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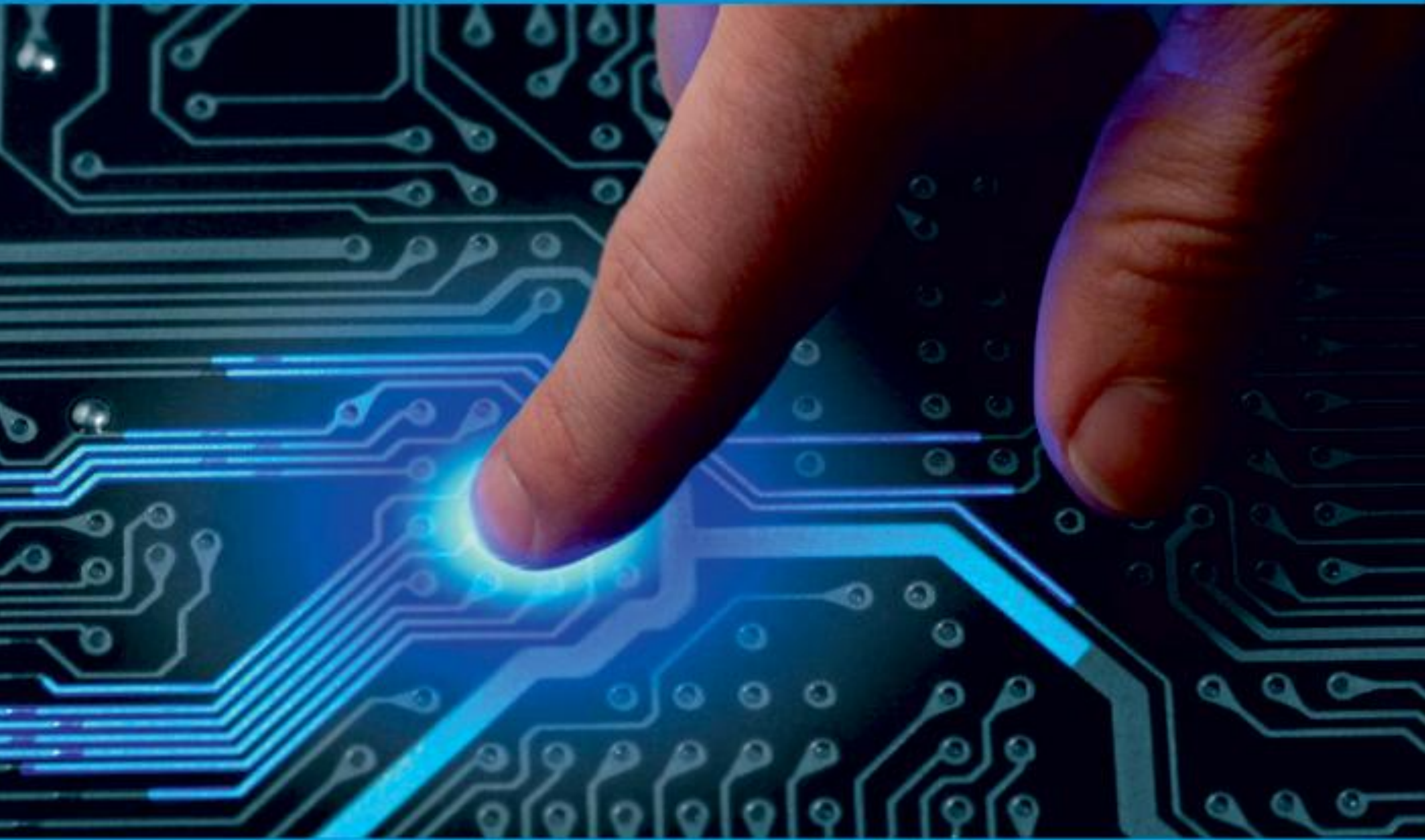

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Review on Histogram Based Resolution Enhancement of an Image by Using ArtificialNeural Network

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ABSTRACT: High resolution (HR) images have more detail in them than low resolution (LR) photos do. Instead of justone LR image, several low-resolution images can be instantly obtained. Since each LR image contains distinctive information, an HR image can be produced by combining several LR photos. Reconstructing an HR image from a single,less-detailed LR image is still more difficult. This study proposes a neural network-based approach to improve resolutionbased on feature extraction from a single image. For each smaller block that is produced from each LR and HR image, the histogram is generated as a feature. The simulation was run on a collection of brain MRI pictures, and the findings demonstrate that the PSNR and RMSE have improved thanks to the neural network model that was produced.

KEYWORDS: Digital Image Processing, Resolution, Histogram, Neural Network.

I.INTRODUCTION

The quality of the image information affects the effectiveness and efficiency of applications including medicalimaging, remote sensing, high-definition television, video surveillance, and video conferences. HR To make these systems more effective, photos are needed [1]. By utilizing HR satellite pictures, the If the HR image is provided, segmentation and the efficiency of pattern identification in computer vision may be improved.

Resolution enhancement techniques range from interpolation-based to transformation-based to reconstruction-based to filtering-based to learning-based, and they can be grouped into five main groups. The simplest method for enlarging an LR image into a nicely rendered version was to employ interpolation-based techniques like bilinear, nearest neighbour, and bicubic interpolations. Artifacts are caused via interpolation [7]. For these effects, an alternate back-projection approach has been developed [8–10]. However, due to the ill-posedness of the inverse problem, it does not offer a single solution. The resolution of medical pictures has been increased using algorithms based on learning, such as dictionary learning [11], but this approach has not proven popular due to the limited resolution enhancement and sluggish executionspeed in the case of 3D MRI images [12].

The resolution of a picture has been increased using a variety of deep learning techniques, ranging from the early Convolutional Neural Networks (CNN)-based approach [13] to more modern resolution improvement techniques utilizing GANs, or Generative Adversarial Nets [14]. The resolution enhancement algorithms that use deep learning techniques generally vary in the following key areas: various network designs [15], various losses functions, and various learning concepts and methodologies [16].In order to increase the resolution of brain MRI images, we have suggested alearning-based technique in this research.

II.RELATED WORK

An improved super-resolution compressive imaging technique was presented by Sun et al. [17] by including the steering kernel regression (SKR) and nonlocal means (NLM) models as two regularisation components. Local smoothness was reduced using regularisation of the SKR, and robustness was increased using regularisation of the NLM. It was suggested to replace just one redundant dictionary with a clustering approach for learning subdictionaries. This learning strategy not only improves efficiency but also gives diverse systems an effective sub dictionary search. Twelve test photographs were used in the investigation, and the results demonstrated that this

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procedure is superior to others.

An method for medical and astronomical HR pictures was presented by Sun et al. [18]. This algorithm's foundation is redundant dictionary and compressive sensing. Training and reconstruction were the two processes that made up the algorithm. During the training phase, the K-SVD algorithm was used to extract features from an HR image.The feature was extracted from the LR image during the reconstruction stage using the bilateral filter, and the HR image was created using the L1-Homotopy algorithm. Better results are produced by the suggested algorithm, which has a decreased RMSEand increased PSNR.

It was recommended by Kallel et al. [19] to use DWT-SVD to improve the contrast adaptive gamma correctionmethod. By doing this, the contrast between CT images was improved. The unique image was thought to degrade into different sub-band images by the DWT. LL sub-band pictures were processed to create an improved image with increasedcontrast and edge protection. Through gamma correction. Each image's gamma correction was dynamically determined. An image enhancement method suitable for enhancing low contrast images was proposed by Sreeja et al. [20]. Edge detection filtering and pixel-wise fusion were applied in the initial phase. The range filter with the ideal kernel size performs better than existing techniques. The fusing of features according to the pixels was completed in the second step. After merging the features, a Gaussian filter is applied to improve the texture, whereas the pixel-based additive gradient fusion improves the edges and texture. Using this technique has increased an image's sharpness.

A denoising method was employed by Diwakar et al. [21] for two linked images with uncorrelated noise. In their approach, noise in the first image was removed using a nonlocal means (NLM) filter, while noise in the second image was removed using wavelet thresholding. The NLM filter's output reduces noise; however the fine features of the input image were improperly retrieved. The wavelet thresholding technique using correlation was employed to restore minute image information.

The noise control and building preservation benefits of this approach are favourable. The proposed method was compared to existing methods, and it was discovered that the new method was more effective than current methods in terms of visual quality, image quality index, peak SNR, and entropy difference.

III. PROPOSED METHOD

In the proposed method, a single LR image is used to boost an image's resolution by two times. In order to prepare a pair of picture blocks (Low and equivalent High dimension block), the histogram was employed as a feature. The dataset used for this method contains 31 brain MRI scans of the LR and matching HR. LR images are [128x128] insize, while HR images are [256x256].The training neural network for the proposed approach included error back propagation.

A. Pre-Processing

Each image was split into blocks before the histogram feature could be extracted; for LR images, the size of each block There were 4096 blocks in each LR and HR image since the size of each block for LR photos was [4x4] andfor HR images it was [2x2]. 21 brain MRI images were incorporated into the neural network during training, totaling [2x4096] blocks for both HR and LR images.

B. Histogram Feature

Histogram is a feature from the LR and HR picture blocks that we have employed. For the histogram feature, bin values of 2, 4, 8, and 16 were selected. Each block was transformed into a feature vector, and the table below displaysan 8 bin feature vector. Each input block is [2x2] in size and contains a feature vector [2x2] with [1x2], [1x4], [1x8], and[1x16] dimensions, accordingly. Due to the fact that each LR block is [2 2] in size, let's.
investigate the scenario for 16 bins.

$$\begin{bmatrix} 15 & 10 \\ 245 & 125 \end{bmatrix}$$

16 bins were considered: 0-15, 16-31, 32-47, 48-63, 64-79, 80-95, 96-111, 112-127, 128-143, 144-159, 160-175, 176-191, 192-207, 208-223, 224-239, 240-255

S. No.	Histogram bin	Pixels lying in these bins	Total number of pixels
1.	0-15	15 & 10	2
2.	16-31	0	0
3.	32-47	0	0
4.	48-63	0	0
5.	64-79	0	0
6.	80-95	0	0
7.	96-111	0	0
8.	112-127	0	0
9.	128-143	125	1
10.	144-159	0	0
11.	160-175	0	0
12.	176-191	0	0
13.	192-207	0	0
14.	208-223	0	0
15.	224-239	0	0
16.	240-255	245	1

Table 1: shows how many pixels there are overall inside these 16 histogram bins.

[2, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1] is the resulting feature vector.
In a similar manner, we determined the feature vectors for various blocks, and each feature vector is given a unique class.Each image has its own feature vector with a size of [4096 16] at the conclusion of this step. Similar to this, the histogramfeature is generated for each block of size [4 4] within an HR image. Each LR block and HR block was mapped, and 1573 such class ids were collected in a repository. As a result, each LR block and associated HR block received a designated class id.
For the eight bins

S. No.	Histogrambin	Pixels lyingin these bins	Total number ofpixels
1.	0-31	15 & 10	2
2.	32-63	0	0
3.	64-95	0	0

4.	96-127	0	0
5.	128-159	125	1
6.	160-191	0	0
7.	192-223	0	0
8.	224-255	245	1

Table 2: The total number of pixels in these 8 histogram bins is shown

in.[2, 0, 0, 0, 1, 0, 0, 1] is the feature vector that is the end result with 8 bins.

The proposed technique has taken into account the brain MRI results. 21 brain MRI pictures were used in the training proposal. were taken into account, producing a [86016 16] feature vector. Blocks from the HR and LR images, measuring[4 4] and [2 2], respectively, were used in this technique.
The bricks in every image are very similar. This approach generates a total of 1573 class ids by assigning the same classid to comparable blocks.
The histogram feature is also extracted for each unique histogram bin, and the feature vector was given a unique class id.

C. Selection of Training Blocks

By determining the class ID of the feature vector of the LR block, the training blocks were chosen. The resultingtraining vector has the size [86016x16] and produces class ids for the appropriate LR and HR picture blocks.

D. Error Back Propagation Neural Network

In our method, we used a histogram feature of 16 bins, so the input layer has 16 inputs, the hidden layer 1 has128 hidden layer 2 has 16 and the output layer has 1 output, which represents the class id. This is because the input layerof a neural network represents a specific feature of the input data. The sigmoid function is utilised as an activation functionfor neural network learning. In the input to hidden layer and hidden to output layer, the bias value of 0.5 is introduced. Error Back Propagation Neural Network was employed in this step to guarantee the connection between the correct classid and feature vector of LR blocks. Hence, the input feature.

E. Testing of neural network

This phase involves dividing an input LR image into [2x2] parts and extracting the histogram feature for eachblock. This input feature vector is fed into the neural network, and the output is compared to the set of feature vectors that have been previously saved. If the difference is less than 10%, the input feature vector is given the same class id.

IV.CONCLUSION AND FUTURE WORK

By creating a neural network for the conversion of images from LR to HR, this article has improved the task ofimage resolution enhancement.

In order to improve the resolution of a single LR image, a histogram feature with 16 bins was derived. This using a back propagation neural network model, the network was trained to identify the appropriate class ids using the histogram feature. The simulations were run on the super resolution of brain MRI pictures having LR image set and associated HR image set dataset of brain MRI images. Results indicate that the PSNR and RMSE values of the suggestedmodel have improved.

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