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FAST SUPER RESOLUTION IMAGE USING CONVOLUTION NETWORK

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Abstract: - *Aim of Super resolution is to generate high-resolution image from single or multiple low resolution of the same picture or image. Super resolution method which based on Total Variation regularization and total variation up sampling with Gaussian noise PSSR which provide better resolution image with preserving only texture components. More processing time due to the calculation of total variation in the input Image. To overcome problem of existing work, Novel approach of convolution neural network (CNN) which is consists of three layers namely convolution layer, max-pooling layer and reconstruction layer. This approach will try to reduce the processing time as well as increasing the PSNR ratio, RMSE And SSIM. The experimental results show that the proposed method can perform better than the wavelet transform based method in some situations.*

Keywords: *Total variation method, Gaussian noise PSSR, Up-sampling TV, CNN, neural network.*

I. INTRODUCTION

Now days, Super resolution is very important in image processing. Super resolution aim to generating the high resolution images from the one or multiple images of the same scene of low resolution images. During the process of the image capture sometimes, the collected images are often with low-resolution due to the poor equipment performance and environment. For getting the more information about an image, high-resolution (HR) images are always required for further image processing and analysis. High resolution images not only give the viewer a pleasing appearance but also helping Better analysis and feature extraction form HR images in several applications such as in medical imaging for MRI (Magnetic resonance imaging),PET(Positron emission tomography),Satellite imaging, Target recognition [1]

II. LITERATURE REVIEW

[1] **Hiroki Tsurusaki, Masashi Kameda, Prima Oky Dicky Ardiansyah** [1]. :In this paper, we propose a single image super-resolution based on total variation regularization (TV) with Gaussian noise to improve sharpness of texture. TV is expected to improve texture, since we can decompose a given input image into structural component and texture component by TV image-decomposition. In proposed method we USED Convolution Neural Network in that there are three layers which generate high resolution image with less processing time and increase the PSNR of image compare to existing work.

[2] **F Shi, J Cheng, L Wang, PT Yap, D Shen** [2] have presented the TV based regularization method for low ranked matrix. its main aim to utilize the information from the image to recover low resolution image. but the main disadvantage of this method is that it is computationally expensive in time to process the calculation of total variation in the image. But in our proposed work the weigth and bias parameters are used frequently to cover up the image from low resolution to high resolution with less expensive time with better PSNR ration.

[3] **Browne, Matthew, Saeed Shiry Ghidary, and Norbert Michael Mayer** [3] have studied on Super resolution method for convolution neural networks (CNN). After examining the training and testing of each layer CNN, we apply the 64 different filters on a single image in convolution layer and extracted the feature map form each filter. Then it forwarded to second layer in which we have apply another 32 different filters on each of images which are generated in convolution layer. At the end of layer the features of images generated in second layer are combined and generated the high resolution image..

III. CONVOLUTIONAL NEURAL NETWORK

A neural network is a system of interconnected artificial “neurons” that exchange messages between each other. The connections have numeric weights that are tuned during the training process, so that a properly trained network will respond correctly when presented with an image or pattern to recognize. The network consists of multiple layers of feature-detecting “neurons”. [4] Each layer has many neurons that respond to different combinations of inputs from the previous layers. As shown in Figure 1, the layers are built up so that the first layer detects a set of primitive patterns in the input, the second layer detects patterns of patterns, the third layer detects patterns of those patterns, and so on

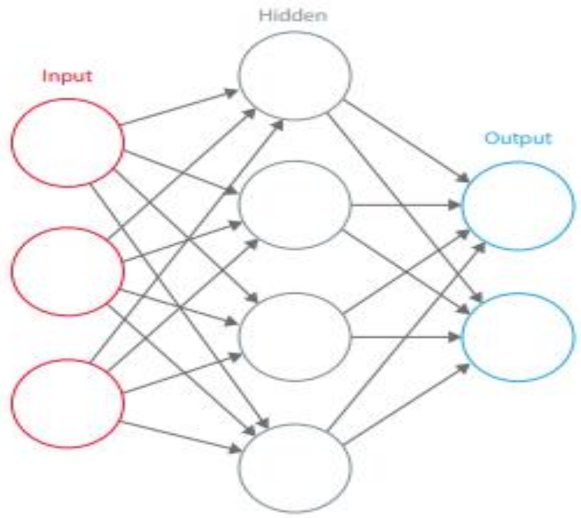

Figure 1. An Artificial Neural network

In a CNN, convolution layers play the role of feature extractor. But they are not hand designed. Convolution filter kernel weights are decided on as part of the training process. Convolution layers are able to extract the local features because they restrict the receptive fields of the hidden layers to be local. CNNs are used in variety of areas, including image and pattern recognition, speech recognition, natural language processing, and video analysis. There are a number of reasons that convolutional neural networks are becoming important. In traditional models for pattern recognition, feature extractors are hand designed. In CNNs, the weights of the convolutional layer being used for feature extraction as well as the fully connected layer being used for classification are determined during the training process. The improved network structures of CNNs lead to savings in memory requirements and computation complexity requirements and, at the same time, give better performance for applications where the input has local correlation.

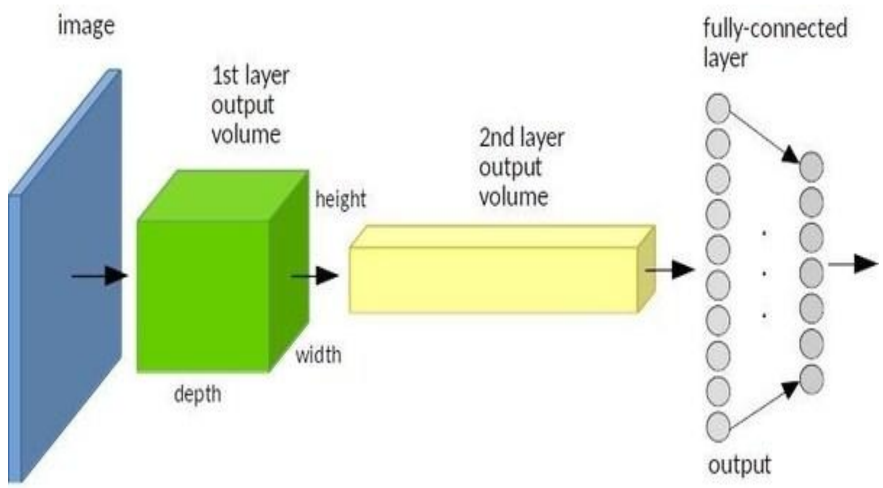

Figure 2. Typical Structure of a CNN [3]

"A deep neural network combines multiple nonlinear processing layers, using simple elements operating in parallel and inspired by biological nervous systems. It consists of an input layer, several hidden layers, and an output layer. The layers are interconnected via nodes, or neurons, with each hidden layer using the output of the previous layer as its input. "

Three hyper parameter would control the size of output volume.

1. **The number of filters** – the depth of the output volume will be equal to the number of filter applied. Remember how we had stacked the output from each filter to form an activation map. The depth of the activation map will be equal to the number of filters.
2. **Stride** – When we have a stride of one we move across and down a single pixel. With higher stride values, we move large number of pixels at a time and hence produce smaller output volumes.
3. **Zero padding** – This helps us to preserve the size of the input image. If a single zero padding is added, a single stride filter movement would retain the size of the original image.

SUPER RESOLUTION IMAGE ALGORITHM USING CNN:

1. Read RGB image
2. Convert into YCbCr
3. Display Y,Cb,Cr component
4. Apply Bicubic interpolation to convert into low resolution by specified scale (x2)
5. Apply Bicubic interpolation to convert again into same size as input (x2)
6. Apply Convolution Neural Network on Y-component
7. Combine the Y-component of CNN with Cb and Cr component and generate YCbCr image
8. Convert YCbCr into RGB

Data Set

We have used 100 images of different size in the training phase and we have used 60 images in our testing purpose of CNN. After that we have applied our CNN method on randomly selected image of different size and type and obtained the high PSNR image with less processing time.

Performance Metrics

1) **PSNR**: It means Peak signal to noise ratio. It IS an expression for the ratio between the maximum possible values (power) of a signal and the power of distorting noise that affects the quality of its representation. In this PSNR calculates the how much resultant image accurate.[8]

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right)$$

2) **MSE**: Mean Square Error it means how much errors Occur in the system.

$$\frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left[I(x,y) - I'(x,y)\right]^2$$

where I(x,y) is the original image, I'(x,y) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images.

3) **RMSE**: RMSE is defined as the square root of mean square error

$$RMSE = \sqrt{\frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N}}$$

4) SSIM: Structural Similarity Index (SSIM) for measuring image quality. It computes the Structural Similarity Index (SSIM) value for image. The resulting structural similarity index measure (ssim) score can vary between -1 and 1

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

IV. DICUSSION AND RESULTS

1. Results are compared with the existing TV-PSSR image results and our method gave the better results than the existing technique.

This section analyzes the proposed system with the accuracy measures or quality measures. These parameters are performed in MATLAB. In the experiment we have used different type of images with different size and by using technique we have obtained more accurate results in quality measures like PSNR,RMSE, SSIM, etc.,. The following table no. I shows the comparison of existing method of results with our proposed method result.

Analysis of proposed system

Form the experimental results we have analyzed that our proposed system gives better result compare to the existing TV-PSSR method. Our proposed method gives the better PSNR ratio with the computational time is less. It’s also gives the better results in other image quality measurement such as RMSE and SSIM. In some of the images existing method gives better RMSE but its take more time to produce the output.

Image	Existing Result	Proposed Result	Type
Baboon	PSNR=20.792 RMSE=6.0731 Time=89.2188 SSIM=0.75307 	PSNR=23.5219 RMSE=16.9998 Time=21.3594 SSIM=0.70832 	Bitmap (color)
Butterfly	PSNR=26.0212 RMSE=6.0419 Time=82.6563 SSIM=0.95358 	PSNR=32.7525 RMSE=5.8738 Time=19.3281 SSIM=0.96406 	Bitmap (color)
Face	PSNR=31.2259 RMSE=6.0182 Time=121.875 SSIM=0.9177 	PSNR=35.7228 RMSE=4.1725 Time=23.9844 SSIM=0.88612 	Bitmap (color)
Bird	PSNR=34.1861 RMSE=6.0146 Time=110.625 SSIM=0.98777 	PSNR=40.9149 RMSE=2.2951 Time=23.5313 SSIM=0.98575 	jpeg (color)

Table I : Existing and Proposed method result comparison

Table II Performance Parameters Of Images

IMAGE	PSNR	RMSE	TIME	SSIM
BUTTERFLY	32.7525	5.8738	19.3281	0.9641
BIRD	40.9149	2.2951	23.5313	0.9858
BABOON	23.5219	16.9998	21.3594	0.7083
MONARCH	27.7737	10.4197	18.8125	0.9376
HEAD	35.7228	4.1725	23.9844	0.8861
ZEBRA	33.494	5.3931	49.6094	0.9423

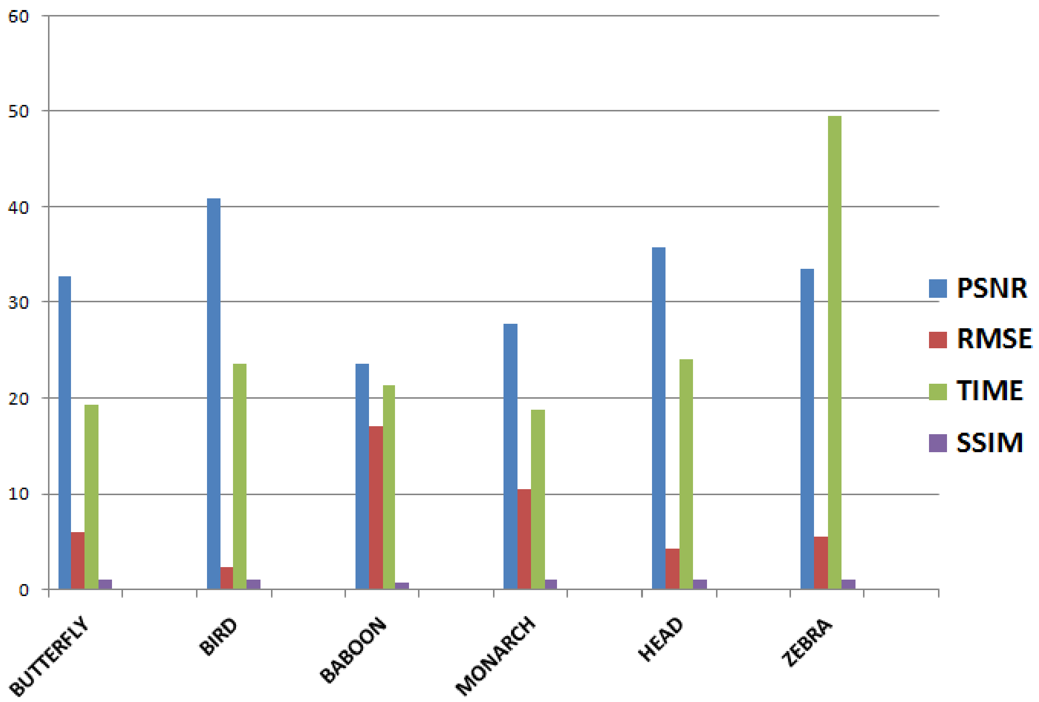

Figure 3 Quality measures of Images

The following Table III shows the comparison of existing results and proposed result. Proposed results are more accurate compared to existing work parameters of methods.

TABLE III Comparison of Performance Parameters

Image	PSNR		RMSE		TIME		SSIM	
	Existing Work	Proposed Work	Existing Work	Proposed Work	Existing Work	Proposed Work	Existing Work	Proposed Work
BUTTERFLY	26.0212	32.7525	6.0419	5.8738	82.6563	19.3281	0.9536	0.9641
BIRD	34.1861	40.9149	6.0146	2.2951	110.625	23.5313	0.9878	0.9858
BABOON	20.792	23.5219	6.0731	16.9998	89.2188	21.3594	0.7531	0.7083
MONARCH	23.8016	27.7737	6.0541	10.4197	80.1563	18.8125	0.9499	0.9376
HEAD	31.2259	35.7228	6.0182	4.1725	121.875	23.9844	0.9177	0.8861
ZEBRA	21.9719	33.494	6.0665	5.3931	67.5	49.6094	0.894	0.9423

V. CONCLUSION AND FUTURE SCOPE

At the end we conclude that, by using CNN method e obtained the high resolution image with less processing time as well as well SSIM and RSME. By providing training to the images we got the weights and biases for each and every layer of the CNN method. After that we applied test to the images and proved that our proposed method gives better result compare to the existing method. By using Conv-net framework we have extracted features from the CNN model weights and biases maps for different types of images were constructed. These weights and biases maps are used in getting the final high resolution image with the help of CNN along with the original images. The experiments are carried out using Matlab and our proposed method results shown better PSNR values , RMSE value and SSIM value. In future, we will implement the CNN with more layers, providing the more training with large numbers of imageset and generate the better resolution images.

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