Image Restoration using Deep Learning Techniques: a Dataset Free Approach

Abhinav Bhogavalli, Harsha Vardhan Chintamaneni,
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Bhogavalli Abhinav[1, a)], Chintamaneni Harsha Vardhan[2, b)], Purandhar Tatarao Adigarla[3, c)], Dr.Suma Kamalesh Gandhimathi[4, d)]

Author Affiliations
[1,2,3]School of Computer Science, Lovely professional University, Jalandhar, Punjab, India
[4]Department of Intelligent systems, School of Computer Science, Lovely professional University, Jalandhar, Punjab, India

Author Emails
[a)] abhinavbhogavalli26@gmail.com
[b)] chharsha420@gmail.com
[c)] purandharptr@gmail.com
[d)] Corresponding author: suma.27353@lpu.co.in

Abstract. Image restoration is a primary computer vision task which involves returning damaged images to their original state. Recently, deep learning has revolutionised the field of image restoration by delivering cutting-edge outcomes on a variety of restoration jobs. This study examines the use of deep learning techniques for image noise reduction and enhancing image resolution. Specifically, we investigate the use of deep neural networks trained on a single noisy image to restore a clean image. The architecture of the ConvNet, a popular neural network model for image denoising and enhancing image resolution, also discussed the latest advances such as residual connections and UNet with skip connections. PSNR and MSE among diverse pictures are used to evaluate the performance of our technique on various image denoising and resolution enhancement tasks. The results demonstrate that deep learning-based image denoising and high resolution can achieve high-quality results and they have the ability that can be used in numerous applications without being trained on a dataset. The traditional CNN is used to denoise the image using reliable functions in a sequential model. To obtain picture super resolution, a randomly initialised ConvNet with untrained convolutional layers are used where the model is not trained on a dataset but rather only one image.

Keywords: Image-restoration, SISR, Image Denoising, CNN, ConvNet, Deep Learning, Single Image super-resolution, Noise, UNet.

INTRODUCTION

The term "noise" in the context of digital photos refers to ad hoc changes in pixel values that may hide or distort the image's underlying content. The image sensor or camera used to record the image may have limitations, the image data may not have been transmitted or stored perfectly, or there may be interference from outside sources or bad lighting. Various types of noise might appear in the image as various patterns or textures, such as banding, graininess, or speckles. The image resolution, the amount of compression used on the image data, or the sensitivity of the camera or sensor can all affect how severe the noise is. Reducing or eliminating noise from a picture is a critical task in image processing and may involve a variety of methods, such as denoising algorithms, filtering or smoothing algorithms, or other image enhancing methods.

The technique of eliminating undesired distortions or artefacts from an image is referred to as image noise reduction. Poor illumination, improper camera settings, or signal interference during image transmission are just a few of the causes of image noise. An image's clarity and quality may be compromised by this noise, making it challenging to analyse or successfully employ. Many methods, including filtering, deconvolution, and machine learning-based methods, can be used to recover an image. These methods try to save as much of the original image data as possible while removing or reducing noise. In a variety of industries, such as medical imaging, surveillance, and scientific research, image noise restoration is a crucial duty. The capacity to recover noisy images can improve image quality, analysis precision, and enable better decision-making.

Image super-resolution is a technique that involves enhancing the resolution and overall quality of an image beyond its original resolution. This technique is useful when working with images that are low-resolution or when one wants to increase the level of detail in an image for better analysis or visualization. The objective of image super-resolution is to improve the resolution of an image to a level that is almost identical to the original, even if the original image has been considerably degraded. There are several techniques for image super-resolution, including upsampling, which refers to the technique of enhancing image resolution by producing a high-resolution version of a given low-level image version using neural networks. This technique can produce images with much greater detail and clarity, making them useful for several uses, including remote sensing, surveillance, and medical imaging. Image super-resolution is a challenging task that requires advanced algorithms and computing power. Nonetheless, picture super-resolution is becoming a more significant and extensively utilised technology in many sectors because of the increased accessibility of powerful computing resources and the growing interest in computer vision and image processing.

In the area of image processing, high resolution and image denoising are two critical methods. Deep learning has evolved into an effective method for solving a wide range of tasks. CNNs have demonstrated to be very efficient at tasks requiring image denoising and resolution enhancement. Since they can extract intricate patterns and characteristics from huge amounts of data, CNNs are fantastic for applications involving image processing. To perform image denoising using deep learning, A noisy image is fed into CNN, which is taught to output a denoised copy of the identical image.

LITERATURE SURVEY

The authors of [1] proposed a methodology for enhancing and denoising the surveillance applications captured noisy image. They used the traditional CNN in two stages for the deployment. First, they sent the noisy image through the first set of CNN networks and in the second phase they sent the image through anisotropic diffusion to get better denoised image. The authors of [2] proposed a feed forward denoising CNN for denoising the image and to speed up the training procedure, residual learning and batch normalisation were employed. The authors of [4] were keen to propose that the dee convolution networks produce great results for image processing but on the other hand they proposed that a simple general adverse network is sufficient to capture the features of image statistics. Kai et al. [5] proposed a method of using the effective CNN denoisers and send them into their approach of model-based optimization to solve the image deblurring.

The authors of [7] first introduced their method for bridging the ends among low resolution and high resolution pictures that is represented using CNN and then shown that conventional sparse-coding oriented super resolution approaches may also be taken as a DCNN. The authors of [8] produced a new approach to deblur the images into better resolution by using random forest to extract sharp edges of the blurry image and introduces a fuzzy kernel to add noise and then enhance it. The authors of [10] illustrated how their suggested CNN model, which extracts image features in low resolution space, works. Z. Wang et al. [14] provided a review of the traditional super resolution methods to allow them to check the better method out of all the available. Out of all these literatures the method of using traditional CNN has produced greater results for denoising and using untrained ConvNet for producing the high-resolution image.

In order to achieve better results while reconstructing the image shape, the authors of [17] presented a modified U-net method that eliminates all batch normalisation layers and one convolutional layer from each block. By doing this step, the model that uses a low resolution image to generate high resolution image has fewer parameters and compiles more quickly. The authors of [18] employed a heuristic algorithm-based methodology in which image enhancement is accomplished by enhancing an objective function and transformation function to enhance image by changing contrast and brightness, which aids in resolving issues with lighting. They also collaborated with blind kernels as they proposed blind deblurring models to produce a clear image with sharp edges.

PROPOSED METHODOLOGY

The image denoisisng model implements the Convolutional Neural Network for denoising the image and provide with the clean image and also a image resolution enhancement model is developed by using the deep neural networks, which does image super resolution by creating a high resolution image that maintains the details and structure of a low resolution image, the quality of the low resolution image is intended to be improved. Both the models are trained only by using single image rather than with a dataset that contains both clean and disorted images.

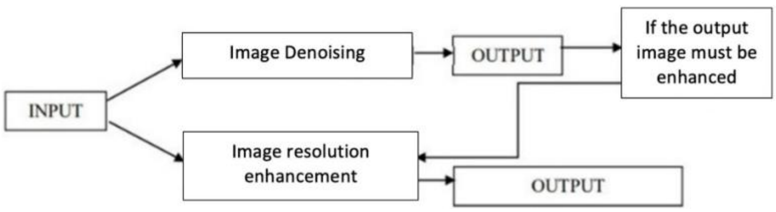


Fig. 1 Flowchart of the proposed system

Image denoising

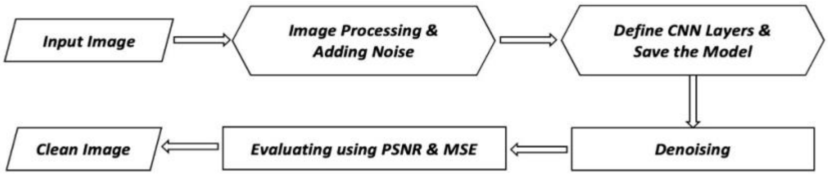


Fig. 2 Flowchart of Image Denoising model

Step by step Procedure for denoising:
Step 1: - Image acquisition
Step 2: - Normalize the image.
Step 3: - See the image and add the noise if required else leave it as it is.
Step 4: - Define the CNN architecture and save the model.
Step 5: - Use the noisy image of your input image to train it with the model for denoising.
Step 6: - Evaluate the Output clean image by using the PSNR and MSE metrics.
Step 7: - Compare the ground truth, noisy and the generated output image.

The conventional approach of utilising a multi-layer CNN architecture for denoising a picture instead of using alternative functional methods. The main deep learning technique utilised in this code is CNNs, that are used to denoise the input image. To generate the model shown in the below architecture, a few layers of convolutional and activation functions are followed by a few layers of transposed convolutional functions. The rectified linear unit (ReLU), a typical activation function in CNNs, is the activation function employed in this code. Adam, a well-liked optimisation technique for training neural networks, was the optimizer employed. mean squared error is the loss function used in the model.

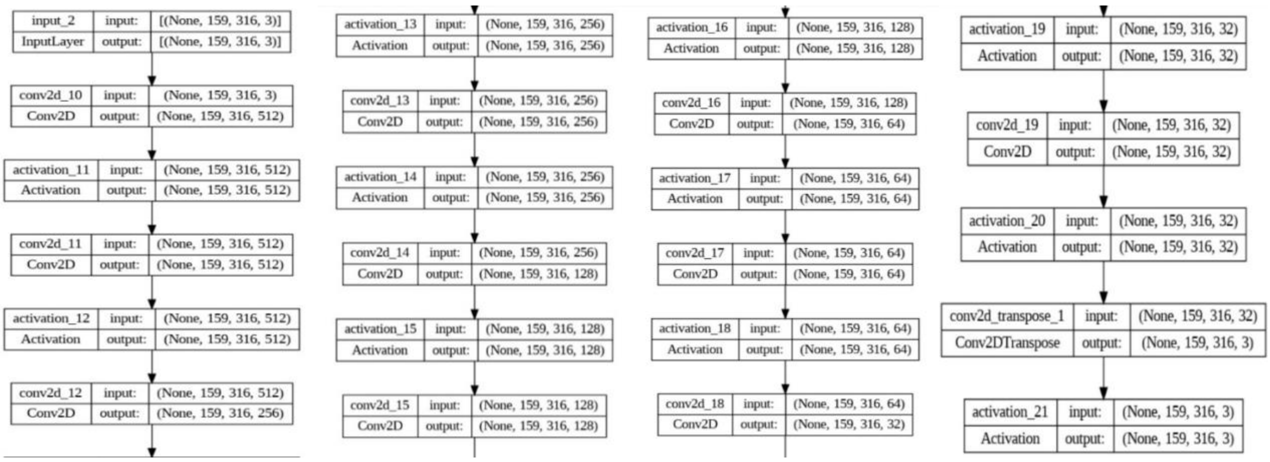


Fig. 3 CNN Architecture of the Denoising Model

Mean Squared Error (MSE) is a popular statistic for assessing how well a machine learning model is performing. The average of the squared discrepancies between a variable's expected and actual values is what MSE calculates. It is determined by adding up the squared discrepancies between the expected and observed values, then dividing the result by the total number of observations.

$$MSE = (1/num) * summation((a\_predicted - a\_true)^2) \tag{1}$$

num: - “number of observations”
a_true: - “actual value”
a_predicted: - “predicted value”.

The model performs better when the MSE value is lower since it shows that the model's predictions are more accurate than the actual values.

Peak Signal to Noise Ratio (PSNR) is the statistic that evaluates the gauge that says how well an image signal performs after being compressed or otherwise transformed. In PSNR, the power of the noise that distorts the signal is compared to the maximum power of the signal. It calculates the difference between the original, uncompressed picture or video and the compressed or modified version when applied to photos or movies.

$$PSNR = 10 * log10((MAX^2) / MSE) \tag{2}$$

MSE: - “mean squared error between original and compressed image”.
MAX: - “highest feasible pixel of an image”.

PSNR is typically expressed in decibels (dB). A higher quality image or video has high PSNR value, as it means that the difference between the original and compressed versions is smaller. A PSNR value of 30 dB or higher is generally considered to be acceptable for most applications.

Image Super Resolution

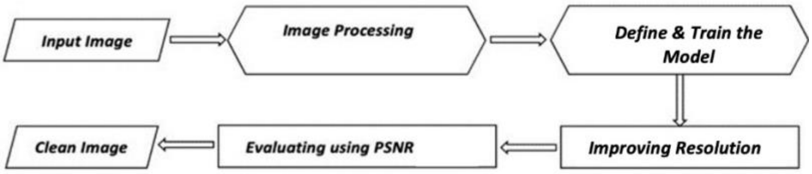
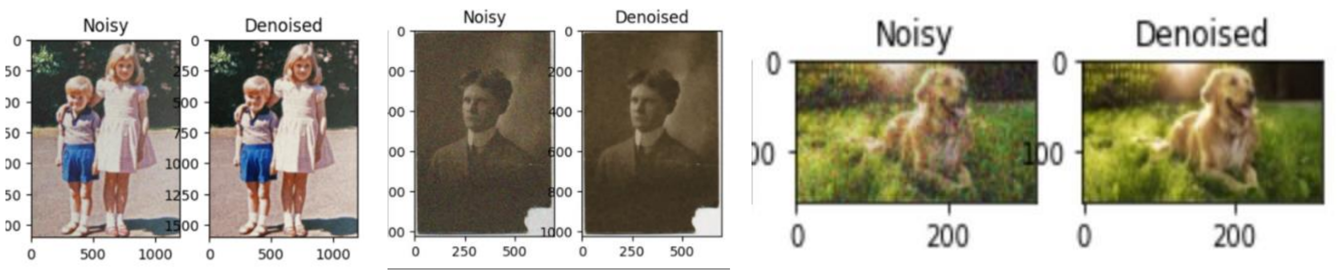


Fig. 4 Flowchart of the image resolution enhancement model

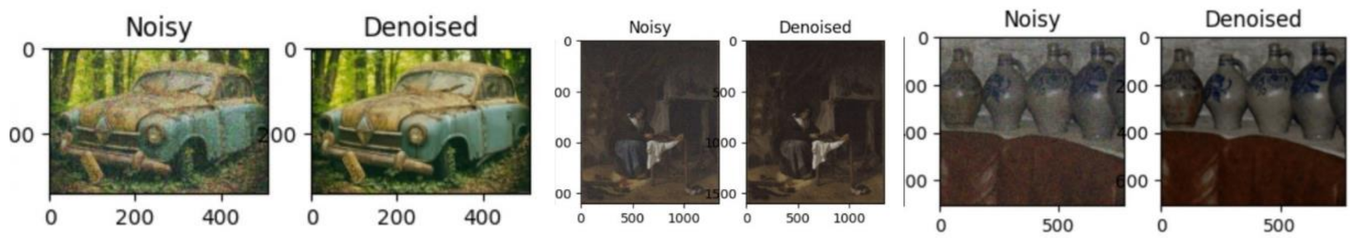
Step by step procedure for image super resolution:
Step 1: - Load the input image
Step 2: - Define parameters for neural network such as input depth, optimization method, learning rate and regularization noise.
Step 3: - Define the network architecture for Unet network and loss function for the super resolution task
Step 4: - Define the closure function to update the network parameters based on the calculated loss
Step 6: - Train and run the model
Step 7: - Evaluate the output image by using the PSNR and MSE metrics.

The Model uses a deep neural network to perform image super-resolution. By creating a high-resolution image(HR) that maintains the details and structure of a low-resolution image(LR), the quality of the low-resolution image is intended to be improved.Proposed model first generates baseline images using bicubic interpolation, nearest neighbor interpolation, and a sharpening filter. The effectiveness of the generated HR image is assessed using these images. The PSNR is calculated for each baseline image to measure its similarity to the HR image. The input depth, pad type, optimization method, and other hyperparameters are set based on the chosen model and scaling factor. A deep neural network is defined using the Unet network where the skip architecture is used, which consists of skip connections that bypass one or more layers. The number of skip connections, filters, and scales can be adjusted. The chosen loss function is mean squared error (MSE) loss, and a TV (total variation) regularization term can be added to encourage spatial smoothness. The code also a need to define the closure function that will be used in the optimization process. The closure function updates the network weights by computing the gradients of the loss function with respect to the network weights and then applying the gradients using an optimizer.The final ouputs are evaluated based upon the PSNR and MSE values.

RESULTS & ANALYSIS



(a) img_sib (b) img_old (c) img_dog



(d) img_car (e) img_pt (f) img_pot

Fig. 5 Comparison of the Input and Output Images of the Denoising Model

	img_sib	img_old	img_dog	img_car	img_pt	img_pot
PSNR	36.6234	41.6663	39.0633	39.3939	39.9074	38.3627
MSE	0.0031	0.0037	0.0016	0.0084	0.0065	0.0013

Table. 1 PSNR & MSE values for different Inputs provided to Denoising Model

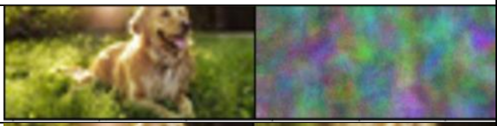
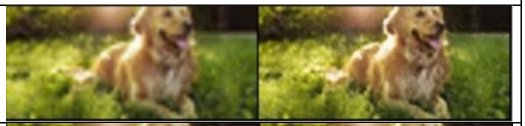
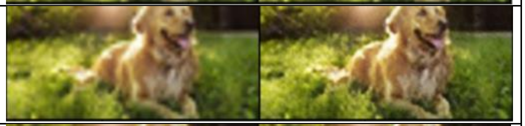
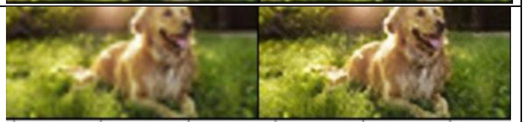
Iteration	Results	Iterations	Results
100		600	
200		700	
300		800	
400		900	
500		1000	

Fig. 6 Comparision of Input and Output Images of Super Resolution Model for every 100 iteration.

PSNR value for input image to output image is 37.068 db, PSNR value for output to ground truth is 22.465 db is given by the image super resolution model whille executed with Fig. 6 image.

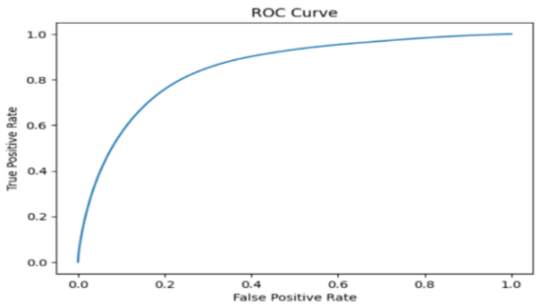


Fig. 7 ROC curve of Denoised Image (img_sib)

CONCLUSION

We have demonstrated the usage of traditional simple CNN architecture had produced results with great accuracy by directly giving input of an image without training the CNN in contray to the current trends of training a CNN on huge real world datasets to provide high end outputs. We were able to acquire greater results by running CNN directly on a single image rather than training it on the datasets.

For increasing the resolution of an image our technique employs a randomly initialised ConvNet to upsample a picture while using the image's structure as an image prior. however, this technique yields considerably cleaner results with finer edges without the need for learning. In fact, our outcomes are fairly comparable to modern superresolution techniques that employ ConvNets trained on big datasets.

The effectiveness of deep learning-based image restoration algorithms has been impressive in a variety of image restoration jobs Based upon the work done in this paper we have came to the conclusion that deep learning models are exceptionaly well for various image restoration tasks even if they are not trained with large datasets but they are practically slow (taking several minutes GPU computation per image.)

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