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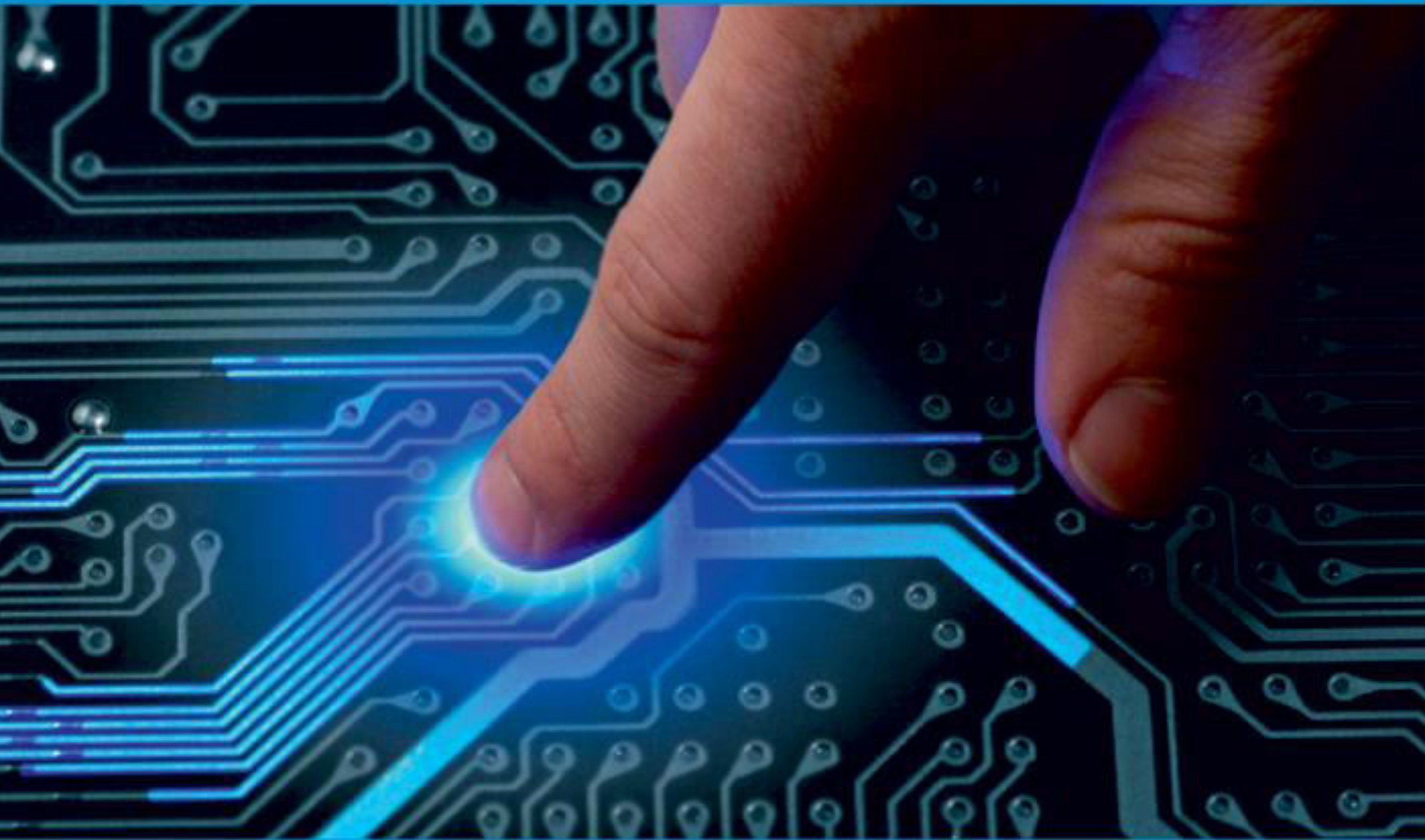

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Image Super Resolution Using Deep Convolutional Neural Network

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ABSTRACT: For single image super-resolution, we present a deep learning technique (SR). Our technique learns an end-to-end mapping between low-resolution and high-resolution images directly. A deep convolutional neural network (CNN) is used to represent the mapping, which takes the low-resolution image as input and produces the high-resolution image. Traditional sparse-coding-based SR approaches can also be seen as a deep convolutional network, as we show. Unlike existing methods, which optimise each component independently, our method optimises all layers simultaneously. Our deep CNN features a lightweight framework that delivers quick performance for practical on-line use while demonstrating state-of-the-art restoration quality. To accomplish compromises between performance and speed, we investigate various network architectures and parameter settings. Furthermore, we expand our network to handle three colour channels at the same time.

KEYWORDS: SRCNN, OpenCV, DeepLearning, Image Resolution, Neural Network.

I.INTRODUCTION

A basic problem in computer vision is single image super-resolution (SR), which tries to recover a high-resolution image from a single low-resolution image. Because there are multiple solutions for each low-resolution pixel, this problem is intrinsically ill-posed. In other words, it's an inverse issue with an underdetermined solution that isn't unique. Strong prior information is usually used to constrain the solution space in such a problem. The majority of contemporary state-of-the-art approaches use an example-based strategy to learn the previous. These approaches either learn mapping functions from external low- and high-resolution exemplar pairs or use internal commonalities of the same image. External example-based algorithms can be created for general picture super-resolution or for domain-specific tasks, such as face recognition.

One of the representative external example-based SR methods is the sparse-coding-based method. The solution pipeline for this method has numerous phases. First, overlapping patches are densely clipped and pre-processed from the input image (e.g.,subtracting mean and normalization). A low-resolution dictionary then encodes these patches. For reconstructing high-resolution patches, the sparse coefficients are passed into a high-resolution dictionary. The final product is created by aggregating the overlapping reconstructed patches..

Most external example-based approaches use this pipeline, which pay special attention to learning and optimising dictionaries or creating efficient mapping functions. The rest of the steps in the pipeline, on the other hand, have rarely been optimised or taken into account in a single optimization framework.
The aforementioned process is shown to be equivalent to a deep convolutional neural network in this research. In light of this, we propose a convolutional neural network that learns an end-to-end mapping between low- and high-dimensional data.

photos with a high resolution Our methodology is substantially different from prior external example-based approaches in that it does not learn the dictionaries or manifolds for modelling the patch space explicitly. Hidden layers are used to accomplish this. Patch extraction and aggregation are likewise formulated as convolutional layers, therefore they are included in the optimization process. Our method obtains the complete SR pipeline entirely through learning, with minimal pre/postprocessing.

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This is referred to as a Super-Resolution Convolutional Neural Network (SRCNN) (SRCNN). The proposed SRCNN has a number of attractive features. First, its structure was created with simplicity in mind, although it outperforms state-of-the-art example-based methods in terms of accuracy.

II.RELATED WORK

Super Resolution (SR) is a method of enhancing picture quality by increasing pixel densities in a Low Resolution (LR) image and resulting in a High Resolution (HR) image. In the last few decades, a slew of SR techniques have been presented. The commonplace insertion strategies, such as Bilinear, Bicubic, Lanczos, and B-Spline interjection techniques, can build pixel-thickness, but they aren't always successful in extracting edge antiques. In a smooth environment, the insertion system works well. The SSI-filtering strategy is essentially a high-recurrence image filtration method that may remove high-recurrence sections such as edge old rarities. The filtration technique effectively increases the image's difference, however it doesn't operate well in the level area. The learning-based strategy is primarily a point-to-point mapping between LR and HR, and this earlier model of LR and HR picture can be mapped with the help of the Super-Resolution Convolution-Neural-Network (SRCNN). This SRCNN strategy presented a preprocessing system only with Bicubic addition, which has a few drawbacks such as the loss of ancient rarities and levelness.

Disadvantages of Existing System:

LOW QUALITY

LOSS OF DATA

TIME CONSUMING

III.PROPOSED ALGORITHM

We propose a new calculation that improves the SRCNN technique by replacing Bicubic interjection preprocessing with SSI-filtration. We also investigate and evaluate super objectives methodologies, such as the change procedure using the SSI filtration system, the SRCNN learning-based strategy, and the proposed computation using the Peak-Signal-to-Noise-Ratio (PSNR).

For image super-resolution, we introduce a fully convolutional neural network. With little pre/post processing beyond the optimization, the network learns an end-to-end mapping between low and high-resolution images.

We show that our deep-learning-based SR approach and standard sparse-coding-based SR methods are related. This relationship serves as a guide for the network structure's design.

We show that deep learning is effective in solving the classic computer vision problem of super-resolution, and that it can obtain good results quality and speed.

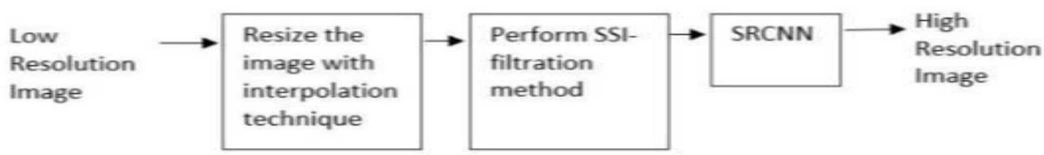

Fig1.Block diagram of proposed system

Advantages of proposed system:
A preliminary version of this work was presented earlier . The present work adds to the initial version in significant ways.

- To begin, we improve the SRCNN by increasing the filter size in the nonlinear mapping layer and adding nonlinear mapping layers to investigate deeper features.

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- Second, we expand the SRCNN to simultaneously process three colour channels (in either YCbCr or RGB colour space). In comparison to a single-channel network, we show that performance can be increased experimentally.

- Third, the basic findings are supplemented with several new studies and intuitive interpretations. The original experiments from Set5 [2] and Set14 [51] test photos are also extended to BSD200 [32]. (200 test images).

- Furthermore, we compare our model to a variety of newly published methods and find that it continues to outperform existing approaches using several assessment metrics.

- Hign quality,No loss of data and fast speed.

IV.PSEUDO CODE

Step 1: Create a folder source and insert the iamges.
Step 2: Take a low resolution image from a specified source file.
Step 3: Create an empty folder with the name image.
Step 4: The low resolution image from source file undergoes interpolation technique inorder to resize the image.
Step 5: Later perform the SSI filtaration method.
Step 6: Those modified images are stored in image folder.
Step 4: Apply SRCNN method on the image.
Step 8: Create a folder with name as output.
Step 5: Finally we will get high resolution image,and store the final image in output folder.
Step 6: End.

V.SIMULATION RESULTS

Here all the images undergoes the three major functions which are peak signal to noise ratio(PSNR),Mean square error(MSE) and structuced similarity index(SSIM).The following figure show the value of each function of the image.

.

```
baboon.bmp
PSNR : 22.157084083442548
MSE: 1187.1161333333334
SSIM: 0.629277587900277

baby_GT.bmp
PSNR : 34.37180640966199
MSE: 71.28874588012695
SSIM: 0.9356987872724932

barbara.bmp
PSNR : 25.906629837568126
MSE: 500.65508535879627
SSIM: 0.8098632646406401

bird_GT.bmp
PSNR : 32.896644728720005
MSE: 100.12375819830247
SSIM: 0.9533644866026473

butterfly_GT.bmp
PSNR : 24.782076560337416
MSE: 648.6254119873047
SSIM: 0.8791344763843051

coastguard.bmp
PSNR : 27.161600663887082
MSE: 375.00887784090907
SSIM: 0.756950063354931

comic.bmp
PSNR : 23.799861502225532
MSE: 813.2338836565096
SSIM: 0.8347335416398209

dog.bmp
PSNR : 34.62179918258802
MSE: 67.30102790014685
SSIM: 0.9671344019851054

eye.bmp
```

Fig1.Quality Metrics Scores

After getting the degraded image we need to perform SRCNN function ,which in result give the reconstructed image.

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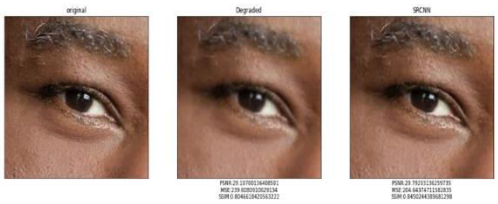
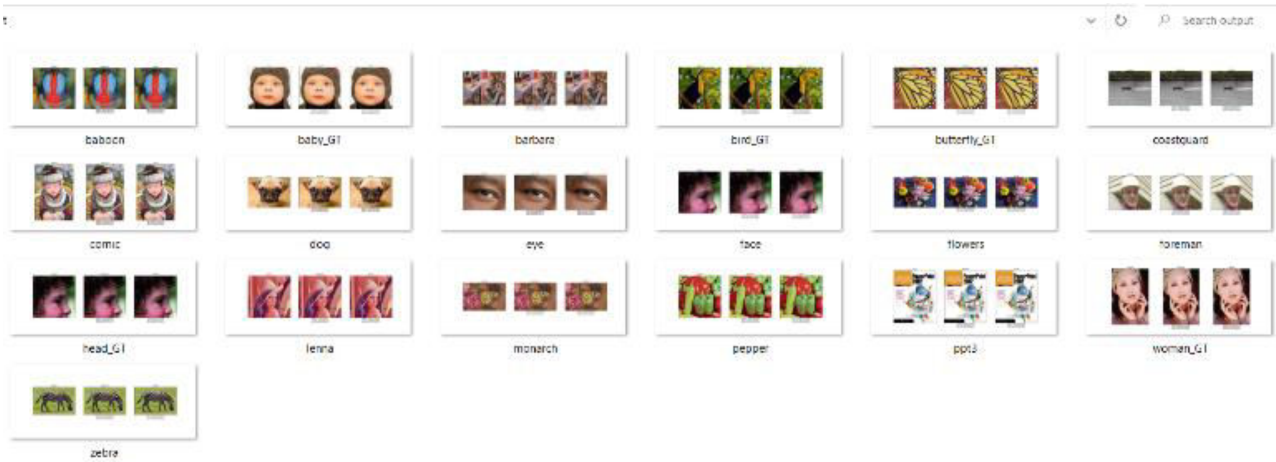
```
scores.append(ssim(target,ref, multi
DegradedImage:
PSNR:34.11563317153722
MSE:75.62028301886792
SSIM:0.9656560668198706

ReconstructedImage:
PSNR:36.96931575003691
MSE:39.198553459119495
SSIM:0.9792521489117009
```

Fig2.Quality Metrics for Degraded and Reconstructed Image

Sample Image as subplot: Each subplot with their values:



Total Images Stored as Subplots:



VI.CONCLUSION AND FUTURE WORK

A unique deep learning strategy for single picture super-resolution has been demonstrated (SR). We illustrate how traditional sparse-coding SR approaches can be rebuilt as a deep convolutional neural network. SRCNN, the suggested method, learns an end-to-end mapping between low- and high-resolution pictures with minimal additional pre- and post-processing. The SRCNN outperforms state-of-the-art approaches thanks to its lightweight construction. We believe that by experimenting with more filters and different training procedures, we can obtain even greater performance. Furthermore, because of its simplicity and resilience, the proposed structure could be applied to additional low-level vision challenges, such as picture deblurring or simultaneous SR+denoising. A network could also be investigated to deal with various upscaling factors.

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REFERENCES

[1] Aharon, M., Elad, M., Bruckstein, A.: K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation. IEEE Transactions on Signal Processing 54(11), 4311–4322 (2006).

[2] Bevilacqua, M., Roumy, A., Guillemot, C., Morel, M.L.A.: Lowcomplexity single-image super-resolution based on nonnegative neighbor embedding. In: British Machine Vision Conference(2012).

[3] Burger, H.C., Schuler, C.J., Harmeling, S.: Image denoising: Can plain neural networks compete with BM3D? In: IEEE Conference on Computer Vision and Pattern Recognition. pp. 2392–2399 (2012).

[4] Chang, H., Yeung, D.Y., Xiong, Y.: Super-resolution through neighbor embedding. In: IEEE Conference on Computer Vision and Pattern Recognition (2004)

[5] Cui, Z., Chang, H., Shan, S., Zhong, B., Chen, X.: Deep network cascade for image super-resolution. In: European Conference on Computer Vision, pp. 49–64 (2014)

[6] Dai, D., Timofte, R., Van Gool, L.: Jointly optimized regressors for image super-resolution. In: Eurographics. vol. 7, p. 8 (2015)

[7] Dai, S., Han, M., Xu, W., Wu, Y., Gong, Y., Katsaggelos, A.K.: Softcuts: a soft edge smoothness prior for color image superresolution. IEEE Transactions on Image Processing 18(5), 969–981 (2009)

[8] Damera-Venkata, N., Kite, T.D., Geisler, W.S., Evans, B.L., Bovik, A.C.: Image quality assessment based on a degradation model. IEEE Transactions on Image Processing 9(4), 636–650 (2000)

[9] [9] Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: ImageNet: A large-scale hierarchical image database. In: IEEE Conference on Computer Vision and Pattern Recognition. pp. 248–255 (2009)

[10] Denton, E., Zaremba, W., Bruna, J., LeCun, Y., Fergus, R.: Exploiting linear structure within convolutional networks for efficient evaluation. In: Advances in Neural Information Processing Systems (2014).