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A Single Image Super-Resolution (SISR) Using Deep Convolutional Networks For Improvement Of Resolution In Natural Images

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Abstract : **In this paper, Single image super-resolution (SISR) is a notoriously challenging ill-posed problem that aims to obtain a high-resolution (HR) output from one of its low-resolution (LR)versions. Recently, powerful deep learning algorithms have been applied to SISR and have achieved state-of-the-art performance. In this paper, Single image super-resolution, which is used to restore high-resolution image from a single low-resolution image, is a difficult challenging problem in computer field. In recent times, dominant deep learning algorithms have been applied to Single image super resolution and have shown an highly efficient performance. In this paper, the deep learning-based super resolution method known as a super resolution convolutional neural network (SRCNN) that takes the low-resolution image as the input and outputs the high-resolution one. SRCNN has a non-complex structure yet provides high quality and fast speed. who is carried out on different networks like Generative Adversarial Networks (GAN) and Convolutional Neural Network comparison between quality and speed.**

Index Terms **-Single Image Super Resolution (SISR), CNN, bi-cubic, Deep Convolutional Networks (DCN), 'Set5' 'Set14' and 'Urban100'.,etc.**

I. Introduction

In past few decades, single image super-resolution (SISR), that seeks for recover a large photograph from a low-resolution (LR) measurement, has grown in popularity in image recognition as a topic of discussion. For recognition systems, single-image super-resolution is necessary, as well as several technologies have been implemented in recent decades. Due to their perceived achievement, these solutions seem to be frequently dependent on various of factors, as well as unique datasets and measurements. The procedure of creating high-resolution photos from low-resolution photos is called as super-resolution (SR). So look at it another way, LR refers for the a single photo input ,HR refers for the actual data, then SR refers for such expected high resolution. High resolution images have more pixel density than low-resolution images. With this feature, high-resolution images are desired for much real-life application because HR images provide more detail and information about the scene [2]. The object using single image super-resolution (SISR) is just to reconstruct the high-resolution frame from with a low resolution frame inside this case. When high-frequency picture information is generally being extracted from such a low-resolution visual, SISR becomes hard. The brightness of large pictures is reduced absent increased signals. SISR is indeed a poorly challenge even though a single low-resolution photo may generate in multiple high-resolution representations [2] [28].

1.1 Machine learning (ML)

This is described as a type of machine learning. It is also the research of software projects to improve continuously using knowledge or the utilization of information .Algorithms build a model statistical inference, commonly called as " "learning algorithm," in order to collect information and outcomes instead of being supervised machine learning. Algorithms were applied inside a variety of uses, like health, web filtering, natural language processing, as well as machine vision, because creating simple equations to be doing the necessary tasks is virtually impossible[30].Learning is a form of analysis of data which it facilitates that construction for simulation solutions. It's just a subfield of AI based on the notion concept machines must study from material, understand trends, as well as decide with little or no user input.

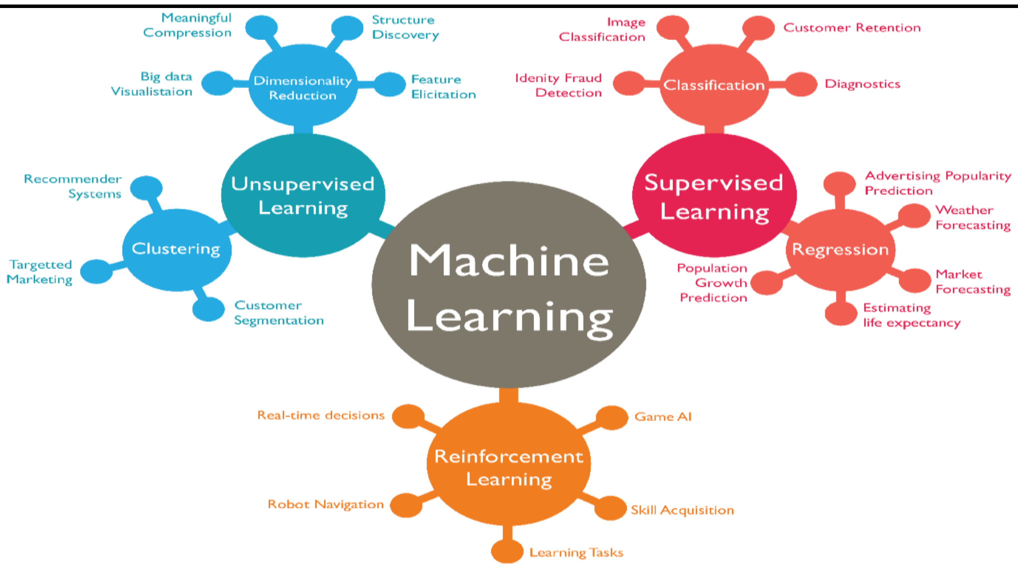


Fig 1. Machine Learning[31].

1.2 Single Image Super Resolution

An imaging device's resolution may be boosted (improved) using super-resolution imaging (SR imaging), a group of methods. In optical SR the diffraction limit of systems is transcended, while in geometrical SR the resolution of digital imaging sensors is enhanced. The ideas surrounding super-resolution raise fundamental issues; there is need at the outset to examine the relevant physical and information-theoretical principles: Diffraction limit- The amount of detail that an optical equipment can capture in a picture is limited by the physical rules of diffraction or the wave concept of light.[3] or equivalently the uncertainty principle for photons in quantum mechanics. The amount of data that can be sent cannot be enhanced beyond this point, however packets outside of this range may be skillfully exchanged for (or multiplexed with) those within. The diffraction threshold is not so much "broken" as "ran around." around. There has been no significant change in the methods used to examine molecular causes of electro-magnetic disturbances [32].

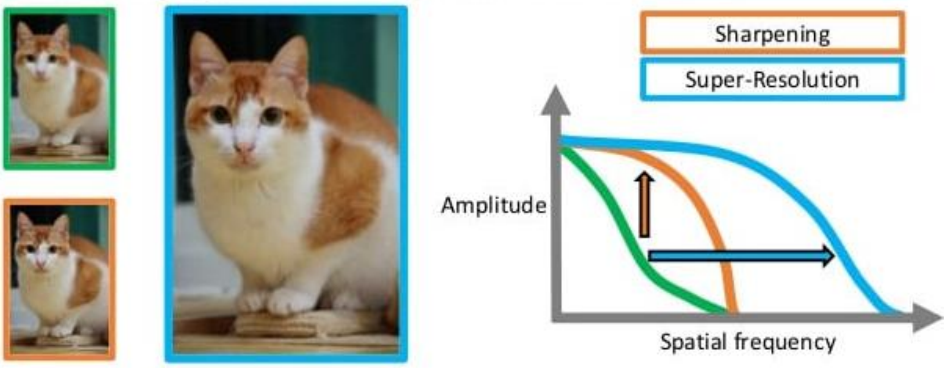


Fig 2. Single Image Super Resolution (SISR)

II. ISR WITH NEURAL NETWORKS

2.1Image Super-Resolution(ISR)

Super-resolution is based on the idea that a combination of low resolution (noisy)sequence of images of a scene can be used to generate a high resolution image or image sequence. A series of collected photos of lesser resolution is used to try and rebuild the original scene's high-quality image. According to this theory, low-resolution photo graphs are just resampled versions of high-resolution ones. The ultimate objective is to get the high-resolution picture from the low-resolution recorded photos by resampling based on the input images and the imaging model. As a result, for super-resolution, an accurate imaging system is critical, as well as improper modelling, such as that of motion, might actually worsen the picture. The observed images could be taken from one or multiple cameras or could be frames of a video sequence. These images need to be mapped to a common reference frame. This process is registration. The super-resolution procedure can then be applied to a region of interest in the aligned composite image. Proper registration as well as the development of a suitable advanced picture structure are essential for effective super-resolution. The figure below shows the stages in super-resolution process.

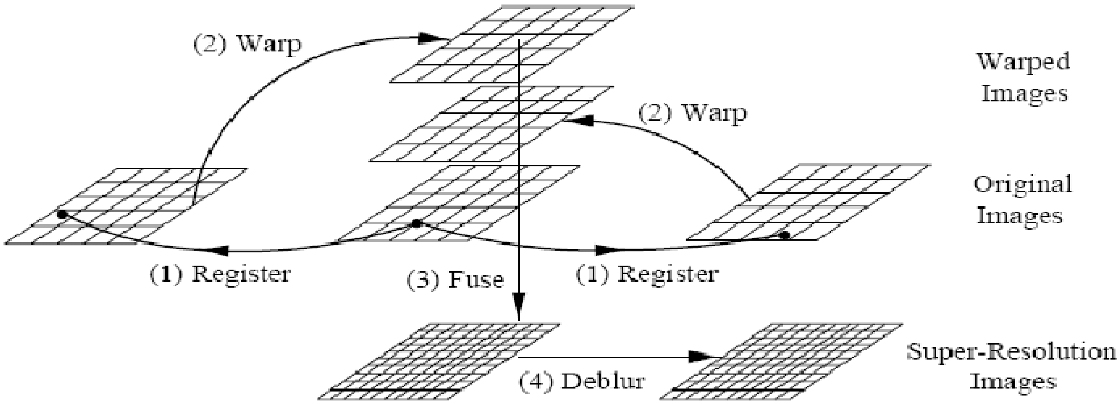


Fig.3. The Stages In Super-Resolution Process

2.2 Neuron Network

A computer model based on the structure and functions of biological neural networks is known as an Artificial Neuron Network (ANN). In terms of Computer Science, it functions as an artificial human nervous system, receiving, processing, as well as transmitting data. A neural network is composed of three layers:—

1. Input Layer of Input (All the inputs are fed in the model through this layer)
2. Layers that are not Visible ,It's possible that more than one hidden state is employed to process the information received from the input layers.
3. Layer of output (The data after processing is made available at the output layer)
4. Here's how these layers are put together:

III. PROPOSED METHOD AND ALGORITHM

In this chapter discuss the proposed solution for single image super resolution that is Modified Very Deep Convolutional Networks (MVDCN). The proposed solution which solve the problem of previous work that is discuss in the previous chapter. The proposed method is design to enhance the resolution of image using single image super-resolution (SISR). The proposed method is widely used in computer vision applications ranging from security and surveillance imaging to medical imaging processing where high resolution image the required for deep analysis of deceases.

Testing Stage

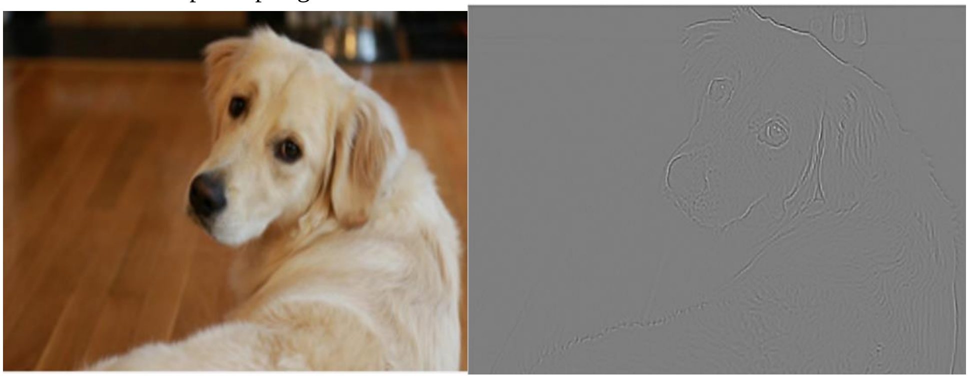
In this stage apply the testing of the image and apply quality check parameters of the proposed method outcomes.

Trsting Steps

1. Query Image Selection- First select the image from data set. The data set is the combination of the three types of images.
   [file name, pathname, filter index]= uigetfile(.{'.jpg','.jpeg','.png'}).
2. After the selection of the qurey image, now apply theScale Factor [2 3 4] selection of the image.
3. In the next stage upload the trained_net that is MAT file. This file is genrated after the complision of training of data set.
4. Now select the index value. Choose the refence image, apply basic operation
   Ireference = readimage(testImages, indx); Ireference = im2double(Ireference);, imshow(Ireference), title('High-Resolution')
5. Apply sclae factore, 0.4. lowres = imresize(Ireference,scaleFactor,'bicubic');
6. Apply bicubic, bicubic = imresize(Ilowres,[nrows ncols],'**bicubic**');
7. Apply rgb to ycbcr ot the outcome **'bicubic'** image.
   Iy = Iycbcr(:,:,1); Icb = Iycbcr(:,:,2); Icr = Iycbcr(:,:,3);
8. Calculate the residual image (Ir), and apply deep nurel network with the network depth of 41.
9. Now apply the fusion of Iy bicubic and Iresidual image.
10. Apply ycbcr to rgb conversion and obtain the final output of the image that is modified very deep convolution network (MVDCN).
11. Calcuate the result parameters.

3.1 Residual Image

A residual image preserves the high frequency components of an image by subtracting a sampled image from the original image. In Super Resolution, the high frequency elements are what the generated image is missing. To ensure that the high frequency components are not dropped, the residual image is added back to the main branch of the network before up-sampling, The residual image is created by first down-sampling the input image (plus bicubic interpolation) from a 32×32 sized image to a 24×24 sized image, and re up-sampling it using bicubic interpolation. This image is then subtracted from the original LR input image to obtain the residual image. The residual image is then fed through a convolutional layer to extract high frequency features, from the residual image, before being added back to the main branch of the network. This approach differentiates itself from Yuewen Sun et al. network by using a different sampling ratio, a shallower skip connection, and adding the results back to the main branch of the network before up-sampling.



(a) VDCN Outcome (b) Residual Image

Fig. 4. Shows the Residual Image

IV. RESULT AND DISCUSSION

In this chapter discuss the simulation model and result of proposed algorithm. For the implementation of proposed algorithm use Matrix laboratory. Matrix laboratory is a well-known tool for such kind of algorithm implementation related to deep neural network and also contain healthy library for image processing related work. MATLAB contain a rich function family of machine learning and image processing related tools.

4.1 Software Used

The MATLAB R2020 version was utilised to put the research plan into practise. Design and implement deep convolutional neural networks using algorithms and models using Deep Learning Toolbox. Convolutional neural networks (ConvNets, CNNs) and long short-term memory (LSTM) nets might be used to do regression and classification tasks on image, time-series, and text data as part of the implementation of proposed. To create network designs like generative adversarial networks (GANs) and Siamese networks, the design tool would use automated differentiation, specialised training loops, and shared weights. GAN architectures include: A network may be modelled visually using Deep Network's tools for analysis and training.

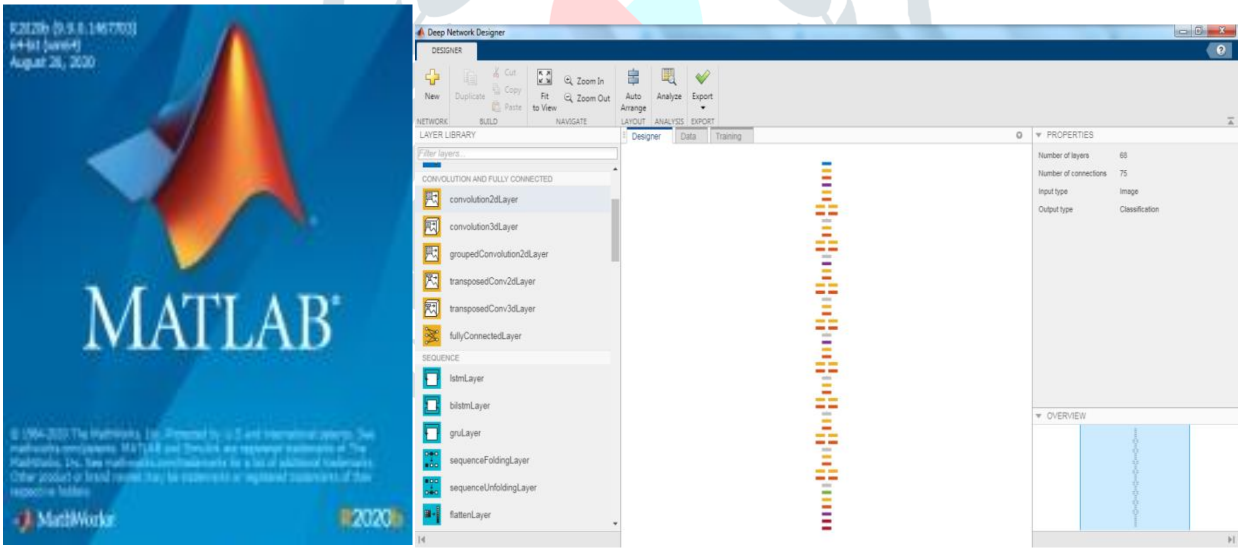


Fig. 5.Show the Software and design tool

4.2 Result Parameters

To measure the performance of proposed method require result parameters. In case of Image Super Resolution (ISR) results for observed on the two different methods first one visually quality check and second one is quantitive result parameters. These two parameters are major parameter for result analysis in quantitive phenomena of image super resolution (ISR). The two basic parameters are peak signal to noise ratio (PSNR) and another one is structural similarity index measurement (SSIM).

1 PSNR

Peak Signal to Noise Ratio (PSNR): The PSNR is computed as:

$$\mathrm{PSNR} = 10\log_{10}\frac{s^2}{\mathrm{MSE}} \tag{5.1}$$

The PSNR is higher for an excellent worth image and lower for a poor quality image. It measures image fidelity, that is, however closely the distorted image resembles the actual image. In our research work on the basis of our image size 255x255.

Mean Square Error (MSE): The MSE measures the standard amendment between the actual image (X) and the noised image (Y) and is given by:

$$\mathrm{MSE} = \frac{1}{N}\sum_{j=0}^{N-1}(X_j - Y_j)^2 \tag{5.2}$$

X_j Shows the cover image

Y_j Shows the stego image

The MSE has been extensively used to quantify image quality and once used alone; it doesn't correlate powerfully enough with sensory activity quality. It ought to be used, therefore in conjunction with alternative quality metrics and perception.

2 SSIM

The SSIM Index of quality evaluation of SSIM consists of brightness, contrast and structural variables that are calculated. These three terms are multiplied together to get the final index value..

$$SSIM(x,y) = [l(x,y)]\alpha[c(x,y)]\beta[s(x,y)]\gamma \tag{5.3}$$

Where

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1},$$
$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2},$$
$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}.$$

with respect to which are the mean values for the pictures of x, and cross-covariance is the standard deviation of the images. If = = = 1 (the default value for Exponents) and C3 = C2/2 (the default value for C3) are used, the index becomes:

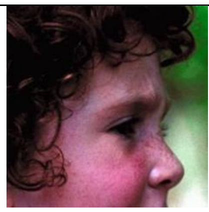
$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{5.4}$$

4.3 Result Discussion

In this section discuss the MATlab simulated outcomes in terms of qualitative research and quantative research.

Table 1 PSNR and SSIM Comparison of Proposed Modified Very Deep Convolutional Networks (MVDCN) With Bicubic

Table 1. PSNR and SSIM Comparison of Proposed Modified Very Deep Convolutional Networks (MVDCN) With Bicubic

S.No.	Scale	Modified MVDCN PSNR/SSIM	Bicubic PSNR/ SSIM	'Set 5' data set Image
Image - 01	×2	36.942992/ 0.977071	36.873737/0.975170	
	×3	28.159598/0.910444	28.743345/0.912121	
	×4	**32.44/0.932698**	31.646623/0.932698	
Image 02	×2	35.494765/0.983686	37.133488/0.986019	
	×3	30.728000/0.955840	31.190594/0.956403	
	×4	**32.232500/ 0.954653**	30.950371/0.945296	
Image 03	×2	**32.688554/0.983664**	31.312586/ 0.978587	
	×3	**28.559421/0.961855**	26.998308/0.946924	
	×4	**26.896937/0.943094**	25.243957/0.921814	
Image 04	×2	**35.175869/0.989835**	36.098076/0.992450	
	×3	**33.001336/0.984207**	31.466563/0.978139	
	×4	**30.347866/0.971672**	28.799117/0.960414	

IV.CONCLUSION

In this research work presented a Modified Very Deep Convolutional Networks (MVDCN) for single image super resolution (SISR). The presented method based on modified CNN, in which apply different image feature for training also apply up-sampling as well as residual Images that is fundamental step of SISR, and dept of network is 20. For the improvement of presented method result apply fusion of of two bicubic method attributes with Very Deep Convolutional Networks. The presented method shows better result in terms of two base parameters of proposed method that is PSNR and SSIM. These two parameters are major parameter for result analysis of image super resolution (ISR).There are different data set available in the for training and testing of presented method such Test data set Datasets ‘Set5’ [15] and ‘Set14’ [26] both are mainly used by different researcher, benchmark in other works data set ‘Urban100’, that’s very interesting as it contains many challenging images failed by many of the existing methods. Final data set ‘B100’, natural images in the Berkeley Segmentation. The presented method compare with different methods, they are Ground Truth data set image A+ [22], RFL [18], SelfEx [11], SRCNN [5] and VDSR [1]. The proposed and presented method “Modified Very Deep Convolutional Networks (MVDCN) for single image super resolution (SISR)” shows better result as compare to other previous methods.

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