e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
Volume:02/Issue:05/May-2020 www.irjmets.com

IMAGE RESOLUTION USING SUPER RESOLUTION CONVOLUTIONAL NEURAL NETWORK (SRCNN)

Dr. Rajashree. V. Biradar[*1], D K Bhagya Lakshmi[*2], Gandrakota Naga Satya Amitha[*3], Gaddam Sai Sruthi[*4], G Sowmya[*5]

[*1]Professor Department of Computer Science Engineering,
Ballari Institute of Technology and Management, Ballari, Karnataka, India

[*2,3,4,5]B.E.Student, Department of Computer Science Engineering,
Ballari Institute of Technology and Management, Ballari, Karnataka, India

ABSTRACT

The main goal of Image resolution is to convert the low resolution image to high resolution image using Deep learning techniques. To perform this operation we have many approaches like FSRCNN, DRCN and VDSR and PSNR. Among these PSNR (Peak signal to noise ratio) is quite simple. In PSNR the input will be of low resolution appearance image and by using convolutional neural network we produce high Lucidity (Quality) appearance image. But this technique cannot produce image with good-looking textures as the whole image will be blurred. So to solve this problem we use SRCNN (Super Resolution Convolutional Neural Network) which produce an image with high quality texture.

KEYWORDS: SRCNN, PSNR, Low resolution (LR), High resolution (HR), Image resolution, Max pooling and Average pooling.

I. INTRODUCTION

Convolution neural networks (CNN) are type of Deep Learning neural network which are mainly used for the image classification or resolution. This network looks like a visual cortex of animal brain. As result of this it has some interesting features to process the data like audio, video and images. CNN is a combination of convolution layers which are responsible for image processing. Convolution is a technique which extracts the visual feature of an image in the form of small chunks. It contains filters/kernel which determines the cluster of neurons. They can produce the unmodified image, they can also blur the original image, sharp the edges etc. This can be done by multiplying the original image values with the convolution matrix.

Image resolution is always an challenging problem because Low resolution input corresponds to a crop of possible High resolution images and here we will try to map the High resolution space with Low resolution input which is not traceable and there some drawbacks like unclear definition of mapping and inefficiency in establishing high dimensional mapping for given raw data. So SRCNN is introduced to overcome these drawbacks and produce High resolute image were breakage of pixel will be very less when it is zoomed.

SRCNN (Super Resolution Convolution Neural Network) is the deep learning method for super resolution which makes a direct end-to-end mapping between the LR and HR images. This SRCNN consists of three layers and each layer has convolution layer along with activation function. Bicubic interpolation image with Low resolution is an input for this network and produce same size image as output with High resolution.

II. METHODOLOGY

Images resampled with the bi-cubic interpolation will be having very smoother surface and have very few interpolation artifacts. So, we need to choose a Bi-cubic Interpolated image as an input and is sent to three convolution layers for further processing.

1. **Convolution layer 1:** In this layer patch extraction will be performed. Patch extraction is a process of selecting the patch i.e. set of pixels in the image. SRCNN technique will perform patch extraction than to select an entire image to make the process much easier.
2. **Convolution layer 2:** In this layer non-linear mapping is performed. Rectified linear unit (RELU) is used. This RELU is a form of activation function which returns 0 if it receives a negative input. The function is as: f(x)=max(0,x).

Padding and pooling operations are performed in the second layer because after patch extraction loss of information may happen at the border of images.

3. **Convolution layer 3:** In this layer reconstruction of image is performed. We need to rebuild the image which is considered as output. This image will have high PSNR values and noise will be completely erased.

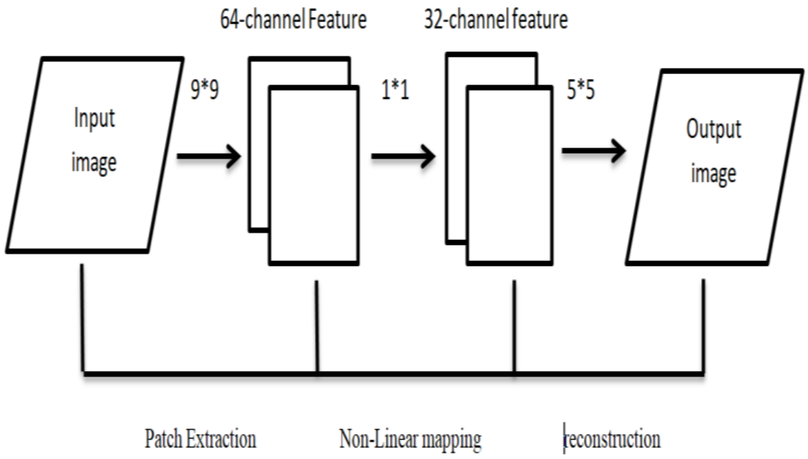


Fig 1: System architecture of SRCNN

III. MODELING AND ANALYSIS

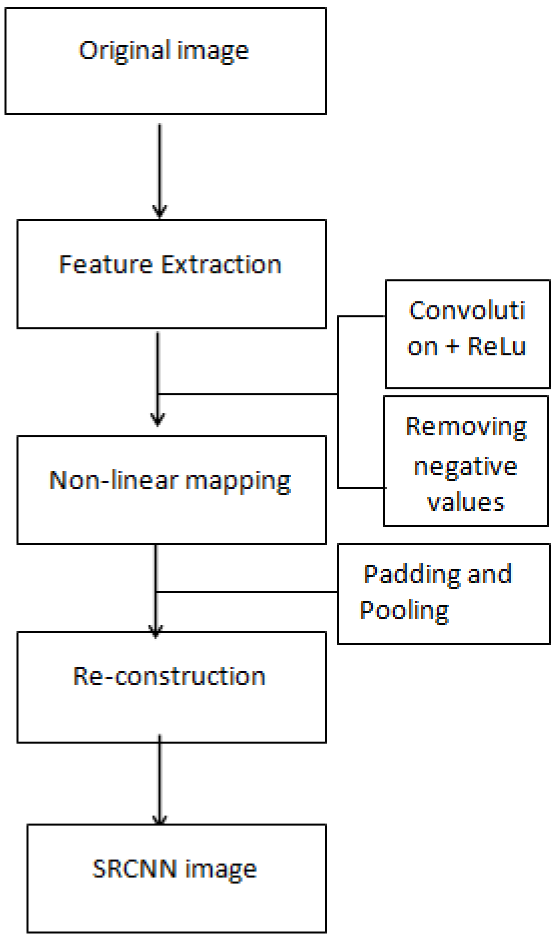


Fig 2: Flow of the model

Low resolution image is taken as input. The image is blurred completely in the next process. This image is given as input for the next three convolution layers, these layers will perform the feature extraction, remove the Negative values by using ReLu (Rectified linear units) and mound the image into required size as same as original image. The process of image modCrop is done by using padding and pooling.

Padding is the process of adding layers of zeros to the input images. While the image is getting processed then middle part of the image gets extracted. The information at the borders will not get preserved. To avoid this problem padding is done at second convolution layer.
Padding is of two types: Valid padding &Same padding.

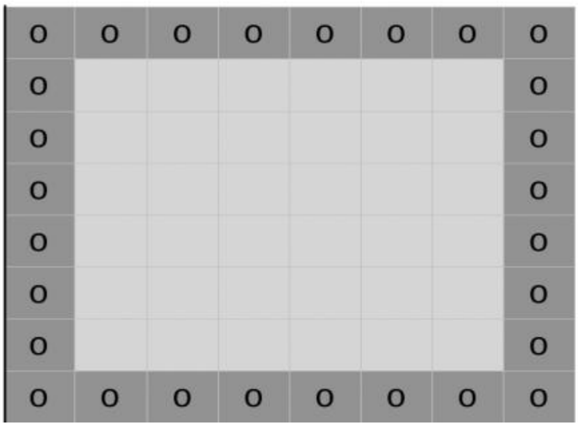


Fig 3: Zero padding to the image

1. **Valid Padding:** It simply indicates no padding at all i.e. the image is in its unaltered position. So,

[(n*n)image] * [(f*f)filter]→[(n-f+1) * (n-f+1) image]

Here * represents a convolution operation.

2. **Same Padding:** To allocate the same dimensions as the input image this Same Padding will add 'P' padding layers. So,

[(n+2p) * (n+2p) image] * [(f*f) filter]→[(n*n) image]

Pooling layer will summarize the features present in the feature maps. So that these summarized features are further performed in the operations of the convolution layer. This increase the robustness of the model in variations in the position of features in the input image. We have two types of pooling. Max pooling & Average pooling.

1. **Max pooling:** In this layer the maximum values of the image pixel gets extracted and these values are further processed by multiplying them with the kernel filter.

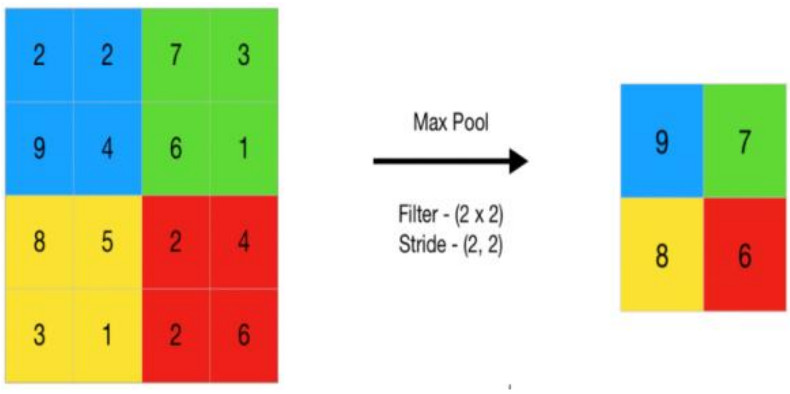


Fig 4: Example of Maxpooling

2. **Average pooling:** The average pooling will extract the average of the elements of the feature maps covered by filter.

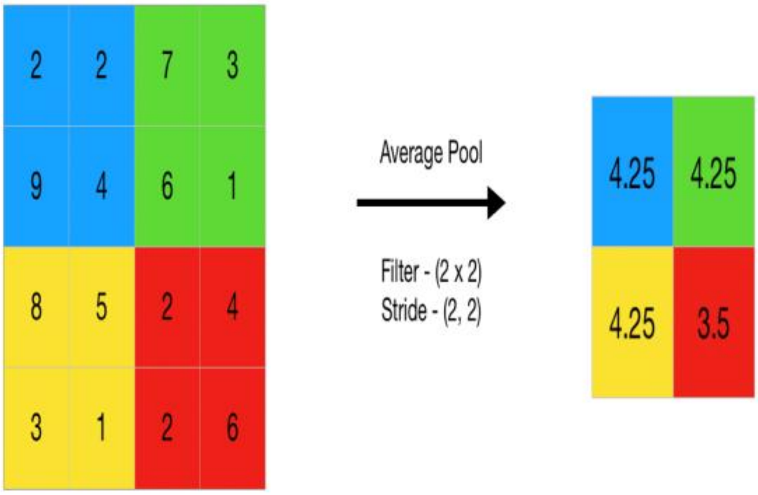
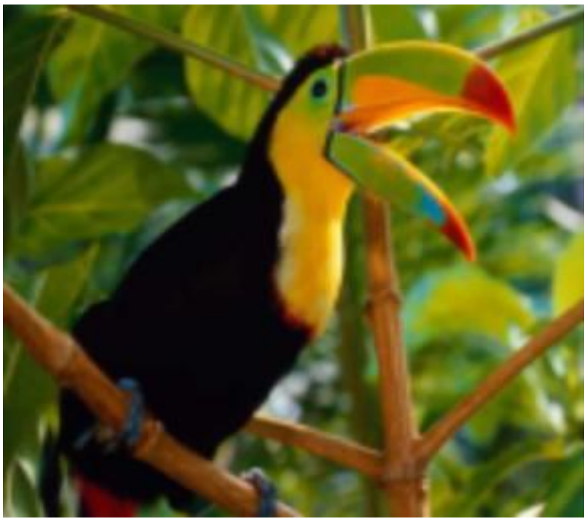


Fig 5: Example of Average pooling

RESULTS AND DISCUSSION

Original Image



Degraded Image

SRCNN Image

Table 1. PSNR and MSE (Mean Squared Error) Values of images

Degraded Image	**PSNR: 32.9711**	**MSE: 98.4065**
SRCNN Image	**PSNR: 36.5471**	**MSE: 43.1992**

In this process PSNR values of the SRCNN image is increased as the increase in PSNR values will result into better quality of the image. In the above figure first convolution layer will perform 64 9*9 filters, second layer will perform max pooling and average pooling using kernel operations and finally output will be the same as original image which is more better in high resolution with good quality of texture.

IV. CONCLUSION

Large scale super resolution and SISR with corruption are the two major challenges in super resolution community. Therefore Deep Learning algorithms are skilled to overcome these drawbacks. Combination of loss functions for image super resolution will give the better quality of the image perceptually. Over many algorithms SRCNN is proved to give the best resolution to the image and no pixel breakage is seen when it is pinched or zoomed. Therefore benchmark has been reached in state of art. This application is more useful in MRI scans in medical imaging, satellite images.

ACKNOWLEDGEMENTS

We thank our Guide Dr. Rajashree V. Biradar, Ph.D., for guiding every one of us and infusing the enthusiasm to work over successfully. We express our sincere thanks to respected Head of the department Dr. R.N. Kulkarni, Ph.D., whose moral support encouraged us throughout the project successfully. We offer our sincere gratitude to the project coordinators and non-teaching staff or supporting us in difficult times.

V. REFERENCES

[1] Y.LeCun, Y. Bengio, and G. Hinton, "Deep learning," nature, vol.521, no.7553, p.436, 2015.

[2] Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in neural information processing systems, 2012, pp. 1097–1105.

[3] D. C. Ciresan, U. Meier, J. Masci, L. Maria Gambardella, and J. Schmidhuber, "Flexible, high performance convolutional neural networks for image classification," in IJCAI Proceedings-International Joint Conference on Artificial Intelligence, vol. 22, no. 1. Barcelona, Spain, 2011, p. 1237.

[4] R. Collobert and J. Weston, "A unified architecture for natural language processing: Deep neural networks with multitask learning," in Proceedings of the 25th international conference on Machine learning. ACM, 2008, pp. 160–167.

[5] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[6] R. Timofte, R. Rothe, and L. Van Gool, “Seven ways to improve example-based single image super resolution,” in Computer Vision and Pattern Recognition (CVPR), 2016 IEEE Conference on. IEEE, 2016, pp. 1865–1873.

[7] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[8] K. He, X. Zhang, S. Ren, and J. Sun, “Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification,” in Proceedings of the IEEE international conference on computer vision, 2015, pp. 1026–1034.

[9] S.C. Park, M. K. Park, and M. G. Kang, “Super resolution image reconstruction: a technical overview”, IEEE signal processing magazine, vol.20, no.3, pp. 21–36, 2003.

[10] R.Keys, “Cubic convolution interpolation for digital image processing,” IEEE transactions on acoustics, speech, and signal processing, vol. 29, no. 6, pp. 1153–1160, 1981.

[11] W. T. Freeman, T. R. Jones, and E. C. Pasztor, “Example-based superresolution,” IEEE Computer graphics and Applications, vol. 22, no. 2, pp. 56–65, 2002.

[12] H. Chang, D.-Y. Yeung, and Y. Xiong, “Super-resolution through neighbor embedding,” in Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on, vol. 1. IEEE, 2004, pp. I–I.

[13] M. Aharon, M. Elad, A. Bruckstein et al., “K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation,” IEEE Transactions on signal processing, vol. 54, no. 11, p. 4311, 2006.

[14] J. Yang, J. Wright, T. S. Huang, and Y. Ma, “Image super-resolution via sparse representation,” IEEE transactions on image processing, vol. 19, no. 11, pp. 2861–2873, 2010.