Library Progress International *Print version ISSN 0970 1052*
Vol.44 No. 3, Jul-Dec 2024: P. 16207-16219 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

Image Up-sampling for Enhancing Quality Image with Deep Learning

Oinam James[1], Th. Rupachandra Singh[2], T. Romen Singh[3]

[1]Computer Science Department, Manipur University, India
[2]Computer Science Department, Manipur University, India
[3]Computer Science Department, Manipur University, India

How to cite this article: Oinam James, Th. Rupachandra Singh, T. Romen Singh (2024) Image Up-sampling for Enhancing Quality Image with Deep Learning. *Library Progress International,* 44(3), 16207-16219

Abstract
This paper introduces an approach to deep learning for improving quality for single high-definition (H.D) picture. The method immediately acquires an end-to-end map from low- and high definition pictures. High image resolution plays a significant role when enhancing the photo as well as frames for video in gadgets including smartphones as well as computers for Better Resolution. When upscaling the image frame, the image get distorted and blurred. A high-definition image with greater clarity is produced by using a deep convolutional neural network which accepts a low-definition image as input and using Discrete Cosine Transformation to create blurred image from low resolution image and subtracting this blurred image from the result of network model . The experimental result shows that the proposed algorithm works better than the other compared algorithms.
Keywords: Image, upsampling, Super-resolution, Machine-Learning, Low-Resolution, High-Resolution.

1. Introduction
Super-resolution (SR) is the approach that enhances a pictures quality by producing an image with excellent resolution using a low-quality input image or frame. The SR approach does not just calculate unknown pixel intensity values; rather, it determines an appropriate value by considering the data contained within the input.
SR uses the interpolation of the sub-pixel shifts that infer a more precise object location with a sub-pixel resolution between multiple low-resolution images/frames of the same continuous scene. Super-resolution (SR) approach seeks to address the shortcomings of the image acquisition device and its ill-posed; during the process of upscaling, the image becomes distorted and blurry. In order to solve this issue, high resolution is required from low resolution; therefore, higher-resolution image techniques are required.[1].
The goal of image Super-Resolution (SR) is to use software approaches that can be efficiently used for imaging purposes in medicine, camera monitoring, intelligence gathering for producing high-resolution (HR) from low-resolution (LR) images [2]. Over the past years, image SR restoration approaches have garnered a lot of interest.

Using a straightforward upsampling technique, Qi Shan (2008) proposed Fast Image/Video Upsampling that suggest maintaining the necessary structural information while automatically improving the image/video resolution. It consist of design for controlling feedback that accurately brings back the high resolution visual data from a source input without adding new local structural restrictions that have been learned from earlier cases. [3]
Block classification is initially carried out in DCT domain to classify 8×8 picture blocks into different sorts, including smooth regions, edges, and others. This method of block-based upsampling for photos and movies was introduced by Ming-Sui Lee in 2009 [4]. Basic patches are applied to increase the picture size for the smooth surfaces and plain backdrop without lowering the visual quality of the end result. Considering that edges are more perceptible to human sight. To create the picture data at subpixel places appropriately, a facets model is employed. This idea may also be use to videos by considering temporal information. If the residual is bearable, obtaining the enlarged image of the matching block from the reference image frame may be possible to upsample an image block in the current frame. [4]
The ability to see small texture features visually is growing more and more with the advent of high resolution. There is an urgent need for a low-cost technique of image upsampling with good quality. In 2015, Yang Zhao proposed High Resolution Local Structure Constrained Image Upsampling which put out an upsampling technique that uses high-

resolution local structural constraints. A bicubic-interpolated image is divided into a sharp edge and textured area using the average local difference. These two areas are then individually reconstructed using predetermined constraints. High-Resolution gradient maps are estimate as an additional constraint for recovering sharp and natural edges in the sharp edge reconstruction area. High-Resolution local texture structure maps are estimated as an additional constraint for recovering fine texture details in the texture reconstruction area. These two rebuilt areas are combined to create the final high-resolution image. [5]

Deep learning methods have been effectively used in various computer vision applications, including simple restoration of image issues. Recently, several models based on deep neural networks have been presented for image super-resolution, and achieved outstanding performance that surpasses all earlier hand-crafted models. The topic concerns whether large-capacity and data-driven approaches have taken the lead in solving the imprecise super resolution problem then becomes relevant. In 2015, Zhaowen Wang and his team proposed a Deep Networks for Image Super-Resolution with Sparse Prior that the conventional sparse coding model's representation of domain knowledge is still important and can be used in conjunction with the fundamental components of deep learning to get even better results. It demonstrates how a neural network can be a sparse coding model specifically created for super-resolution and trained in a cascaded structure from beginning to finish. A network's interpretation according to sparse coding produces significantly greater effective and efficient training while also resulting in a smaller model [6].

The computer-generated image as well as video frame's High-definition technology improves the imaging system's ability to extract high definition resolution from low-definition resolution data. The difficulties in achieving high definition resolution are video/image denoising, blur detection, computing effectiveness, as well as performance constraints. S. Muthuselvan in 2019 recommended a method called Super Interpolation(SI)[7] for achieving the low complex upscaling of frames of video with High definition (HD) Resolution. This was done to address the issues of information lost during restoration as well as computational cost resulting from repeated steps in the existing high-definition resolution strategies Upscaling Phase and Training Phase are the two steps of the SI technique During the training stage, edge alignment orientation assessment is performed on a significant collection of external training pictures and video frames. In the initial upscaling stage, the LR video frame is upsampled and interpolated using the bicubic interpolation technique. After that, a canny edge detector performs edge detection on the interpolated frame in order to smooth it out. The HR video frame is sharpened using a local laplacian filter and an edge preservation approach. The Real-Time (RT) - India dataset and the YT dataset were used to test the suggested technique.

Because of the incorporation of deep learning methods as well as the expanding accessibility of training data, the area of licence plate recognition (LPR) has seen considerable improvements in recent years. However, it is still difficult to rebuild licence plates (LPs) from low-quality resolution (LR) video.To resolve this problem, In 2023, Valfride Nascimento introduces the Single-Image Super-Resolution (SISR) method, which integrates attention and transformer components to improve the recognition of structural and textural information in LR pictures[9]. The method employs a loss function and sub-pixel convolution layers (sometimes called PixelShuffle) to extract features from an optical character recognition (OCR) model. They used synthetic pictures generated through heavily gaussian-noise high-definition resolution Licence Plate images from two open datasets, bicubic down sampling is then used, to train the suggested architecture.

This paper demonstrates how the previously mentioned workflow compares favourably to a deep convolutional neural network. This feature prompts us to consider a convolutional neural network that systematically generates an end-to-end transforming among low- definition resolution and high-definition resolution pictures. We name the proposed model Image up-sampling for enhancing quality image with Deep Learning. The suggested approach offers a number of desirable qualities. First off, compared to modern example-based approaches, its structure is purposely simple while still offering higher accuracy. Second, even on a CPU, our solution delivers fast performance for useful online usage with a reasonable amount of filters and layers. And thirdly, its use the Iterative process to generate an end-result image with more clarity.

2. Related Work

Factor that can affect image quality is the resolution. More specifically, low-resolution (LR) images contain a low number of pixels representing an object of interest, making it hard to make out the details. This can be either because the image itself is small, or because an object is far away from the camera thereby causing it to occupy a small area within the image. Super-Resolution (SR) is a branch of Artificial Intelligence (AI) that aims to tackle this problem, in which an existing LR picture may be upscaled to provide a greater high definition resolution image with more detectable features, which can then be applied to subsequent tasks like objects categorization, facial recognition, and so on. Sources of LR images include cameras that may output low-quality images, such as mobile phones and surveillance cameras[10].

The need of high definition-resolution images is to enhance the image's quality for example, while modern mobile phone cameras do capture fairly good quality images, they still yield several imperfections caused primarily by the need to use lenses and image sensors that are compact enough to fit on the phone without making it too bulky, while also being relatively cheap.

The majority of SR algorithms emphasis high-resolution of single-channel or grayscale images, when dealing with color pictures, the aforementioned techniques first convert the issue into a separate color space (YCbCr or YUV), and then only apply SR to the luminance channel. There are also works that try to super-resolve every channel at once. As an illustration, Kim, Kwon, and Dai et al. used their model to analyze each RGB channel and then merged the data to arrive at their conclusions. [11]

The nearest neighbor interpolation method is the most straightforward interpolation method. This method uses the closest pixel to fill up any missing pixels. In these situations, it copies the pixel values rather than changing them. It is less efficient since it duplicates the pixel to fixed the missing pixel of the image [12][13]; It would appear as shown in image in figure 1. It is the simplest version since the pixel value is constant, therefore it is crucial to preserve its grey level.

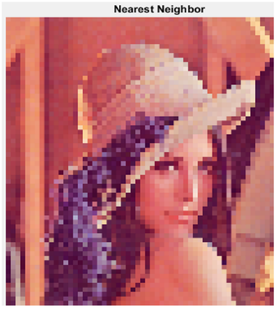


Fig 1: Image form using Nearest Neighbour

111	123	145	179	196	199
111	123	146	180	196	199
113	123	143	184	196	206
113	123	144	184	196	207
112	122	144	185	197	207
112	122	145	185	198	208
111	121	146	186	198	209
111	122	144	184	196	205
112	122	145	184	196	206
113	123	145	185	197	206
114	124	146	185	197	207

Fig 2: Pixel values obtained using Nearest Neighbor

Using Nearest Neighbour Interpolation, the pixel values is shown in figure 2.

The closest 2x2 known pixel values surrounding the unknown pixel are used in bilinear interpolation. A weighted average of these 4 pixels is utilised to determine the final interpolated value in order to determine the unidentified pixel.

To fill in the image's missing pixel

$$\boldsymbol{Differences\ of\ neighbouring\ pixel} = (\boldsymbol{d2} - \boldsymbol{d1})/(\boldsymbol{n} + \boldsymbol{1})$$

where d2 – d1 represents the difference between the adjacent pixel.

n represents the number of lost pixels.

$$\boldsymbol{Missing\ Pixel} = \boldsymbol{d1} + \boldsymbol{Differences\ of\ neighbouring\ pixel}$$

2	4
6	9

a) 2x2 Image pixel value

2	0	0	4
0	0	0	0
0	0	0	0

b) 4×4 Upsampled image pixel with missing pixel values

2	2.666667	3.333334	4
3.33333	4.111111	4.888889	5.666667
4.666667	5.555555	6.444445	7.333334
6	7	8	9

c) Upsampled Image Pixel

Fig 3: Interpolation using Bilinear upscaling

This results in smoother visuals when compared to the nearest neighbour. The image produced by using Bilinear is shown in figure 4.

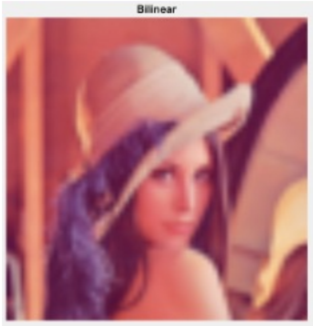


Fig 4: Image form by using Bilinear Interpolation

In image processing, bi-cubic up-scaling is commonly preferred over nearest neighbour up-scaling or bilinear up-scaling when the expedition is prohibited or considered less important. [13]. Bi-cubic up-scaling considers 16 pixels (4x4) as opposed to the standard 4 pixels (2x2). Pictures produced by bi-cubic interpolation are smoother as well as containing lower interpolation noise [13]. The method used most frequently for image processing is bi-cubic interpolation. Figure 5 displays the result of bi-cubic interpolation as a picture.

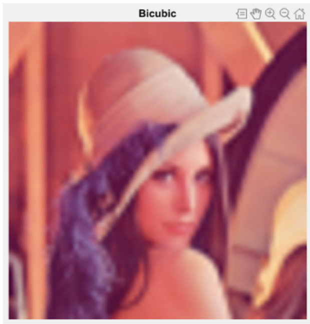


Fig 5: Image form by Bi-cubic Interpolation

The Lanczos upscale function uses the Lanczos filter and interpolation to alter the size of a picture. Depending on the final picture size, the image size may be enlarged or shrunk in each direction. The three-lobed Lanczos window function serves as the foundation for this interpolation technique. A mathematical formula has two applications: Lanczos filtering and Lanczos resampling. It has two applications: one is for low-pass filtering, and the other is for smoothly interpolating a digital signal's value between samples. In the latter scenario, each sample of the input signal is mapped to a translated and scaled copy of the Lanczos kernel, which is a longer, sinc function with its centre lobe serving as a window. At the required positions, the total of these translated and scaled kernels is subsequently assessed. Lanczos resampling is commonly employed to enhance a digital signal's sampling rate or modify it by a portion of the sampling interval. In order to rotate or resize a digital image, for instance, it is frequently utilised for multivariate interpolation. Among a number of straightforward filters, it has been deemed the "best compromise". Image obtained using lanczos function have been shown in the figure 6.

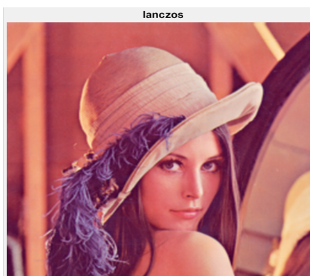


Fig 6: Lanczos Interpolation

3. The Proposed Method

In this study, we present a Image Up-sampling for Enhancing Quality Image with Deep Learning to develop for enhancing of image with upsampled image. The proposed system preprocess the image from dataset, image low resolution $m \times n$ color image is read to get High Resolution Image.

By employing a convolutional neural network architecture, we are able to obtain picture super-resolution as well as Discrete Cosine Transformation (DCT). The conversion between low to high-resolution pictures is learned by the network. Since high-resolution and low-resolution photos differ mostly in high-frequency features and have similar image content, this mapping is achievable. By using a residual learning method, our technique teaches the network to determine a residual picture. The discrepancy between a low-resolution picture that has been upscaled using Lanczos interpolation to match the size of the reference image and a high-resolution reference image is known as a residual image in the context of super-resolution. A residual image contains a picture's high-frequency characteristics.

The residual picture is identified by the network based on the luminance image. In the luminance channel of a picture, the brightness of each pixel is indicated by a linear combination of the red, green, and blue pixel values.

. And the two chrominance channels in a picture, are the distinct linear combinations of the values of the red, green, and blue pixels that indicate information about color differences. Because variations in brightness are more perceptible to humans than changes in color, the model is trained exclusively on the luminance channel.

Once the network has learned to predict the residual picture it is rebuild high-resolution photos by first adding it to the low-resolution upsampled image and then transforming it into RGB. To get enhanced image DCT is apply to the source low resolution image for generating blurred image with resizing by padding zero's and generating IDCT that is subtracted from the previous high resolution image to get the final up sampled super resolution image.

The Inverse Discrete Cosine Transform (IDCT) is a mathematical operation that converts data from a domain wavelength into another. The Discrete Cosine Transform (DCT) is a technique widely used in signal processing and image compression, e.g. JPEG to express data as sum of frequency components. This step is reversed in the IDCT to reconstruct a time-domain signal from its frequency representation.

The transformation for a 1D IDCT is shown mathematically as the following:

$$X_n = \frac{1}{2}C(0)X_0 + \Sigma_{k-1}^{N-1} C(k) X_k cos\,[\frac{\pi k(2n+1)}{2N}]$$

for $n = 0,1,2,\dots,N-1$, where:

$\boldsymbol{x_n}$ is the reconstructed data point at position $\boldsymbol{n}$,

$X_k$is the $k-th$ DCT coefficient,

N is the number of data points,

$\boldsymbol{C(k)}$ is a normalization factor defined as

$$C(k) = \begin{cases} \frac{1}{\sqrt{N}} & for\ k = 0 \\ \sqrt{\frac{2}{N}} & for\ k > 0 \end{cases}$$

For a 2-dimensional IDCT, which is commonly used in image processing, the formula is:

$$X_{m,n} = \frac{1}{4}\sum_{u=0}^{N-1}\sum_{v=0}^{M-1} C(u)C(v)X_{u,v} cos\left[\frac{\pi u(2m+1}{2N}\right] cos\left[\frac{\pi v(2n+1}{2M}\right]$$

For $m = 0,1,2,,,,,N-1$ and $n = 0,1,2,,,,,M-1$, where:

$X_{m,n}$ is the reconstructed pixel value at position (m,n)

$X_{u,v}$is the DCT coefficient at position (u,v)

$\boldsymbol{N}$ $and\ M$ are the dimensions of the data (e.g., the width and height of an image).

we propose the following algorithm to gain better results for processing images. The figure 9 depicts the suggested architecture.

Proposed algorithm

1. Read low resolution color image $m \times n$.
2. Upsampled the low resolution image to $p \times q$. using lanczos interpolation.

3. Transformed the image into luminance and two chrominance channel using rgb2ycbcr function.
4. Passed the luminance image to the network framework to produced the residual image (residual picture contains an image's high-frequency features)
5. Using the estimated residual image and combining with upsampled luminance image, high-resolution images is rebuilt.
6. The output of the step 5 is concatenated with the upsampled chrominance channel image to get the color component of the image using ycbcr2rgb function.
7. To get more enhance in the image, Discrete Cosine Transformation (DCT) is applied to the source low resolution image for generating Blurred image.

i) Use DCT Function for generating DCT Coefficient.
ii) Resizing DCT to $p \times q$ by padding zero's.
iii) Use Power law to modify DCT coefficient.
iv) Use Inverse Discrete Cosine Transformation function (IDCT) to get Blurred Image.

8. The output from step 7. is subtracted from the result of step 6. To obtain the final super resolution upsampled image.

Fig7: Input Source

By examining a small section of the image, compared to the original source image, the recommended super-resolution image has finer edges as well as greater clarity.

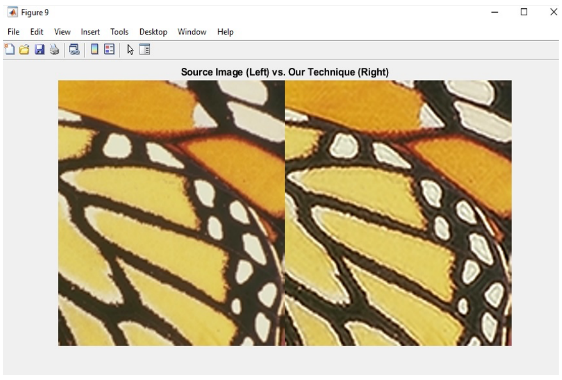


Fig 8: Examination of output image with source image using small section of the image

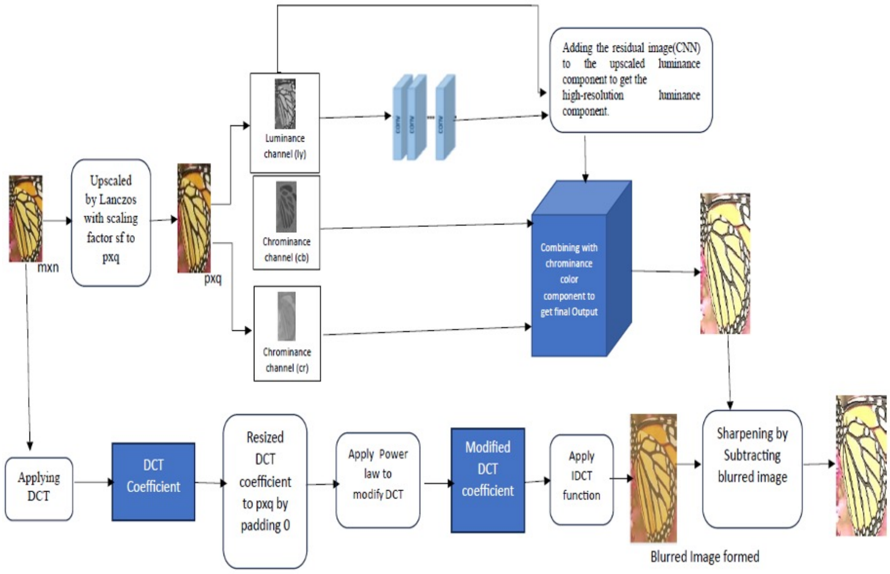


Fig 9: Framework diagram of the experimental Design

4. Experimental Analysis and Discussion

4.1 Datasets

Datasets for testing: In this study, we use well-known SR datasets, including Set5 [29], Set14 [30], and the test dataset of DIV2K [28], to equitably assess the SR performance of our architecture.

4.2 Analysis of PSNR and SSIM

The peak signal to noise ratio is often utilized to assess reconstruction standard-quality for pictures and videos subject to lossy compression.

$$PSNR = 20log_{10}(\frac{Max_f}{\sqrt{MSE}})$$

In which the MSE (mean square error) is:

$$MSE = \frac{1}{mn}\Sigma_0^m\Sigma_0^{n-1}||f(i,j) - g(i,j)||^2$$

The highest possible signal value in the image is indicated with **Max_f .**

Matrix representing the original image data is indicated by **f.**

The image's degraded matrix data is represented by **g.**

The row's pixels number for the pictures is denoted by **m.** and the number that represents the index of that row is represented by **i.**

The number of pixel columns within the image is **n,** and that column's index is **j.**

The Structural Similarity Index Measure (SSIM) is used to estimate how good a picture or video is evaluated to be. It is also employed to ascertain how comparable the two pictures are.

Table.1: PSNR and SSIM Analysis of different Technique for different images

PSNR/SSIM ANALYSIS													
Method	**Scale**	**Images**											
		Lena		**Butterfly**		**Sherlock**		**Lighthouse**		**Vegetables**		**Skin Cancer (ISIC_0015483)**	
		PSNR	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**
Nearest neighbor	0.5	22.41509	0.966621	21.12572	0.900339	37.81064	0.793931	25.13208	0.892996	24.7902	0.805071	33.5891	0.807821

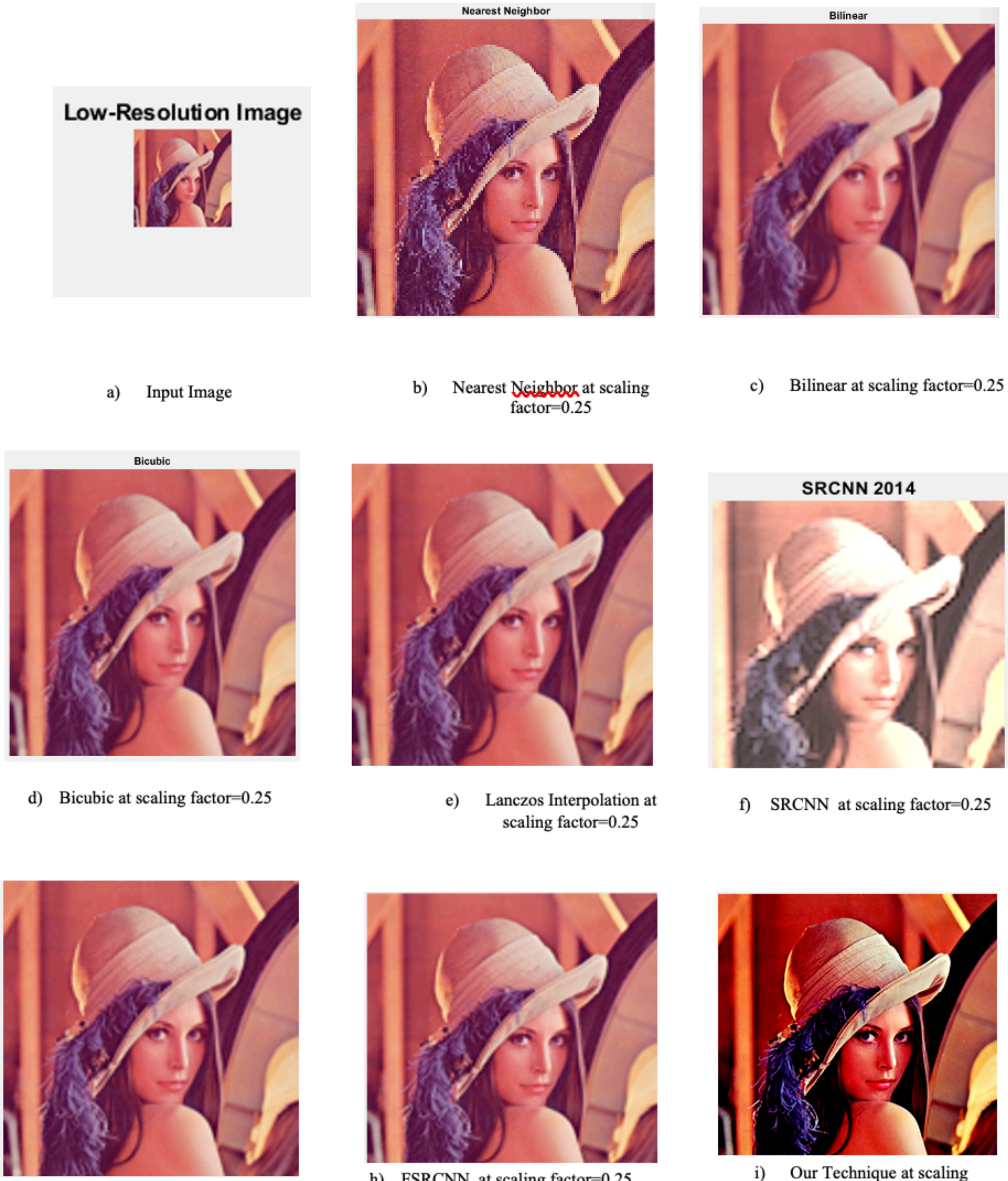
Bilinear	0.5	26.72327	0.978737	23.41443	0.92502	40.92665	0.811604	27.50107	0.905068	29.61136	0.820448	36.659576	0.831741
Bicubic	0.5	27.68655	0.982687	26.13144	0.942566	41.34272	0.81319	29.49213	0.913604	30.256955	0.833511	38.159222	0.779327
Lanczos	0.5	32.34502	0.856375	25.27535	0.929122	41.77971	0.89372	28.87067	0.92174	30.549143	0.851842	38.763337	0.98115
SRCNN	0.5	11.02688	0.638978	11.79293	0.640176	11.54285	0.606487	11.86828	0.633012	11.644546	0.71481	10.445581	0.47291
FSRCNN	0.5	32.69329	0.641723	26.07253	0.648254	40.56414	0.613095	29.34515	0.638286	29.408866	0.720167	38.234852	0.478639
Joint Learning of Multiple Regressors for Single Image Super-Resolution (2024)	0.5	32.92691	0.849857	26.18327	0.831059	40.62391	0.906189	29.41806	0.8026793	30.192755	0.953919	38.348198	0.479956
VDSR	0.5	33.02351	0.971582	26.73044	0.949293	42.45703	0.987573	29.44751	0.966795	30.49723	0.984646	39.355506	0.990195
DSRNet (2024)	0.5	33.38192	0.984266	26.52917	0.862374	43.01703	0.971925	29.51403	0.884952	30.359163	0.891786	39.926405	0.987341
Our Technique	0.5	**33.41801**	**0.985982**	**26.7381**	**0.956798**	**43.96635**	**0.993681**	**30.11337**	**0.970107**	**30.928521**	**0.985417**	**40.742807**	**0.991609**
Nearest neighbor	2	33.01219	0.891927	24.01639	0.61951	23.91274	0.620647	22.75618	0.60127	25.529106	0.61276	21.691402	0.602891
Bilinear	2	36.49622	0.914002	30.16685	0.984409	46.14247	0.997541	33.61356	0.989487	37.680556	0.996389	43.225314	0.996831
Bicubic	2	38.70167	0.936328	32.97881	0.991767	48.352	0.998436	36.11594	0.99408	40.358671	0.997948	45.636546	0.998002
Lanczos	2	39.63814	0.937043	34.24523	0.993895	49.40642	0.998789	37.27924	0.995544	41.584452	0.998468	46.92758	0.998529
SRCNN	2	11.03744	0.635947	11.77873	0.630082	11.54851	0.605857	11.87904	0.631816	11.733099	0.711998	10.477095	0.471851
FSRCNN	2	13.53819	0.650281	11.80968	0.651826	12.39103	0.610274	11.93482	0.641392	11.739245	0.710128	11.023849	0.483193
Joint Learning of Multiple Regressors for Single Image Super-	2	33.5111	0.839001	26.87001	0.88312	28.56381	0.892813	27.23912	0.889124	26.19234	0.874913	27.943921	0.891901

Resolution (2024)													
VDSR	2	41.70584	0.981045	37.67246	0.996942	48.97783	0.98951	40.01751	0.983195	43.909733	0.985701	47.279857	0.9823
DSRNet (2024)	2	38.29	0.942639	37.61	0.9584	48.43501	0.984012	40.63105	0.986192	43.98532	0.98723	47.4193	0.985391
Our Technique	**2**	**42.9571**	**0.998089**	**64.98411**	**0.867738**	**49.16511**	**0.998457**	**42.50148**	**0.996852**	**44.19125**	**0.998797**	**47.9231**	**0.998374**

The comparison analysis is done using two methods, firstly downsampling and secondly upsampling. Firstly, we downsampled with scaling factor 0.5 and restored it back, the psnr and ssim values compared with other method, our method has gain more and produce excellence result compared to others. Secondly Upsampling with scaling factor 2, the psnr and ssim values of our method produce higher value compared with others methods.

Figure: Comparison of car2.jpg image region of interest using different technique.

4.3 Output Image Analysis



a) Input Image

b) Nearest Neighbor at scaling factor=0.25

c) Bilinear at scaling factor=0.25

d) Bicubic at scaling factor=0.25

e) Lanczos Interpolation at scaling factor=0.25

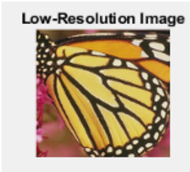
f) SRCNN at scaling factor=0.25

g) VDSR at scaling factor=0.25

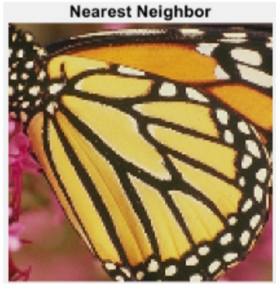
h) FSRCNN at scaling factor=0.25

i) Our Technique at scaling factor=0.25

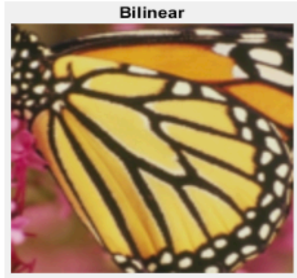
Fig 11: Image Result Analysis for Lena at scaling factor 0.25



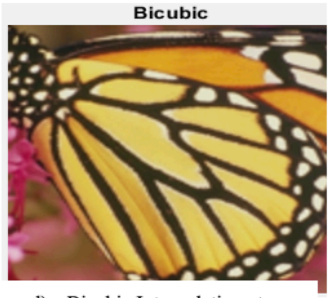
a) Input Image



b) Nearest Neighbor at scaling factor 0.50



c) Bilinear at scaling factor 0.50



d) Bicubic Interpolation at scaling factor 0.50

e) Lanczos Interpolation at scaling factor 0.50

f) SRCNN at scaling factor 0.50

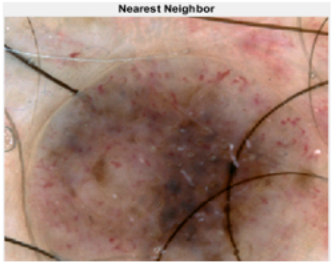
g) VDSR at scaling factor 0.50

h) FSRCNN at scaling factor 0.50

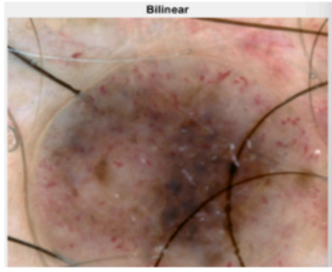
i) Our Technique at scaling factor 0.50

Fig 12: Image Result Analysis for Butterfly at scaling factor 0.50

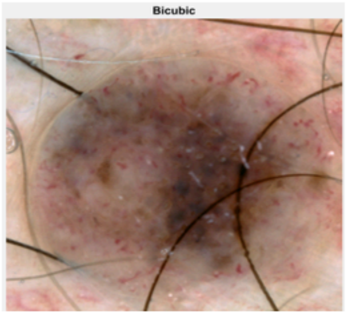
a) Input Image



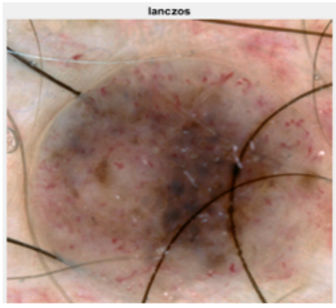
b) Skin cancer image obtained using Nearest Neighbour at scaling factor 0.60



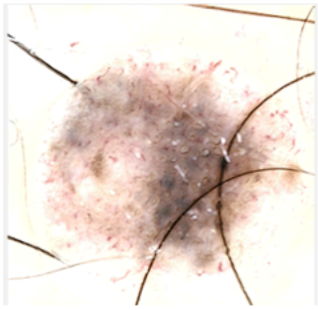
c) Skin cancer image Obtained using Bilinear Interpolation at scaling factor 0.60



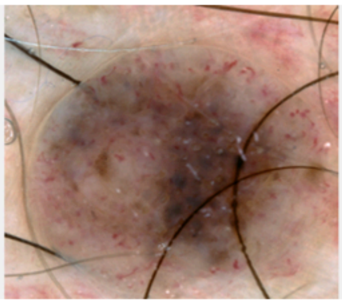
d) Skin cancer image Obtained using Bicubic Interpolation at scaling factor 0.60



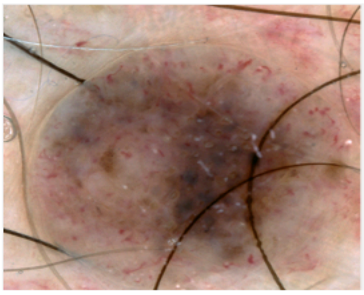
e) Skin cancer image Obtained using Lanczos Interpolation at scaling factor 0.60



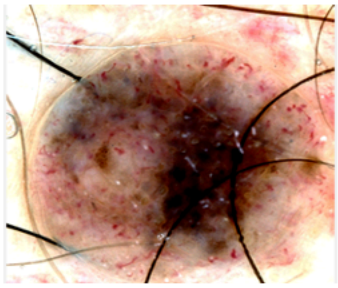
f) Skin cancer image Obtained using SRCNN at scaling factor 0.60



g) Skin cancer image Obtained using VDSR at scaling factor 0.60



h) Skin cancer image Obtained using FSRCNN at scaling factor 0.60



i) Skin cancer image Obtained by Our Technique at scaling factor 0.60

Fig 13: Image Result Analysis for Skin Cancer at scaling factor 0.60

From the above experimental analysis our method gain better than the compare algorithm.

5. Conclusion

Although state-of-the-art non-machine learning algorithms for image denoising exist, we are constantly wondering if we can achieve better performance with deep learning. This paper proposes a deep learning denoising network of super-resolution images that achieves statistically significant improvements over traditional benchmark algorithms. Significant advancements have been achieved in super-resolution image processing, which now offers better image quality and reveals finer details. In certain situations, real-time implementation of super resolution methods might be difficult since they require computationally demanding operations. There are still issues, though, and current study is aimed at finding solutions and breaking new ground in this ever-evolving sector.

Acknowledgment
The authors acknowledged the computer science department, Manipur University for the assistance provided to us.

Data availability The dataset analysed during the current study available in web links https://www.researchgate.net/figure/Sample-image-Lena-image-size-512-512-pixels-clustered-by-the-original-SLIC-middle_fig1_262916451,https://www.mathworks.com/matlabcentral/answers/54439-list-of-builtin-demo-images, https://challenge.isic-archive.com/data/

Declaration
Conflict of interest: The authors declare that they have no conflict of interest.

References

1. Oinam James, Th. Rupachandra Singh, T. Romen Singh," A SURVEY ON IMAGE AND VIDEO UPSCALING AND MEASURING MATICES," Journal of Critical Reviews 2020
2. O. James, T. R. Singh and T. R. Singh, "Image Super Resolution Based on Machine Learning for Enhancing Quality Image," IEEE 2023
3. Qi Shan Zhaorong Li Jiaya Jia Chi-Keung Tang, "Fast Image/Video Upsampling," ACM Transactions on Graphics, Vol. 27, No. 5, Article 153, Publication date: December 2008.
4. Ming-Sui Lee and Chen-Wei Chang," An Efficient Upsampling Technique for Images and Videos," Springer-Verlag Berlin Heidelberg 2009.
5. Yang Zhao, Ronggang Wang, Wenmin Wang, and Wen Gao,"High Resolution Local Structure Constrained Image Upsampling," IEEE Transactions on Image Processing 2015
6. Zhaowen Wang, Ding Liu† Jianchao Yang, Wei Han, Thomas Huang," Deep Networks for Image Super-Resolution with Sparse Prior," IEEE in 2015.
7. S. Muthuselvan, S. Rajaprakash, J Hemanth Sai, Byrapaneni Nikhil,"Resolution Enhancement in Video Using Super Interpolation Algorithm," International Journal of Innovative Technology and Exploring Engineering (IJITEE) 2019
8. Valfride Nascimento, Rayson Laroca, Jorge de A. Lambert, William Robson Schwartz, and David Menotti," Super-Resolution of License Plate Images Using Attention Modules and Sub-Pixel Convolution Layers," Computer & Graphics Science Direct 2023
9. Jianchao Yang, John Wright,Thomas S. Huang and Yi Ma, "Image Super-Resolution Via Sparse Representation" in IEEE, 2010.
10. Chao Dong, Chen Change Loy, Member, IEEE, Kaiming He, Member, IEEE, and Xiaoou Tang, Fellow" Image Super-Resolution Using Deep Convolutional Networks," in IEEE, 2016
11. Xinbo Gao, Kaibing Zhang, Dacheng Tao, and Xuelong Li, "Joint Learning for Single-Image Super-Resolution via a Coupled Constraint" in IEEE, 2012
12. Xiaoyan Li, Hongjie He, Ruxin Wang, and Dacheng Tao, Fellow," Single Image Super-Resolution via Directional Group Sparsity and Directional Features," in IEEE, 2015
13. Gilad freedman and raananfattal," Image and Video Upscaling from Local Self-Examples," in ACM, 2011
14. Weisheng dong, lei zhang, rastislavlukac and guangmingshi, "Sparse Representation Based Image Interpolation With Nonlocal Autoregressive Modeling," IN IEEE, 2013 .
15. Mehdi S. M. Sajjadi, RavitejaVemulapalli, Matthew Brown, "Frame-Recurrent Video Super-Resolution" in IEEE, 2018
16. S. Muthuselvan, S. Rajaprakash, J Hemanth Sai, Byrapaneni Nikhil, "Resolution Enhancement in Video Using Super Interpolation Algorithm", in IJITEE, 2019
17. Soo Ye Kim, Jeongyeon Lim, Taeyoung Na, Munchurl Kim, "3DSRnet: Video Super-resolution using 3D Convolutional Neural Networks", in arXiv, 2019