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Image Enhancement Techniques Using CNN

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Abstract: *The most significant area in imaging study and processing is image processing technique. The major goal is to improve quality images artificially through other means. The images that are obtained at times through certain mediums may end up distorted making the image unclear. One option to enhance the image quality is to change camera lens, which is costly. Thus, an alternative is required. A conventional neural network (CNN) may give priority to distinct aspects in an image and differentiate between them. A clear review of the literature on a few CNN-based picture enhancing techniques is carried out.*

Keywords: CNN, Image processing, Image enhancement, Denoising.

I. Introduction

1.1 Image Processing

Image is processed by applying many operations on it in order to improve it or extract relevant information from it which is called Image Processing. The input is an image, and the output may be an image or a characteristic or features which is likely a sort of signal processing. The most quickly evolving technology today is an Image processing [1]. It is also a critical research field in engineering and computer science. The image processing as three phases that makes up the process which are as follows:

- To import the image using image acquisition tools.
- The Image Examination and modification.
- Output that either include an altered image or a report image - based analysis.

Analog and digital image processing are the two types of image processing methods employed. Hard copies, such as prints and photographs, can benefit from analogue image processing. When employing these visual tools, image analysts employ a variety of interpretive fundamentals. Digital image processing techniques allow for computer-assisted alteration of digital images. Pre-processing, augmentation, and presentation, as well as information extraction, are the three general processes that all sorts of data must go through when using digital techniques.

1.2 Image Enhancement

Image enhancement is the process of improving the quality and information content of raw data prior to processing. For picture improvement, a variety of software is employed, such as filters, image editors, and other tools for changing various aspects of a full image or parts of an image [2][3].

A few basic sorts of image enhancement technologies merely alter an image's contrast or brightness or edit its grayscale or red-green-blue colour patterns. Basic filters can also be used to convert a colour image to black and white or sepia tone, as well as to add visual effects.

Image enhancement software that is more advanced can apply adjustments to areas of an image. Professional packages, such as those offered by Adobe, enable designers to perform more specialized or professional image enhancements, or to pursue results for graphic design projects in which the original image is stylized or otherwise enriched. Other complex resources for restoring or clarifying images that may be in poor condition due to sub-optimal image capture conditions, ageing, or other causes are included in more advanced types of image enhancement tools, such as Wiener filters for actual de-blurring of images and other complex resources for restoring or clarifying images that may be in poor condition due to sub-optimal image capture conditions, ageing, or other causes.

1.3 Image Enhancement And Convolutional Neural Network (CNN)

CNNs are used for image categorization and recognition because of their high accuracy. The Convolutional Neural Network is a hierarchical model that builds a network in the shape of a funnel, after that produces a fully connected layer. Which is of all interconnected neurons which are connected to one another, and the output is obtained. CNN outperform traditional neural networks using visual, speech, or audio signal inputs [3].

There are three different sorts of layers:

- Convolutional layer
- Pooling layer
- Fully connected (FC) layer

The convolutional layer is the initial layer of a convolutional network. After convolutional layers, more convolutional layers or pooling layers can be added, but the fully connected layer is the last layer. With each layer, the CNN grows more sophisticated, identifying bigger portions of the image. The first layers focus on the most fundamental aspects, such as colours and borders. As the visual data passes through the CNN layers, it starts to recognize larger parts or features of the item, eventually identifying the target object [4].

II. Literature Review

Here in this paper, we'll see at how some of the techniques that are based on the Convolutional Neural Network are being used to improve image quality in areas including denoising, low-light improvement, and contrast correction in this section.

2.1 Image Denoising

In image processing, denoising takes a major part. Vision is obstructed by Noise and diminishes its quality. As a result, denoising is the initial stage in image enhancement. The BM3D algorithm was utilized before neural networks. A Convolutional-Deconvolutional model with 30 layers was presented as part of a deep CNN architecture [1]. Symmetric Skip Connections (SSC) were also added in the architecture between the Conv-DeConv layers. The findings of this method were superior to those of the BM3D algorithm.

Direct Symmetric Connection (DSC) was the concept presented including 5 Conv and DeConv layer and 10 Convolutional Neural Network [2].

Each layer of Conv is linked to its equivalent layer of Deconv in DSC, resulting in four direct connections. The pixel-wise Mean Squared Error, which is the most generally used loss minimizer, is used to denoise the image. Traditional down sampling - up sample structures performed worse than the DSC model.

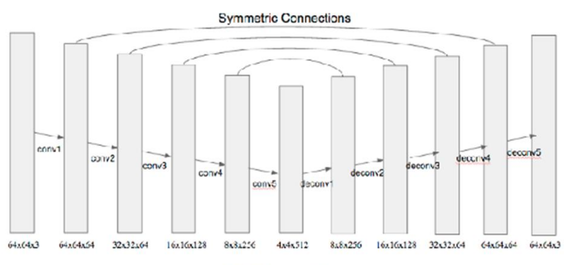

Figure 1: DSC with 10-layer model [2]

2.2 Low Light Image Enhancement

When it is low-light situations, images have a low brightness and contrast level. In many circumstances, only low-light photos are possible to acquire. As a result, improving these low-light photos is crucial. There have been several low-light picture improvement algorithms proposed, which can be divided in the form of two individual groups: Histogram-based approaches and Retinex-based methods.

Histograms based method are simple and commonly utilized. Anyway, the fundamental disadvantage of these approaches is that they treat individual pixel separately, resulting in inconsistency. The Retinex theory and the CNN are the foundations of the model [3]. The Multiscale Retinex and the Feedforward CNN with different Gaussian kernels are demonstrated to be similar.

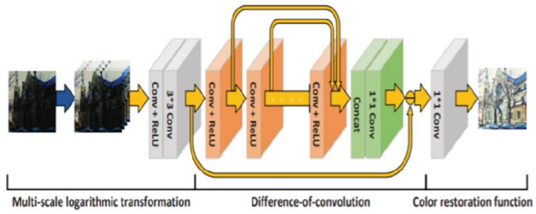

Figure 2: The architecture of the model [3]

The model will have four steps:

- Multi-scale
- Logarithmic Transformation
- Difference-of-convolution
- Color Restoration Function

The Multiscale logarithmic transformation improves the original dark image by combining the weighted sums of numerous logarithmic transformations, speeding up the network's convergence. Color distortions and grey zones are mostly eliminated using the color restoration function.

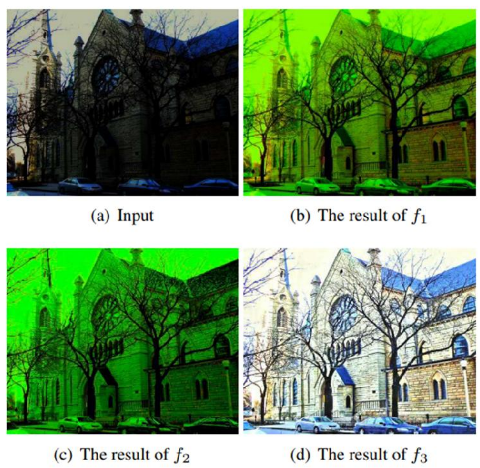

Figure 3: The model result after the three steps [3]

This model enhances the original dark image as well as corrects the color. Methods [4], [5], and [6] process data quicker on the GPU. However, the possibility of a halo effect on specific photographs is not ruled out by the model. L. Tao et al [7], developed an approach for improving contrast by using Denoising Convolutional Neural Network (DCNN) low light images using a low light model. With the use of low light model using an image prior and bright prior channel the transmission parameter is computed.

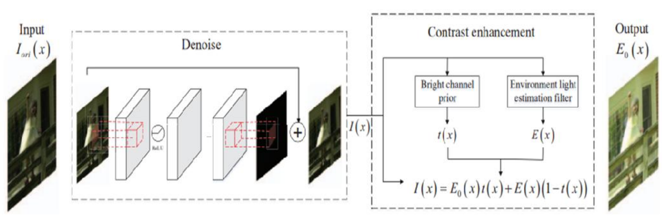

Figure 4: The model framework [7]

The model will also present a method for estimating environment light that is both accurate and adaptable. This model achieves a compromise between contrast and texture preservation. The colour distortion problem is eliminated by the model. [8] proposes a different but successful way. This technology boosts the image's brightness and contrast in an adaptable manner. The Convolutional Neural Network's architecture is based on the and residual learning and inception module.

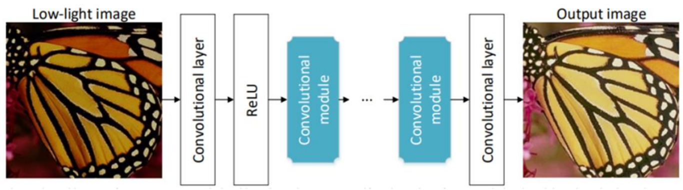

Figure 5: The LLCNN Architecture [8]

The original input is pre-processed to provide uniform input, and the enhanced image is produced by the other Convolutional layer. The convolutional modules are located between the two layers, as seen in the diagram below:

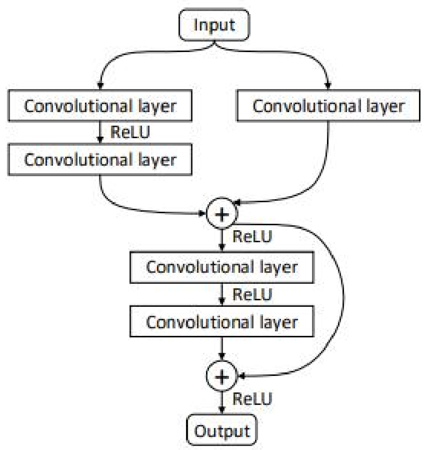

Figure 6: The convolutional model of LLCNN structure [8]

Improved image is significantly more than the achieved by other approaches like [9] and [10] when use this model. The result demonstrates that the improved image created by this model is significantly more natural than that achieved by other approaches like [9] and [10].

2.3 The Resolution Enhancement

When using texture information, there is a loss of texture information. The significant problem is that when we use the deeper convolutional neural network in a super resolution of single image will result in the loss of texture. It's a significant deal to use DCNN for super resolution of single image.

Christian Ledig et al [11], A generative adversarial network was proposed for image super resolution (SRGAN). An adversarial loss and a content loss are combined to provide a perpetual loss function. To restore image realistic texture, they use a skip connection DCNN. MSE-caused content loss has been replaced. Mean Opinion Score (MOS) test is used to compare the ability of the various approaches, and that is verified that the more picture realistic reconstructions for large upscaling factor produced by than the other methods. Super-resolved with a 4K upscaling factor was done for a photo-realistic image is shown in Figure.

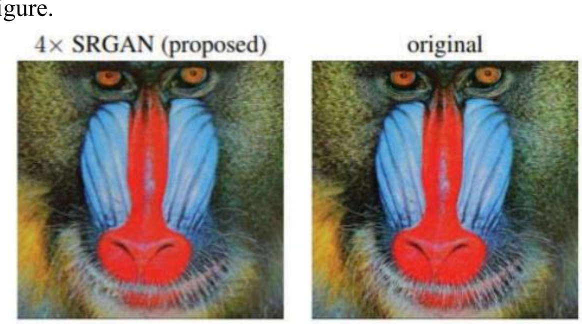

Figure 7: The texture of the original image is preserved in super resolved image [13]

The SRGAN approach of resolution enhancement is far superior to the methods described in [12] and [13].

III. Result Comparison

The field of image enhancement is extensive. There are a variety of approaches that can be used to improve an image. One will outperform the other in terms of efficiency. The following are comparisons of the strategies stated in the literature review for various picture enhancement applications:

3.1 Denoising The Image

The architecture proposed by [1] uses a 30-layer Conv-Deconv model using Symmetric Skip Connections (SSC) between different Convolutional-Deconvolutional layers. [2] proposes a ten-layer CNN based on the Direct Symmetric Connection (DSC) model, with five Convolutional and five Deconvolutional layers. When compared to the 5 Convolutional and 5 Deconvolutional layers proposed by [2,] the approach proposed by [1] has one important flaw: it has multiple Conv-DeConv layers, which increases complexity and requires more computer power. The improved image acquired by [1] is, however, significantly more accurate than that obtained by [2.]

3.2 Low Light Image Enhancement

The model proposed by [3] uses a model based on Retinex theory, in which image improvement is accomplished by first boosting the black image and then applying colour to the image's objects by removing colour distortions and grey zones. The model presented by [7] is a low-light model that uses an image prior, bright prior channel to improve picture contrast. It also calculates the amount of light in the environment and balances the image pixels depending on all the data.

3.3 Enhancing The Resolution

The model proposed by [11] is a Generative Adversarial Network for Image Super Resolution as a paradigm (SRGAN). It recovers photo realistic textures and then enhances the resolution of the original image depending on the parameters found, resulting in a considerably improved image as the output. It is significantly more effective than the models proposed by [12] and [13].

IV. Conclusion

Overall, the review concludes that CNNs are the most effective mathematical framework for image improvement. Because CNNs look for patterns in the data they're given, they're efficient. They stack them using convolutional layers to produce abstract concepts. In every category, including low-light enhancement, contrast modification, and picture denoising, CNNs surpass conventional image improvement techniques. This could also mean that the approaches discussed above deal with individual pixels in a particular image, hence enhancing the technique's efficiency.
Various basic strategies for picture enhancement that can be employed in a large-scale image processing project have been reviewed in this literature study.

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