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Resolution Enhancement of Brain MRI Images Using Deep Learning †

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Abstract: One of the most widely used imaging techniques in medicine is magnetic resonance imaging (MRI). It is a tool that doctors use to comprehend human anatomy and carry out more accurate analyses. In the study of brain anatomy, image processing super resolution technology has become important to overcome physical restrictions due to image deterioration caused by hardware constraints, lengthier scanning periods, and artefacts. Super resolution is an approach to raise an image's resolution while improving the image's quality from a low-resolution (LR) image to a higher-resolution (HR) image. The study provides an overview of deep learning techniques for creating super-resolution (SR) MRI brain images. A widely used deep learning (DL) technique, accessible brain MRI dataset, and quantity evaluation matrices have been presented, mostly used for image super resolution. Factors affecting hardware constraints and artifacts, including magnetic field homogeneity, gradient nonlinearity, radiofrequency (RF) coil sensitivity, signal-to-noise ratio (SNR), and gradient coil performance, have been taken into account. This research focuses mostly on brain MRI images as a contribution to the medical industry for super resolution.

Keywords: super resolution; MRI images; resolution enhancement; deep learning

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1. Introduction

Super resolution image processing techniques, such as MRI, are crucial in image processing and computer vision. They recover high-resolution images from low-resolution images, providing insights into specific diseases and aiding doctors in diagnosing brain illnesses [1,2]. Interpolation methods, including reconstruction, learning, and interpolation, are used to reconstruct high-resolution images from low-resolution data [3,4]. The paper's primary objectives are:

(a) Examine the deep learning framework used for super resolution, specifically for MRI brain images, to overcome physical constraints and artefacts that reduce image quality.
(b) Analyze the brain MRI dataset commonly used for the super resolution approach to deliver exact diagnosis.
(c) Image quality assessment (IQA) for evaluating an image's visual quality is covered for several imaging modalities.

2. Materials and Methods/Methodology

The study uses deep convolutional layers in SRCNN architecture to learn intricate features between low-resolution and high-resolution picture patches [5]. The network learns in hierarchical formats and directly maps low-resolution patches to high-resolution patches without intermediary stages [6,7]. The study minimizes mean squared error and employs techniques like wavelet-based MRI denoising, reconstruction, noise filtering, noise estimation, and restoration.

2.1. Supervised or Discriminative Learning

To perform specific data-processing tasks, the entire model is trained using input-output samples [8].

2.1.1. Convolutional Neural Network for Super-Resolution for MRI Brain Image

A CNN is an artificial neural network with few connections between the layers and an emphasis on maintaining spatial correlations in the data. With the input structured in a grid and transferred across layers that maintain these linkages, each layer action in a CNN operates on a small portion of the preceding layer [9,10].

2.1.2. Densely Connected Architecture for Super Solution of the MRI Dataset

The application of deep learning, CNN, has greatly improved the resolution of MRI datasets. As can be seen, it has used (DCSRN) 3D Densely Connected Super-Resolution Networks [11]. When techniques like bicubic interpolation, nearest neighbor up-sampling, and three other deep learning models— 3D-FSRCNN, DCSRN, and 2D-FSRCNN—were compared, it was shown that the DCSRN-trained model was the fastest deep learning model [12].

2.1.3. Residual Learning for Super-Resolution of the MRI Dataset

The dilated convolutional neural network model uses skip-connection, which mixes local texture information with global abstraction information, to achieve better super-resolution performance [13]. The gradient-guided residual network in [14,15] is therefore based on two intuitions. The recovery of higher-frequency information in a high-resolution image is facilitated by the CNN-based SR approach and gradient features of the LR image [16].

2.2. Unsupervised or Generative Learning

A deep learning method called unsupervised super-resolution enhances image resolution without the need for annotated data. An unsupervised super-resolution method known as "Generative Adversarial Networks" (GANs) consists of two networks: a generator network and a discriminator network [17].

2.2.1. Generative Adversarial Networks (GAN) for Super-Resolution of MRI Brain Image

Generative modeling is a machine learning task that uses unsupervised learning to identify patterns in input data. It has been compared to modern models like Pix2Pix, DECNN, LA-GANs, and MedGAN, demonstrating improved performance in brain MRIs [18].

2.2.2. Reduce Scan Time Using GAN Methods

Potential applications exist for a deep-learning SR approach that interpolates medical images using a 3D perceptually tuned GAN network [19]. Deep learning architecture is used for de-aliasing and conditional generative adversarial network-based rapid CS-MRI. Generator network architecture (GAN) was used for skip connections and the GAN training technique that is constantly enhanced [20].

2.3. Hybrid Architecture

Deep learning hybrid models combine generative and discriminative models to tackle practical issues [21]. Three types include combining multiple models, fused models, and non-deep learning classifiers. Brain MRI images can be generated using deep learning models like CNNs, MobileNetV2, ResNet152V2, and GAN-based augmentation methods. A mixed convolutions algorithm is proposed for this purpose [22–25].

3. Results and Discussions

When digital photos are acquired, processed, compressed, stored, transmitted, or reproduced, a number of distortions might occur that could degrade the visual quality.

Image quality assessment (IQA) is used to evaluate an image's authenticity to its intended or original images. IQA is broken into two types: (i) subjective evaluation, which is evaluated by humans, and (ii) objective assessment, which is calculated using mathematical methods.

3.1. Qualitative and Quantitative Analysis

3.1.1. Peak Signal-to-Noise Ratio (PSNR)

PSNR is the most often used quality measures for loss reconstruction. For the purpose of calculating the PSNR for image super-resolution, the MSE between images and the maximum pixel value is employed.

3.1.2. Structure Similarity Index (SSIM)

A flawless reference image and a test image are compared side by side for brightness, contrast, and structural attributes via SSIM. A few elements were then added together to determine the total similarity.

3.1.3. Optimizers

ADAM (Adaptive Moment Estimation): ADAM adjusts the learning rates based on the first and second moments of the gradients for each parameter. ADAM uses bias correction in the early training phases to correct the initial bias and guarantee stronger convergence. Regardless of the quantity of arguments, ADAM keeps a certain number of state variables. As a result, it functions effectively with huge models and uses less RAM.

SGD (Stochastic Gradient Descent): SGD is suited for large datasets due to its stochastic nature, which speeds up processing. SGD is more effective than batch gradient descent because it changes the model parameters after handling each mini-batch. Faster convergence is possible thanks to frequent parameter updates, particularly in noisy or non-conv situations.

RMSProp: The learning rate for each parameter in the model is altered by RMSProp according to the historical average of squared gradients. The learning rate is dynamically altered by computing a running average of the magnitudes of earlier gradients. Some of the difficulties involved in manually choosing an acceptable learning rate are lessened by this adaptive learning rate.

3.1.4. Loss Function

The following loss functions are used during experiments. These are Mean Square Error (MSE), Mean Absolute Error (MAE), and Perceptual Loss.

3.2. Performance of ADAM Optimizer and Use of Loss Functions Using Super Resolution Convolution Neural Network (SRCNN)

Figures 1–6 show the performance of ADAM optimizer and MSE, MAE, and perceptual loss functions which are used for error computation using the Super Resolution Convolution Neural Network (SRCNN).

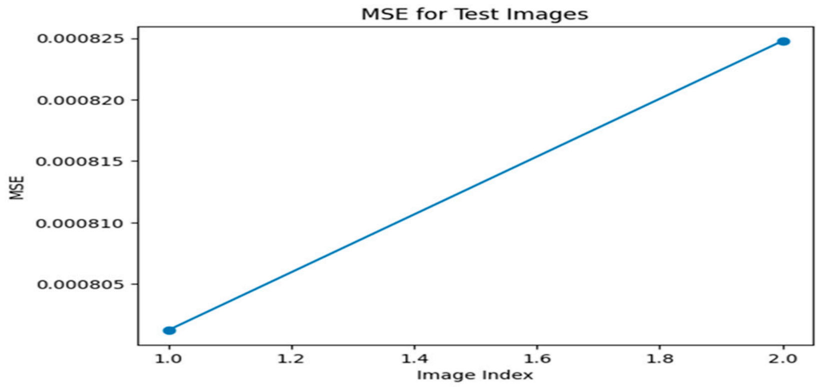

Figure 1. MSE graph for Optimizer—ADAM, Loss function—MSE.

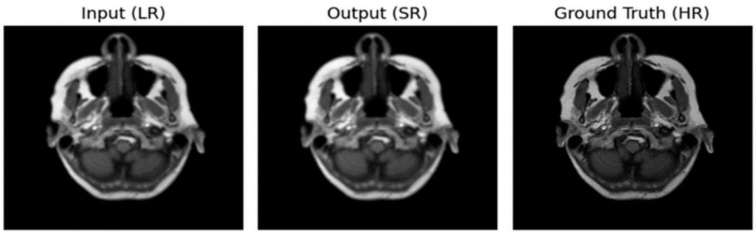

Figure 2. Image using Optimizer—ADAM, Loss function—MSE.

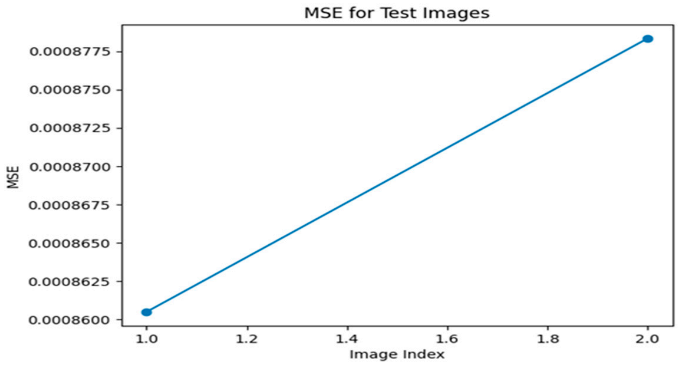

Figure 3. MSE graph for Optimizer—ADAM, loss function—MAE.

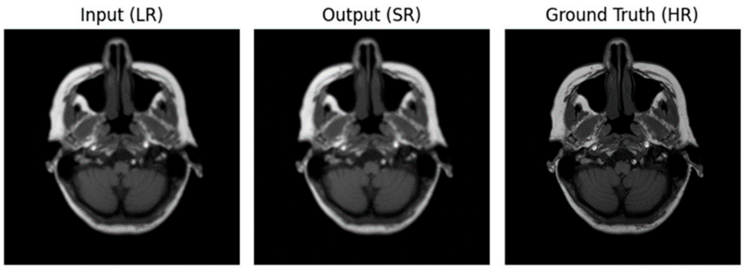

Figure 4. Image for Optimizer—ADAM, loss function—MAE.

Figure 5. MSE graph for Optimizer—Adam, loss function—Perceptual.

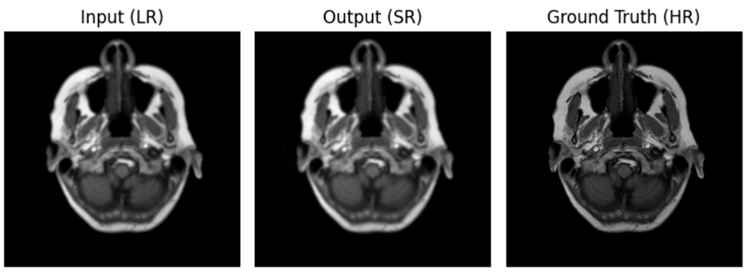

Figure 6. Image using the Optimizer as Adam and loss function as Perceptual.

3.3. Performance of ADAM Optimizer and Use of Loss Functions Using Super Resolution Residual Network (SR ResNet)

In Figures 7–12, we show the performance of the ADAM optimizer and MSE, MAE, and perceptual loss functions, which are used for error computation using a Super Resolution Residual Network (SR ResNet).

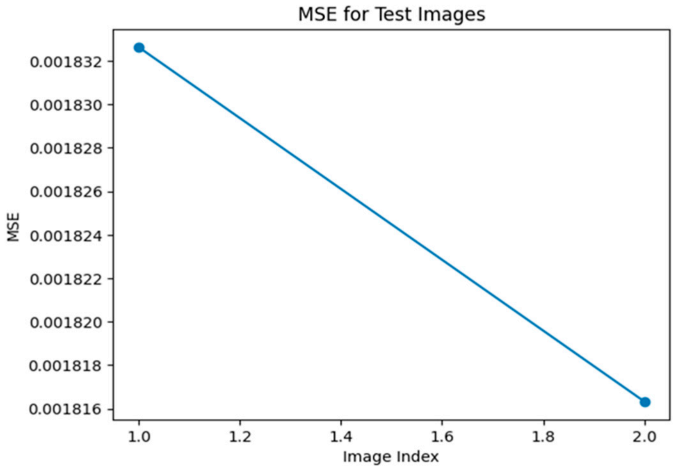

Figure 7. MSE graph for Optimizer—Adam, loss—MSE.

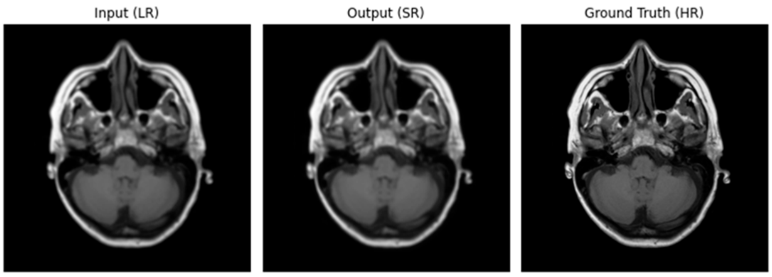

Figure 8. Image after using Adam Optimizer and MSE loss function.

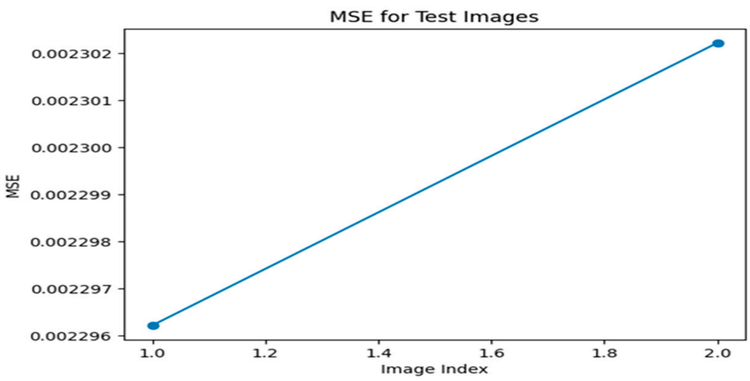

Figure 9. MSE graph for Optimizer—Adam, loss—MAE.

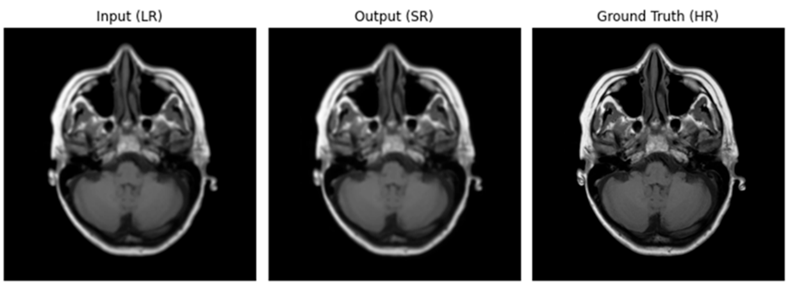

Figure 10. Image using Optimizer as ADAM and loss function as MAE.

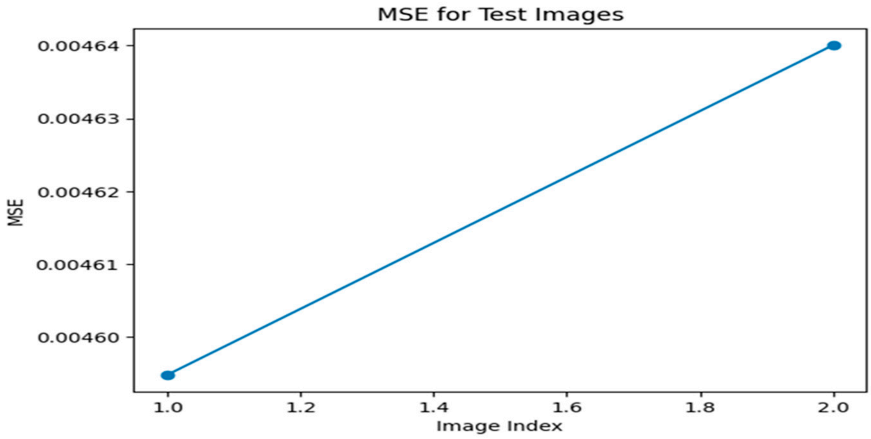

Figure 11. MSE graph for Optimizer—Adam, loss—Perceptual Loss.

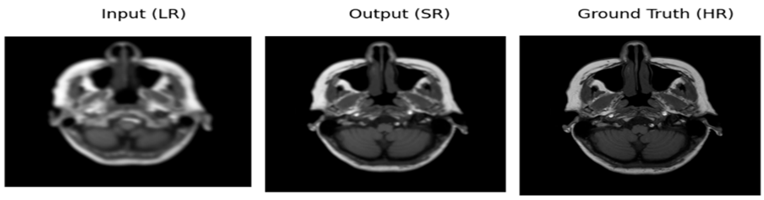

Figure 12. Image using Optimizer as ADAM and loss function as Perceptual Loss.

3.4. Comparative Analysis Table of SRCNN and SR ResNet with ADAM Optimizer and Loss Functions

In Tables 1 and 2, the comparative analysis of SRCNN and SR ResNet with the ADAM optimizer and loss functions are shown below:

Table 1. SRCNN (ADAM optimizer and loss functions).

Sl. No	Optimizer	Loss Function	PSNR	SSIM	MSE
1	ADAM	MSE	27.37	0.81	0.0008
2	ADAM	MAE	26.29	0.75	0.0009
3	ADAM	Perceptual loss	28.64	0.76	0.0008

Table 2. SR ResNet (ADAM optimizer and loss functions).

Sl. No	Optimizer	Loss Function	PSNR	SSIM	MSE
1	ADAM	MSE	30.84	0.90	0.0008
2	ADAM	MAE	30.65	0.91	0.0009
3	ADAM	Perceptual loss	30.93	0.90	0.0008

4. Discussion

The study uses the ADAM optimizer to improve MRI image quality using SRCNN and SR ResNet. SR ResNet achieves higher PSNR and SSIM values, while SRCNN produces super-resolved images with higher accuracy and less noise. The study focuses on improving precision, clarity, and dependability in medical imaging, and addressing limitations like dataset representativeness and generalization concerns. Reliable evaluation methods and clinical validity are crucial for real-world application.

5. Conclusions

In our study, the optimizer used for super-resolution of input images was consistent for SRCNN and SR ResNet. The motive behind using the ADAM optimizer for both networks was for drawing a relative comparison on a selected set of loss functions. In future research, other optimizers, such as SGD, RMSProp, etc., may be used for the comparison of super-resolution of low-resolution images.

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