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Original research article

Reconstruction of an Improved High-Resolution Image from Low-Resolution Image Using Image Enlargement and Enhancement Algorithm

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ABSTRACT

The resolution of images in the medical field plays an important role in taking decisions to identify diseases, but if the image resolution is low, then disease identification may go wrong. For the correct decision, the image should be of high-resolution. High-resolution images can be taken using efficient hardware devices also, but then it is a costly proposition. Thus, we propose a model to reconstruct a low-resolution image into a high-resolution image using four image enlarging algorithms and an image enhancement algorithm. Initially, images are enlarged using enlarging algorithms to generate four images, followed by an image enhancement algorithm to generate four enhanced quality images. Thereafter, one high-resolution composite image is constructed using these four images. Experimental results were compared with the results of existing image enlarging approaches. Significant improvements in important image parameters like Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Structural similarity (SSIM), and Mean Squared Error (MSE) could be achieved.

Keywords: Composite image; High-resolution image; Image enhancement algorithm; Image enlargement algorithm

1. Introduction

High-resolution images are required in the medical field so that diseases can be adequately diagnosed. Image enlarging is a process that reconstructs the image in high-resolution from its low resolution. During this process of increasing the image size, image quality is taken care of. In image enlargement algorithms, the image size is increased by increasing the number of pixels that are present in the original image. If we are increasing the size of the image by twice the actual size, then we need to add the same number of pixels already present in the actual image. New pixels can be generated using various algorithms. In our

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work, we have used the Nearest Neighbour Interpolation Algorithm, Bilinear Interpolation Algorithm, High-Quality Scale (Hqx) and Scale by rules (xBR) [1].

The Nearest Neighbour Interpolation Algorithm is the most straightforward algorithm to enlarge the image with the help of the neighbour of the pixels available in the actual image. It checks the value of the nearest neighbour, ignoring the other pixels. An image can be enlarged by 2x, 3x, and so on. If we are enlarging the image by 2x, then it will increase the pixels in double; one row and column will be added just after each row and column in the original image [1].

The Bilinear Interpolation Algorithm is the updated version of neighbour interpolation to interpolate the pixel. This algorithm works in two directions instead of a single direction to get the pixel value. This algorithm takes an average of the four nearest pixels to find the value of the unknown pixel [2].

High-Quality Scale (Hqx) comes under the category of pixel art scaling algorithms that usually work better on a very low-resolution image. This technique gives undistorted and sharp images. Three filters are used to enlarge the image, defined as hqx2x, hqx3x and hqx4x, which enlarges the image by 2, 3 and 4 factors, respectively. Single pixels can be enlarged into 2x2, 3x3, or 4x4 pixel arrangements. The algorithm checks similar or dissimilar neighbours by comparing the surrounding pixels [3-4].

Scale by rules (xBR) is another type of pixel art scaling algorithm. It has six filters in the family: xBR, xBRZ, xBR-Hybrid, Super xBR, xBR+3D and Super xBR+3D. xBR can handle complex and zig-zagged images and generates a smooth image. No-blend xBR is more popular than another variant that is with a blend. No-blend xBR sometimes gives jaggy outputs, but it maintains image sharpness [3, 5].

Image enhancement is a process to improve the quality and content of the image. The iterative back-projection (IBP) algorithm generates a super-resolution image using enhancing the pixel information. When this algorithm is applied to a single image, blurring can be removed without increasing the sampling rate. This algorithm is suitable for both computer generated images and real-time images. In the IBP algorithm, pixels are reconstructed by comparing the past values of the pixel and the best-suited value will be assigned to enhance the image. The algorithm divides the whole process into two parts. The first part builds the imaging process so that the old values of the pixel can be compared. The second part assesses new values of the pixels through the image enrollment approach [6-8].

The 4 enlarging algorithms described above have certain limitations when applied independently.

For example, the enlarged image obtained using the Nearest Neighbour Interpolation Algorithm gives jaggies at boundaries that increase the noise, affecting the quality of the output image [1]. Likewise, the Bilinear Interpolation Algorithm produces images with blurring and edge halos. Due to this issue, the image produced is of low quality [2]. Similarly, Hqx and xBR are pixel-art enlarging algorithms that produce artifacts in the output image [3-4].

In the proposed methodology, we have used the IBP algorithm to enhance the images enlarged using the Nearest Neighbour Interpolation Algorithm, Bilinear Interpolation Algorithm, High-Quality Scale (Hqx) and Scale by rules (xBR).

The use of the IBP algorithm overcomes the aforesaid limitations of the enlarging algorithms and improves the quality of the output image by enhancing while smoothing the boundaries, removing the blur effect and artifacts [6-8]. Further composite images are generated to improve the overall quality of the output image received from the IBP algorithm.

We have identified that high-resolution images play a crucial role in the identification of any object in the medical field. In this paper, we have proposed a model by which images can be reconstructed in high-resolution from low-resolution with improvement to the quality of the image. In our experiments, we have focused on the reconstruction of MRI images from low-resolution images. This model has improved the quality of the image after converting it to high-resolution from low-resolution.

This paper has the following sections. In section 2, the literature review is presented. In section 3, the methodology is described. Results and Analysis are given in section 4. Section 5 describes the conclusion and future work. Finally, a list of references is provided.

2. Literature Review

Zhu et al. [9] proposed a new technique for super-resolution image reconstruction that uses Surveying Adjustment in which they used a sequence of low-resolution images as observations and then equations for the observations are considered for the construction of a super-resolution image. We have constructed four images using different algorithms that will work as a sequence of enlarged images.

Sundar et al. [10] proposed an algorithm to reconstruct super-resolution. They used the Discrete Wavelet Transform and combined multiple low-resolution images to improve image quality. We have used iterative back-projection algorithms and constructed a composite image to enhance the overall quality of the image.

Yu et al. [11] proposed an algorithm named adaptive inverse hyperbolic tangent (AIHT) to consider the image feature during the enlargement of the image. They enhanced the image before enlarging. We have enhanced the image after enlarging so that their features should also be enhanced.

Liu et al. [12] proposed a methodology to construct a super-resolution image using a revised regularization method to resolve the ill-posed problem and enhance the edges also. We have used an ensemble technique to enhance the edges of the image.

Tanaka et al. [13] proposed an algorithm to reconstruct a high-resolution image using a MAP-based technique. The algorithm optimizes cost function in the frequency domain of the high-resolution image. We use four different algorithms that collectively optimize the cost function of the enlarged image.

Li et al. [14] have proposed a method for image deblurring by relaxed initialization and pixel-wise updates of the iterative method. Li et al. [15] proposed an improved Iteration Back Projection method to construct super-resolution images using a low-resolution image and applied it to Advanced Land Observing Satellite (ALOS) imagery. Irani et al. [16] proposed an approach to improve resolution by an image registration technique. They determined that while improving the resolution the resulting image may be blurry. Purkait et al. [17] proposed a regularization method to reduce the blurring effect and also reduced the noise generated during low-resolution image formation while preserving edge information. We have used the Iterative Back Projection algorithm with improved parameters to enhance the image quality of the medical image by reduction of noise and blur.

3. Methodology

We have used four enlarging algorithms, namely the Nearest Neighbour Interpolation Algorithm, Bilinear Interpolation Algorithm, High-Quality Scale (Hqx) and Scale by rules (xBR) to enlarge the input low-resolution image. Then the generated low-resolution images get enhanced and finally, these enhanced images are grouped together to generate enhanced high-resolution images. Fig. 1 depicts the overall process of reconstruction of a high-resolution image.

The whole process was done in the following three phases:
Step 1: Enlarging the low-resolution images using four different enlargement algorithms.
Step 2: Enhancement of enlarged images using back-projection algorithm
Step 3: Finally, enhanced images are grouped to generate a composite enhanced final high-resolution image.

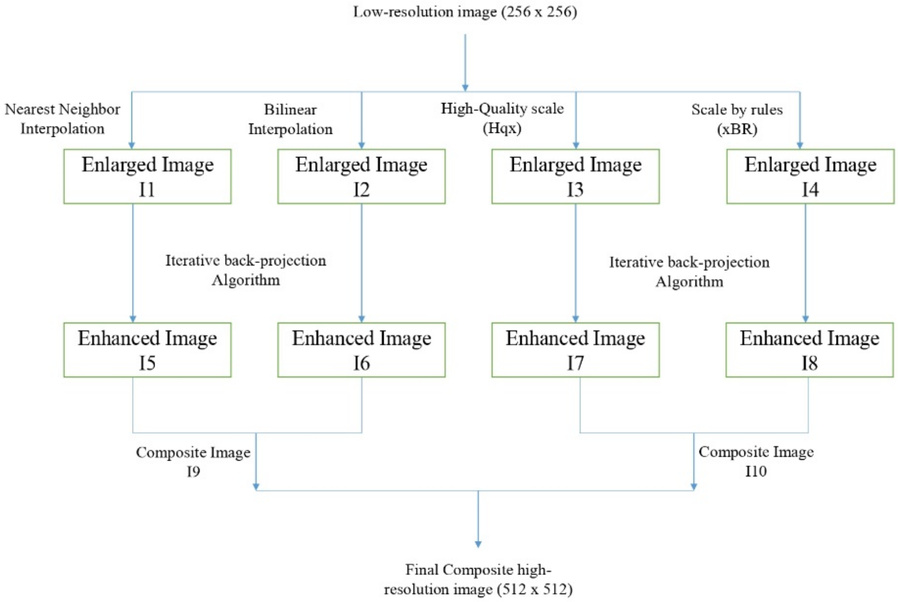


Fig. 1. The proposed model to reconstruct a high-resolution image from a low-resolution image.

For the purpose of reconstruction of enhanced high-resolution image (512x512), we have taken low-resolution (256x256) Magnetic Resonance Imaging (MRI) images of the human brain [18-19]. Four enlarging algorithms, namely the Nearest Neighbour Interpolation algorithm, Bilinear Interpolation algorithm, High-Quality scale (Hqx), Scale by rules (xBR) are used to enlarge the image and images I1, I2, I3 and I4 are generated using these enlargement algorithms, respectively.

All the enlarging algorithms have their significance. The Nearest Neighbour Interpolation algorithm is the most straightforward algorithm and takes very little time to generate an enlarged image. As the number of pixels doubles, it needs to interpolate the same number of pixels present in the image and the nearest Neighbour property is used to find the value of the pixels.

The Bilinear Interpolation algorithm interpolates the pixel value as per the nearest pixel. So we have enlarged the same low-resolution image to generate one more image using a bilinear interpolation algorithm that interpolates the pixel value by averaging the most adjacent pixels, which also preserves the edge.

Two other algorithms, Hqx and xBR, are used to enlarge the low-resolution image. Both algorithms are a type of pixel art scaling algorithms. While enlargement images may produce distortion, Hqx handles it and gives a sharp image. Hqx2x is used for the enlargement. The xBR algorithm is used to remove the zig-zagged effect of the image.

These four image enlargement algorithms convert a 256x256 size image into a 512x512 size image. I1, I2, I3 and I4 are the 512x512 images generated by the image enlargement algorithms. Image enlargement algorithms generate images by increasing the number of pixels. We have increased twice the number of pixels to enlarge the image.

In the next step, we reduce the noise and the blur effect produced during the enlargement of the image.

Iterative back-projection (IBP) was applied to generate enhanced images from images I1, I2, I3 and I4. The image enhancement algorithm was applied to the four images received from the previous step to generate enhanced images I5, I6, I7 and I8 with less noise and blurring. The function of IBP in MATLAB is shown in Listing 1 and flow chart is shown in Fig. 2

List 1. Basic function of IBP to reduce the noise and blur.

```
numImages = 4;
blurSigma = 1;
[ images offsets croppedOriginal ] = SynthDataset(im,
numImages, blurSigma);
%% for enhanced image
[ lhs rhs  ] = SREquations(images, offsets, blurSig-
ma);
K = sparse(1 : size(lhs, 2), 1 : size(lhs, 2), sum(lhs,
1));
initialGuess = K \ lhs' * rhs; % average image pro-
duced from the LR images.
```

Next, two images are grouped together to construct a composite image. This grouping of images was done using the imfuse function of MATLAB. We are grouping I5 with I6 and I7 with I8 to generate two composite images I9 and I10, respectively. Finally, these two images are grouped together to construct a final enhanced high-resolution image of 512 x 512. MATLAB code for composite image construction is shown in Listing 2 and flow chart is shown in Fig. 3

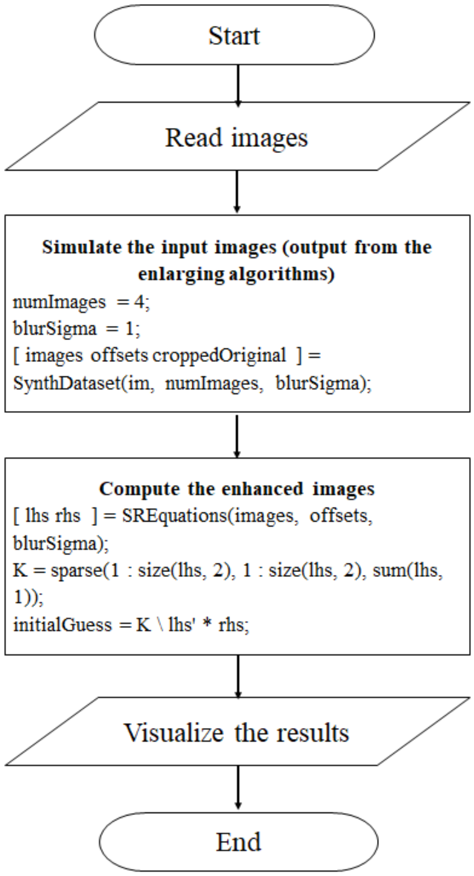


Fig. 2. Flow Chart of the basic function of IBP to reduce the noise and blur.

List 2. MATLAB code to construct composite image

```
image-sr-nn = imread(sr_nearest.png');
image-sr-bi = imread('sr_bi_output.png');
image-sr-xbr = imread('sr_xbr.png');
image-sr-hqx = imread('sr_hqx.png');
c=imfuse(image-sr-nn, image-sr-bi);
d=imfuse(image-sr-xbr, image-sr-hqx);
imwrite(composite-1,'bilinear_plus_nearest.png')
imwrite(composite-2,'xbr_plus_hqx.png')
hr-image=imfuse(composite-1, composite-2);
imwrite(hr-image, 'final_composite.png')
```

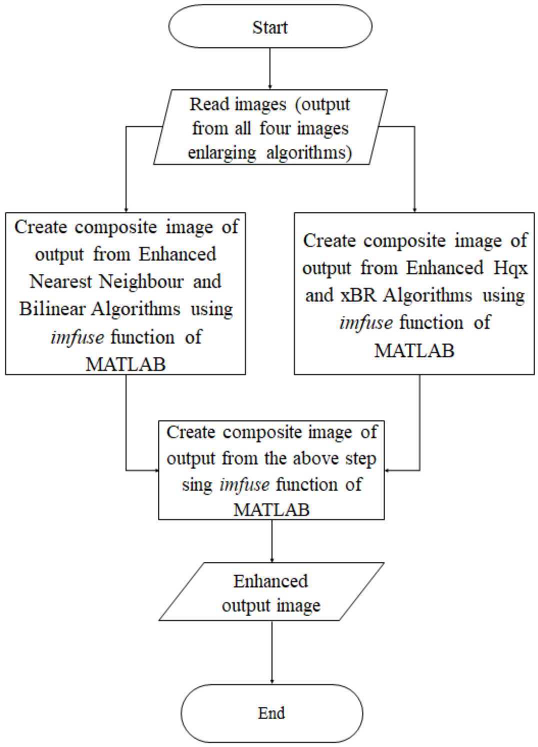


Fig. 3. Flow Chart to construct composite image.

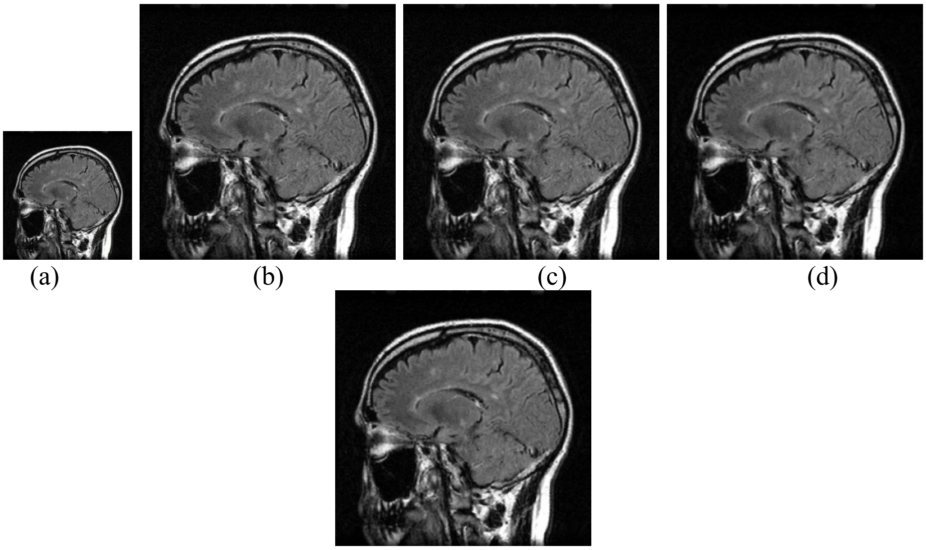
In this paper, we have used the parameters of Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Structural similarity (SSIM) and Mean Squared Error (MSE) to compare the image quality. PSNR checks the noise in the image. The value of noise should be minimum to increase the value of PSNR. A better image always has a high PSNR. SNR indicates a signal to noise ratio, the signal should be higher than the noise. A high value with threshold will have a good quality image. SSIM shows the similarity of structure between the images. A higher value of SSIM produces images of similar structure. MSE is a mean squared error between the corresponding pixels, and the lower value indicates that the predicted pixels are very near identical to the original pixels. We have compared the reconstructed image with the original image of size 512x512 to calculate the values of image parameters.

MATLAB's online environment was used to generate all the intermediate images and the final high-resolution image. We have developed the functions to enlarge the image using the Nearest Neighbour Interpolation algorithm, Bilinear Interpolation algorithm, High-Quality scale (Hqx), and Scale by rules (xBR). These functions take a low-resolution image of size 256x256 as an input and give an enlarged image of 512x512. All input and output images are of PNG format. Enlarged images are passed to the IBP algorithm to reduce the image blurring.

4. Results and Analysis

The proposed methodology produced a high-resolution image from a low-resolution image of the human brain MRI [18-19].

Fig. 4 shows the input and output images after applying the image enlargement algorithm and values of image parameters are shown in Table 1. It is evident from Table 1 that different enlargement algorithms improve different parameter values of the input image. The Bilinear Interpolation image enlargement algorithm gives us the best PSNR value. Hqx gives the lowest PSNR and the highest structural similarity. MSE of the image is minimum with Nearest Neighbour Interpolation. Similarly, we are getting maximum SNR with xBR image enlargement algorithm.



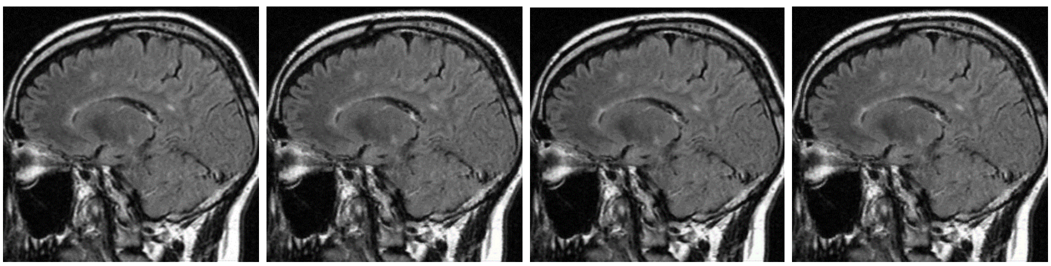
(a) (b) (c) (d) (e)

Fig. 4. Input and output images after applying image enlargement algorithms, (a) input image (b) Nearest Neighbour Interpolation (c) Bilinear Interpolation d) Hqx (e) xBR.

Table 1. Image parameters after applying Image Enlarging Algorithms.

	Nearest Neighbour Interpolation	Bilinear Interpolation	HQX	xBR
PSNR	21.1468	21.2471	21.0172	21.1422
SNR	11.4698	11.5701	11.3403	11.5952
SSIM	0.7040	0.6969	0.7165	0.7058
MSE	483.3434	487.9484	514.4660	499.8716

We have used the IBP algorithm to improve image quality. The improved images are shown in Fig. 5, and new parameter values are shown in Table 2. As compared to Table 1, the values of parameters have been significantly improved.



(a) (b) (c) (d)

Fig. 5. Images after applying iterative back-projection (IBP) algorithm on the four images received from the previous step, enhanced images of the output of (a) Nearest Neighbour Interpolation (b) Bilinear Interpolation (c) Hqx (d) xBR.

Table 2. Image parameters after applying Iterative Back Projection Algorithm on enlarged images.

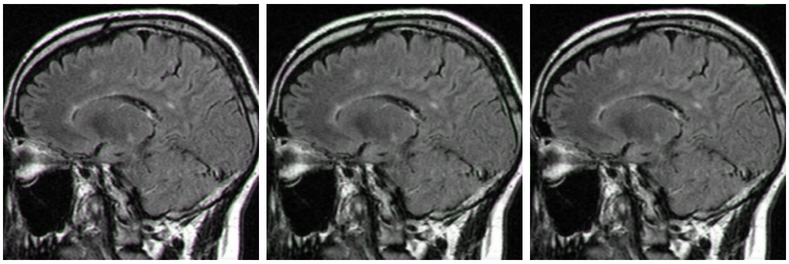
	Enhanced-Nearest Neighbour Interpolation	Enhanced-Bilinear Interpolation	Enhanced-Hqx	Enhanced-xBR
PSNR	21.1759	21.5021	21.2734	21.2586
SNR	11.4989	11.8252	11.5964	11.6217
SSIM	0.6975	0.7232	0.7310	0.7115
MSE	456.0142	460.1153	484.9981	486.6495

Figs. 6a and 6b show the results of the composite images. Two composite images are generated: the first using Enhanced-Nearest Neighbour Interpolation and Enhanced-Bilinear Interpolation and the second using Enhanced-HQX and Enhanced-xBR. Parameter values of composite images are shown in Table 3. These composite images have further improved PSNR, SNR, SSIM and MSE.

The final enhanced composite image, shown in Fig. 6c, is generated using the images received from Fig. 6a and 6b. As is evident from Table 3, the PSNR, SNR, SSIM and MSE values of the final image have better parameter values as compared to images obtained after applying the image enlargement algorithm and further after using the IBP algorithm.

Table 3. Image parameters of composite images and final high-resolution image.

	Composite of Enhanced-Nearest Neighbour Interpolation and Enhanced-Bilinear Interpolation	Composite of Enhanced-HQX and Enhanced-xBR	Final Image
PSNR	21.7207	21.7970	22.0599
SNR	12.4337	12.1200	14.3829
SSIM	0.7587	0.7374	0.8420
MSE	437.5337	429.9160	302.6586



(a) (b) (c)

Fig. 6. Composite images of, (a) enhanced images of Nearest Neighbour Interpolation and Bilinear Interpolation (b) Hqx and xBR (c) final enhanced high-resolution image, composite of previous two images (a) and (b).

Likewise, we applied the proposed methodology to the image shown in Fig. 7(a). Fig. 7(b), 7(c) and 7(d) show enhanced images from MIEBF[21], KBIE[22], and the proposed approach, respectively.

We have also compared the results obtained from our approach with two other algorithms for image enhancement, namely MIEBF and KBIE. The comparison is shown in Table 4. It is evident from Table 4 that for 3 of the parameters, namely PSNR, SNR and SSIM, values of the resultant image obtained using our methodology are better than the other two approaches.

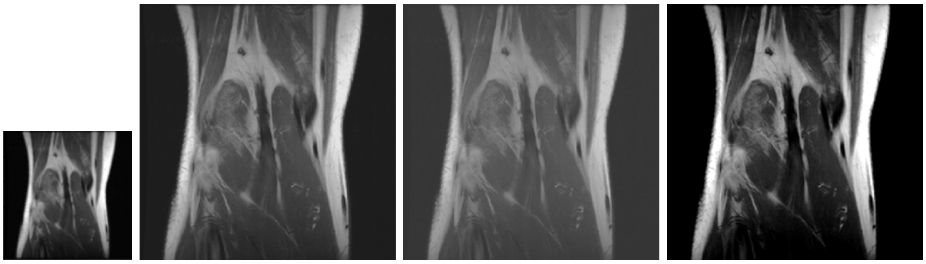


Fig. 7. Input and outout image of Knee MRI image dataset MRNet [20], (a) Input image (b) MIEBF [21] (c) KBIE [22] (d) Proposed Methodology.

Table 4. Comparison of parameters of the image shown in Fig. 7 with methodologies [21] & [22] and proposed methodology.

	MIEBF[21]	KBIE[22]	Proposed Methodology
PSNR	27.0021	27.9658	28.4514
SNR	18.9887	19.5521	19.8822
SSIM	0.8778	0.8696	0.8852
MSE	178.0215	152.2374	200.8541

Furthermore, we applied our methodology on 177 knee MRI images of the MRNet [20] and the PSNR, SNR, SSIM and MSE parameters were improved for most of the images as depicted in Fig. 8.

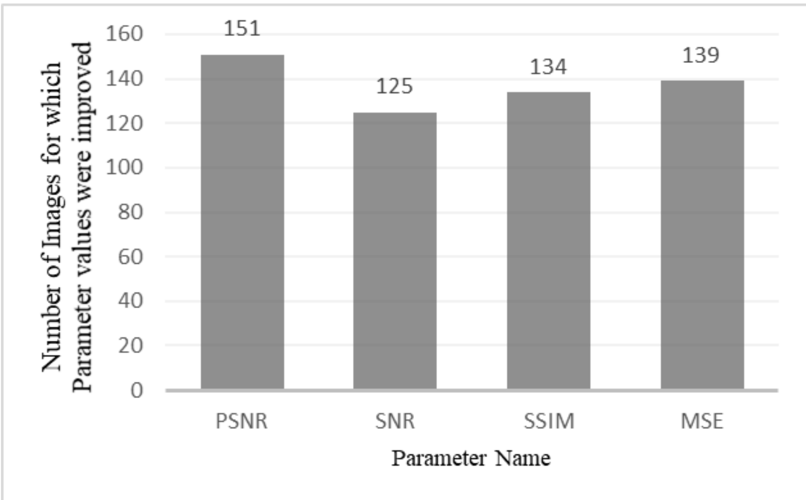


Fig. 8. Number of images for which PSNR, SNR, SSIM and MSE parameters were improved.

5. Conclusion and Future Work

We proposed a methodology to reconstruct an enhanced high-resolution image from the low-resolution medical image. We have used four image enlargement algorithms. The enlargement algorithms are also able to generate a high-resolution image but may have less detail, so to improve the quality of enlarged images, the IBP algorithm has been applied to the enlarged images, followed by the construction of composite images. Experimental results have shown that the proposed method has reduced the noise and enriched the details. The proposed methodology has resulted in improved image parameters, namely PSNR, SNR, SSIM, and MSE, in each step. The final high-resolution image has significantly improved the values of the image parameters under consideration. Our methodology evaluated the performance of the composite image before and after the reduction of noise and blur. In the future, we intend to improve the image quality by creating a composite image using other algorithms so as to experiment and observe how finer details of the images can be preserved. Different image enlargement algorithms can also be applied for experimentation.

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