Image enhancement using Convolutional Neural Network

Abstract

Recent works on plug-and-play image restoration have shown that a denoiser can implicitly serve as the image prior for model-based methods to solve many inverse problems. Such a property induces considerable advantages for plug-and-play image restoration (e.g., integrating the flexibility of model-based method and effectiveness of learning-based methods) when the denoiser is discriminatively learned via a deep convolutional neural network (CNN) with large modeling capacity. However, while deeper and larger CNN models are rapidly gaining popularity, existing plug-and-play image restoration hinders its performance due to the lack of suitable denoiser prior. To push the limits of plug-and-play image restoration, we set up a benchmark deep denoiser prior by training a highly flexible and effective CNN denoiser. We then plug the deep denoiser prior as a modular part into a half quadratic splitting-based iterative algorithm to solve various image restoration problems. We, meanwhile, provide a thorough analysis of parameter setting, intermediate results, and empirical convergence to better understand the working mechanism. Experimental results on three representative image restoration tasks, including deblurring, super-resolution, and demosaicing, demonstrate that the proposed plug-and-play image restoration with deep denoiser prior not only significantly outperforms other state-of-the-art model-based methods but also achieves competitive or even superior performance against state-of-the-art learning-based methods.

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Introduction

Nowadays, image preparation is among quickly developing advancements. It forms a core research zone inside designing and software engineering disciplines too. Images and recordings of good quality are significant for some undertakings. Notwithstanding, not all images are of great characteristics since they are caught in different light conditions. Image processing is a type where input is an image, like a video frame or photograph and output may be an image or characteristics associated with that image. Usually, an Image Processing system includes treating images as two-dimensional signals while applying already set signal processing methods to them. Nowadays, image processing is among rapidly growing technologies. It forms a core research area within engineering and computer science disciplines too.
In [1],[3] proposes, the movement forward by investigating the improvement of the Deep Convolutional Neural Network to understand the progress in huge arrangement, and learning tally, regularization technique image denoising. In particular, remaining the discriminating model learning and clump standardization are used to accelerate the preparation procedure just as lift the denoising execution. The assorted existing discriminative[4] denoising models which generally train a specific single convolutional neural network model for included substance white Gaussian racket at a particular common level, our convolutional neural system model can manage Gaussian denoising with cloud commotion level (stupor Gaussian denoising).

Related Work

In [5] proposes it is important to improve the nature of images. To save an image surface SSIM misfortune was used. The principle goal of our undertaking is to obtain a clear image utilizing convolution modules among basic image improvement techniques and accomplish the best performance. An image is made out of pixels which can be little specks on the screen. In [6] proposes dependent on the disturbance surface measurement, a smooth base layer is adaptively separated from the BM3D channel, and another detail layer is evacuated by the essential solicitation differential of the steamed image and smoothed with the fundamental channel. These two layers are adaptively combined to get a bustle-free and detail-spared image. The Contrast Limited Adaptive Histogram Equalization (CLAHE) improves the identification of simulated speculations in thick mammograms. Lines reproducing the appearance of speculation, a typical marker of harm when visualized with the masses, were installed in thick mammograms digitized at 50-micron pixels, 12 bits profound. In [7], [8] proposes a difference improvement method dependent on histogram leveling (HE) calculation is proposed. In this technique, the Dynamic Histogram Equalization (DHE) assumes responsibility for the impact of customary histogram leveling so it plays out the upgrade of an image without making any loss of subtleties in it. In papers [9], [11] DHE allotments the image histogram dependent on nearby minima and appoints, explicit dim dimension ranges for each segment before balancing them independently. In [12], [15] an epic joined image upgrade system for both differentiation improvement and denoising is proposed. First, the image is portioned into superpixels, and the proportion between the neighborhood standard deviation and the nearby slopes is used to evaluate the clamor surface dimension of every superpixel. At that point, an image is altered to be prepared for the accompanying advances. In [16] proposes finally, a versatile upgrade parameter is embraced in obscurity channel earlier de rite of passage procedure to amplify, differentiate and anticipate over/under improvement. In [17] this technique propels us to prepare a solitary Deep Convolutional Neural Network model to handle some general image denoising assignments, for example, a JPEG image blocking, [18] Gaussian denoising, and single image super-resolution. In [19],[20] proposes the chosen CLAHE settings ought to be tried in the facility with computerized mammograms to decide if the location of speculations associated with masses recognized on mammography can be improved.

Methodology

1. Histogram matching

Histogram matching is the change of an image with the goal that its histogram coordinates a predefined histogram. The surely understood histogram equalization strategy is an exceptional case in which the predetermined histogram is consistently appropriated.

2. Contrast-limited adaptive histogram equalization (CLAHE)

It is used to enhance the contrast of the grayscale image assumed as I by transforming. CLAHE works on small regions in the image called tiles, rather than the whole image. The contrast of every tile is enhanced, therefore, the histogram of the output region approximately matches the histogram predefined by the “Distribution” parameter.

3. Wiener filter

Wiener filter is a filter used to create a gauge of a coveted or target arbitrary process by linear time-invariant (LTI) filtering of an observed noisy process, accepting known stationary signal and noise spectra, and added substance noise. The Wiener filter limits the mean square error between the evaluated random process and the desired procedure.

4. Median filter

The median filter is a nonlinear computerized filtering method, regularly used to expel noise from an image. Such noise reduction is a common pre-processing step to enhance the results of later processing, for example, edge recognition on an image. Median filtering is broadly utilized as a part of digital image processing because, under specific conditions, it preserves edges while removing noise.

5. Linear contrast adjustment

In this, the contrast adjustment block changes the contrast of an image by linearly scaling the pixel values between lower and upper limits. Pixel values that are below or above this range are saturated to the lower or upper limit value, individually.

6. Unsharp mask filtering

Unsharp masking (USM) is an image sharpening method, frequently accessible in the digital image processing software. The "unsharp" of the name gets from the way that the procedure utilizes an obscured, or "unsharp", negative image to make a mask of the original image. The unsharpened mask is then joined with the positive (original) image, constructing an image that is less blurred than the original. The subsequent image, even though clearer, might be a less precise portrayal of the image's subject.

7. Deep neural network

Execute image processing undertakings, for example, removing noise from images and constructing high-resolution images from low-resolution images, utilizing convolutional neural networks. Deep learning utilizes neural networks to learn valuable portrayals of highlights straightforwardly from the information. For instance, you can utilize a pertained neural network to recognize the images and remove the various types of noise from images.

8. Salt and Pepper Noise

Salt and pepper noise is an impulse type of noise in images. We consider salt-and-pepper noise, for which a certain amount of the pixels in the image are either black or white (black or white dots). Normally if there are black dots in the image we called it pepper noise and if there are white dots in the image we called it salt noise. This noise is generally caused by errors in data transmission, failure in the memory cell,s or analog-to-digital converter errors. If we consider an 8-bit image, salt and pepper noise randomly occurs a certain amount of pixels into two extremes, either 0 or 255. The noise significantly damages the image information which leads to difficulties in succeeding image processing tasks such as edge detection or image segmentation and image recognition tasks. Because the noise pixel differs from most of its local neighbors, it has a large gradient value the same as the edge pixel

Proposed Solution Architecture

1. Convolutional Neural Network

The Convolutional Neural Network (CNN) can be a form of profound fake neural network. The Convolutional impartial network has sort of benefits, for example, multidimensional information input, and fewer parameters. Be that because it could, the system faithfully has a downside of overfitting because of parts of connections within the entire associated layer. In solicitation to overcome the warming issue, the denoising procedure is utilized to deteriorate data, information, and covered unit yield, which can actualize the framework learning an unrivaled element outline of the occasion information. In the reenactment, many circumstances are a unit thought of, as an example, input data debasement and shrouded unit layer yield pollution, and a correlation is displayed.

CNN has been broadly utilized for voice examination and image acknowledgment. CNN is initially a multilayer neural system that was prepared effectively. CNN employs weight sharing to diminish the unpredictability of the model and the quantity of the weights. A multi-dimensional image can include the neural system straightforwardly. Even though the image might be a high goals figure, the local gathering documented the weight sharing system will downsize the parameters variably.

Even though the parameters are regularly diminished forcefully, their square measure army loads inside the full convolutional layer. The system constantly contains a downside of overfitting Therefore; they have to adopt some strategies to beat this drawback. The denoising methodology is often employed in automobile encoder coaching to induce a higher generalization capability. During this work acquaint this strategy with CNN to fortify the speculation capacity and beat the overfitting downside of the system.

2. CNN Architecture

For a convolutional neural network, there's constantly a full association between the layers. Along these lines, if an image might be a high goal an image and with many concealed units run, and consequently the affiliation weight is a huge parameter set that is illogical for learning. CNN utilizes the local gathering document to claim a convolution of an image. There are consistently numerous convolution bits. The components of the convolution part agree that the local gathering field estimates an extraordinary load between the yield maps. Anyway, the complete image can have a convolution by each convolution portion. Subsequently, the parameters are set by the local gathering size and in this manner, the convolution bit extends. A CNN constantly has many Concealed layers. The shrouded layers exemplify the convolutional layer and accordingly the sub-examining layer. Inside the convolutional layer, the unmistakable convolutional parts are utilized for the complete image. The images are renewed to a component map with the expanded element. The Convolutional Neural Network has some benefits, and it can deal with the 2D image legitimately which is reasonable for advanced image preparation as appeared in fig. 3.2. Thusly, discoveries of a superior method to accelerate system learning will be the accompanying work for us. There are three primary components of a Convolutional Neural Network,

- Pooling layer
- Fully connected layer
- Convolutional layer

Although picture upgrade has a place with image handling assignments, it varies a ton of super goals. For these two undertakings, constituent esteems in the corrupted image are round the real qualities, and therefore the normal pixel esteems nearly does not modified, which is unique in respect to our trip. In this segment, we initially examine the effect of various profundities of our model. They investigate the adequacy of utilizing SSIM misfortune contrasted and the Euclidean misfortune. Finally, a CNN model that has created progress in super goals and image denoising are prepared as a CNN gauge for low-light image upgrade task. In our projected CNN model and different conventional complexity upgrade strategy, even as profound learning-based methods, and therefore the CNN pattern.

3. Activation function

Each layer of the neural network needs to choose one activation function, and the value of each neuron needs to be calculated by the activation function to obtain a final value. In neural networks, the role of the activation function is to transform the neural network from linear to nonlinear, so that the neural network can better solve more complex problems. Common activation functions are the “sigmoid” function, the “hyperbolic tangent” function, the “Relu” function, and the “ELU” function. There is a paper [18], the experiment compares four activation functions. The CNN model was also used in the experiment. The “ELU” activation function reached the highest accuracy.

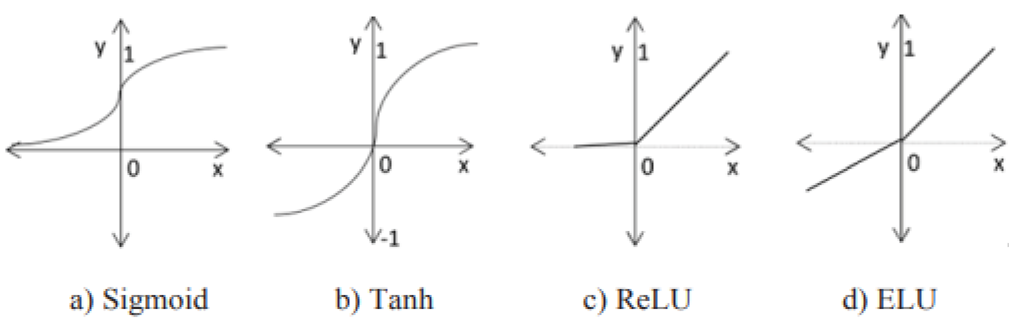


Fig 1. Activation Functions

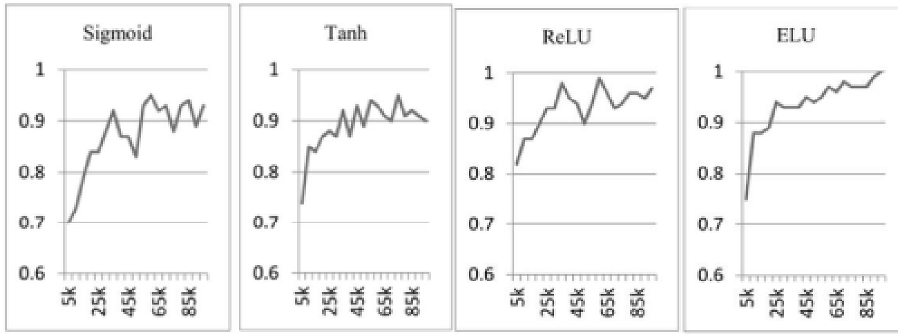


Fig 2. Performance of Activation Functions

4. Optimization function

When training a neural network, it is necessary to update the parameters in the neural network by an optimization algorithm to minimize the value of the loss function, such as weights and bias in each layer of the network. The most classical optimization function is the gradient descent function, but the gradient descent function has very obvious shortcomings: it is easy to reach the local optimal value but it is difficult to reach the global optimal value. Therefore, many optimization algorithms are updated based on the gradient descent algorithm. A paper proposes an optimization algorithm called "Adam". The Adam 15 optimization algorithm is a ramification of the stochastic gradient descent algorithm. Recently, it is widely used in deep learning applications, especially tasks such as computer vision and natural language processing. The Adam algorithm differs from the traditional stochastic gradient descent. Stochastic gradient descent maintains a single learning rate (i.e. alpha) to update all weights, and the learning rate does not change during training. Adam calculates an independent adaptive learning rate for different parameters by calculating the first-moment estimation and second-moment estimation of the gradient. Overall, Adam is a good optimization function on the deep learning model.

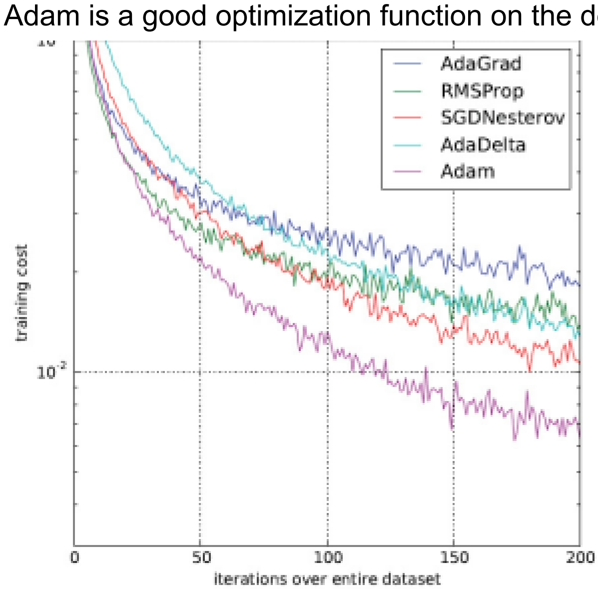


Fig 3. Performances of different optimization functions

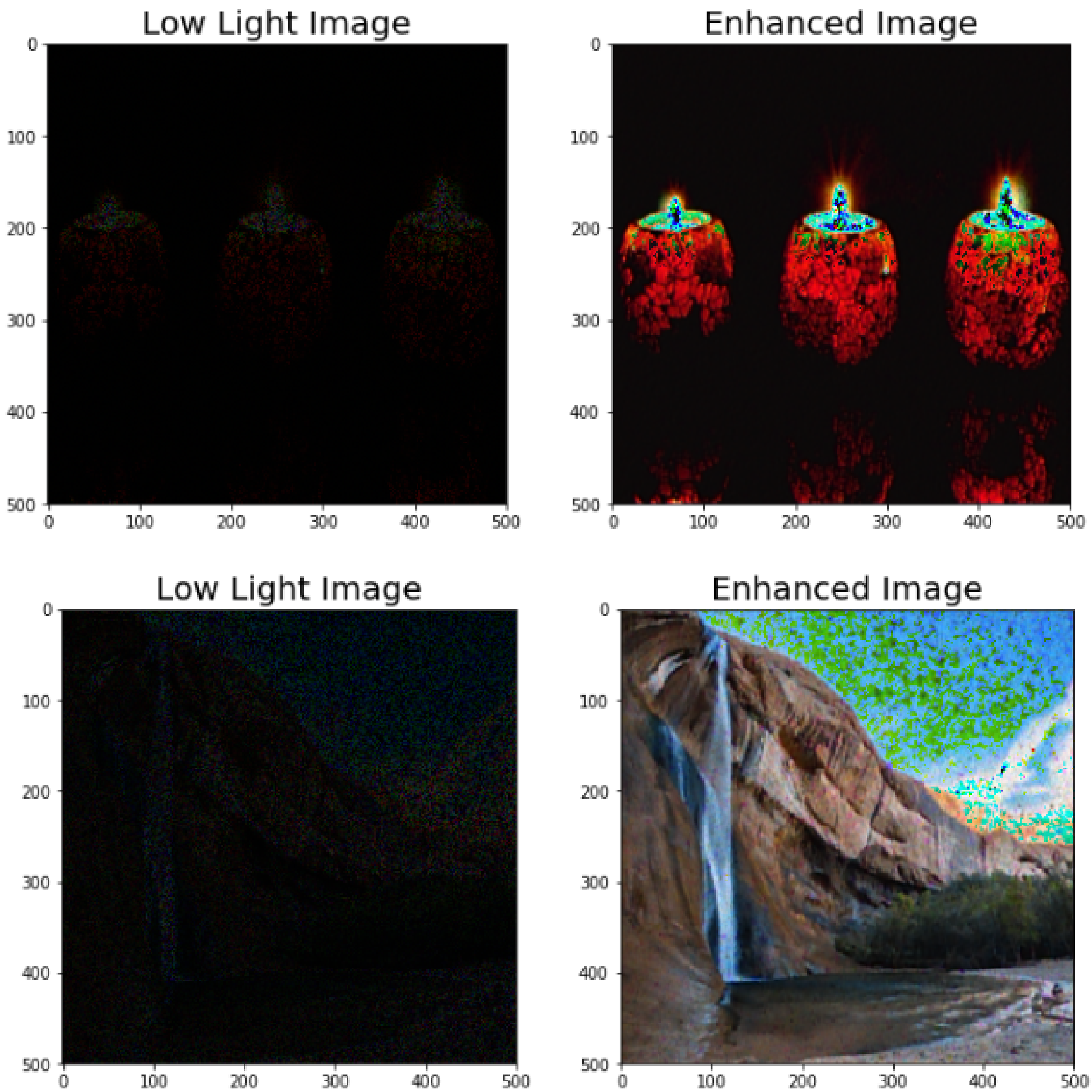
Experimentation and Results

Model Summary

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 500, 500, 3)	0	
conv2d_1 (Conv2D)	(None, 500, 500, 16)	448	input_1[0][0]
conv2d_4 (Conv2D)	(None, 500, 500, 32)	896	input_1[0][0]
conv2d_2 (Conv2D)	(None, 500, 500, 32)	4640	conv2d_1[0][0]
conv2d_5 (Conv2D)	(None, 500, 500, 64)	8256	conv2d_4[0][0]
conv2d_3 (Conv2D)	(None, 500, 500, 64)	8256	conv2d_2[0][0]
conv2d_6 (Conv2D)	(None, 500, 500, 64)	16448	conv2d_5[0][0]
add_1 (Add)	(None, 500, 500, 64)	0	conv2d_3[0][0] conv2d_5[0][0] conv2d_6[0][0]
conv2d_7 (Conv2D)	(None, 500, 500, 64)	36928	add_1[0][0]
conv2d_10 (Conv2D)	(None, 500, 500, 32)	18464	add_1[0][0]
conv2d_8 (Conv2D)	(None, 500, 500, 32)	18464	conv2d_7[0][0]
conv2d_11 (Conv2D)	(None, 500, 500, 16)	2064	conv2d_10[0][0]
conv2d_12 (Conv2D)	(None, 500, 500, 16)	4112	add_1[0][0]
conv2d_9 (Conv2D)	(None, 500, 500, 16)	2064	conv2d_8[0][0]
add_2 (Add)	(None, 500, 500, 16)	0	conv2d_11[0][0] conv2d_12[0][0] conv2d_9[0][0]
conv2d_14 (Conv2D)	(None, 500, 500, 16)	9232	add_1[0][0]
conv2d_13 (Conv2D)	(None, 500, 500, 16)	2320	add_2[0][0]
add_3 (Add)	(None, 500, 500, 16)	0	conv2d_14[0][0] add_2[0][0] conv2d_13[0][0]
conv2d_16 (Conv2D)	(None, 500, 500, 16)	1040	add_3[0][0]
conv2d_17 (Conv2D)	(None, 500, 500, 3)	435	conv2d_16[0][0]

Total params: 134,067
Trainable params: 134,067
Non-trainable params: 0

Comparison of Low Light Image VS Enhanced Image by the model



Screenshots of API or working model

Github link:

https://github.com/coderBolt/DataScience/blob/main/Image_Enhancement.ipynb

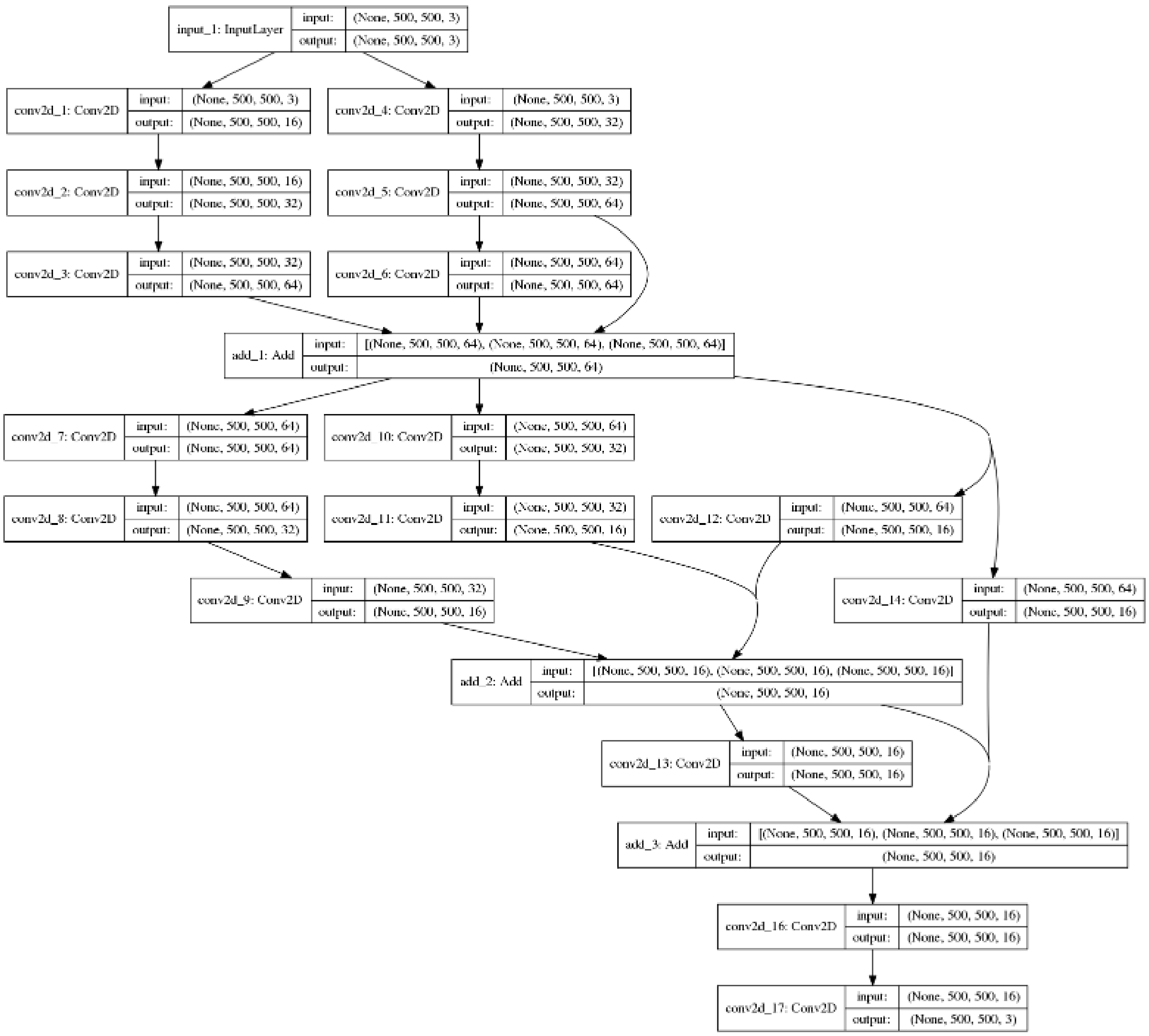


Fig 4. Neural Network Model Summary

Conclusion and future scope

In this work is proposed the images are enhanced by utilizing DnCNN-Deep Convolutional Neural Networks. Both the previous method and the proposed methods are implemented using various noisy input images. Also, a comparison of the enhanced ability of the proposed methodology with the existing method is finished. Also, a Qualitative performance comparison of the projected method with the previous technique was done. From the recreation results, it's resolved that the visual nature of the proposed strategy is improved than the past technique. This work proposed approach to the convolutional neural network technique that figures out how to adaptively differentiate and improve the image to increase image brightness. On CNN, an extraordinary module is to improve the exhibition. In general, the technique also understands that SSIM misfortune suits for a higher image upgrade.

To reduce the external validity threat of the experiment, more data sets and more image enhancement algorithms will be used in the experiment in future work. In addition, the image enhancement algorithms will be chosen based on the characteristics of the data sets. Moreover, using more CNN models and more strategies of transfer learning can also reduce external effectiveness threats in experiments. Moreover, more experiments can be designed to specifically research the impact of Laplace operators on the performance of CNN models.

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