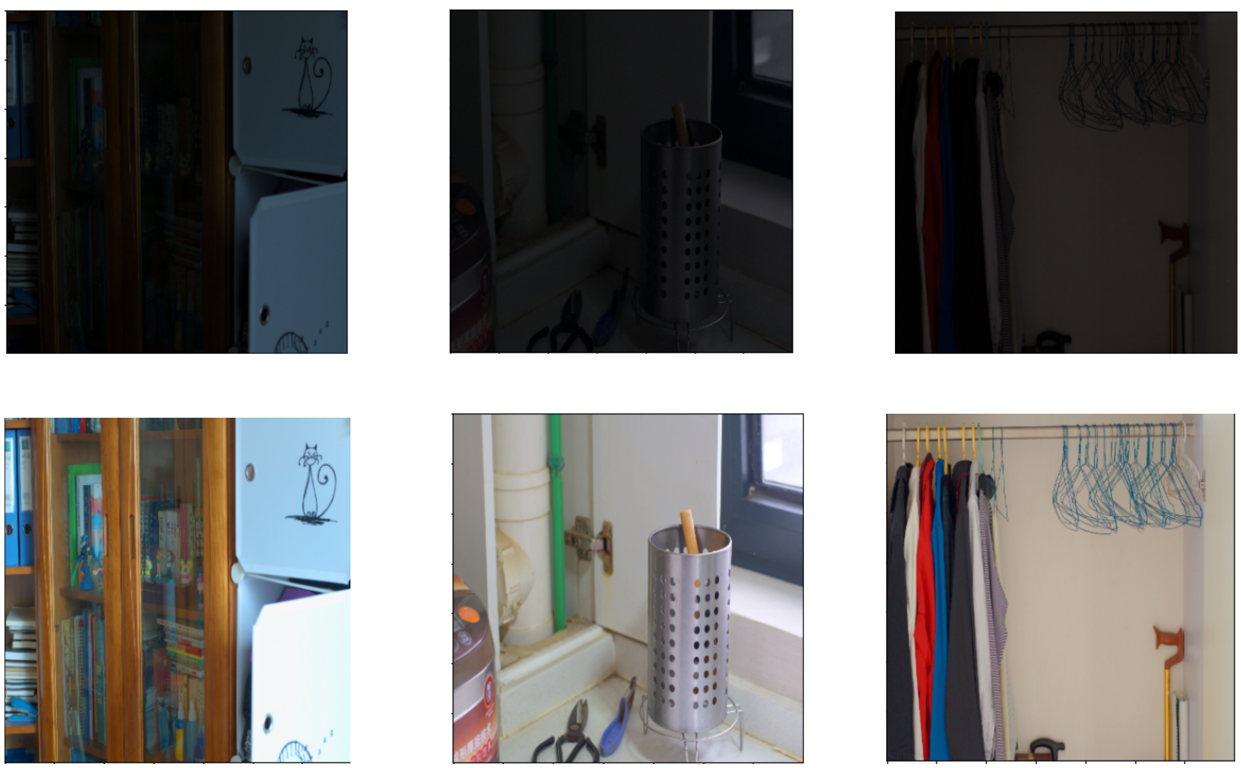
- **Color constancy loss -** It corrects the color deviations that occur in the enhanced image.
- **Exposure loss-** To prevent areas from being too dark or too bright, we use the exposure control loss. This method checks how close the average brightness of a small area is to an ideal level of 0.6.
- **Illumination smoothness loss-**To keep the brightness changes smooth between neighboring pixels, we add the illumination smoothness loss to each curve parameter map.
- **Spatial consistency loss-**The spatial consistency loss ensures that the enhanced image looks natural by maintaining the contrast between neighboring areas in both the original and enhanced images.

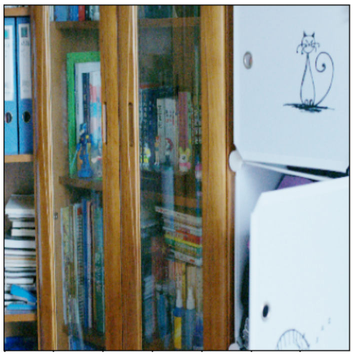
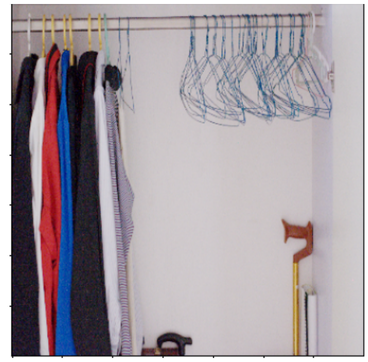
The final model is implemented such that the loss functions and the neural network model work cohesively to attain enhanced images. It sets up the model with custom loss functions and metrics to monitor the training process. During training, it computes the total loss by combining several losses: illumination smoothness, spatial consistency, color constancy, and exposure. The model processes images through multiple stages of enhancement, applying learned parameters to adjust pixel values iteratively. It features methods for training and evaluation, including calculating gradients and updating weights using the Adam optimizer.

Training

The model is trained over 100 epochs with a learning rate of 1e-4. It takes about 30-40 mins to train on the T4 GPU provided by google collab.

Results



The above images are respectively the low light image, the actual image and the enhanced images. The PSNR score achieved for the above model is 16.27. The MSE score is 0.07 and the MAE score is 0.351. The above score is evaluated on the eval set consisting of 15 images.

References

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