**Critical Analysis:**

**Image Super-Resolution Using Deep Convolutional Networks, CNN model for single image super-resolution (SRCNN)**

Paper published by Chao Dong, Chen Change Loy, Member, IEEE, Kaiming He, Member, IEEE, and Xiaoou Tang, Fellow, IEEE on 31st July 2015 explain their deep learning method for single image super-resolution. As a successful deep model applied in image super-resolution (SR). The network directly learns an end-to-end mapping between low and high-resolution images, with little pre/post processing beyond the optimization. The method is faster as it is fully-forward and there is no need to solve any optimisation problem. Traditional methods were able to optimize all the layers and handle each component separately but new method jointly optimizes all layers.The deep model is not speciﬁcally designed to be an end-to-end solution, since each layer of the cascade requires independent optimization. On the contrary, the proposed SRCNN optimizes an end-to end mapping. Further, the SRCNN is faster at speed. It is not only a quantitatively superior method, but also a practically useful one. In the traditional methods, the predicted overlapping high-resolution patches are often averaged to produce the ﬁnal full image. In this model, all the ﬁltering weights and biases are to be optimized. Also experiments done on SRCNN showed the evaluation on keeping more width of the filter, Increasing number of layers but not too deep, large filter size for richer structural information and effect of the dataset i.e. to have larger dataset rather then the smaller one.

**Since the original publication there were certain work done on the topic.** **SRCNN has been published in 2015[1].** Super-Resolution Convolutional Neural Network (SRCNN) has demonstrated superior performance and accuracy to the previous state-of-the-arts models either in speed and restoration quality.

Accelerating the Super-Resolution Convolutional Neural Network also known as **Fast Super-Resolution Convolutional Neural Network (FSRCNN)** by chao dong , Chen Change Loy, Xiaoou Tang published on 1 Aug 2016**.** FSRCNN has a relatively shallow network which makes us easier to learn about the effect of each component. It is even faster with better reconstructed image quality than the previous SRCNN. By comparing SRCNN and FSRCNN-s, FSRCNN-s has a better PSNR (image quality) and much shorter running time. The proposed model achieves a speed up of more than 40 times with even superior restoration quality.

.This paper aim at accelerating the current SRCNN, and propose a compact hourglass-shape CNN structure for faster and better SR. We re-design the SRCNN structure mainly in three aspects[2].

* Introduction of a de-convolution layer at the end of the network.
* Shrinking the input feature dimension before mapping.
* They adopt smaller filter sizes but more mapping layers.

A preliminary version of this work was presented earlier in 2014[3]. The present work of 2015 on SRCNN adds to the initial version in signiﬁcant ways.

* It improves the SRCNN by introducing larger ﬁlter size in the non-linear mapping layer, and explores deeper structures by adding nonlinear mapping layers.
* It extends the SRCNN to process three color channels (either in YCbCr or RGB color space) simultaneously which was not possible.
* It demonstrates that performance can be improved in comparison to the single-channel network.

However, the high computational cost still hinders it from practical usage that demands real-time performance.

Performance issue:

1. In terms of accuracy, all the system are not accurate whereas other proposed system are better
2. Suffers from high computational complexity and artefacts degrade the performance.
3. No system is reusable or to be precise do not provide standalone solution (Anyone can use it).

As per the paper published in corresponding years the most interesting and unsolved issue I believe is using the padding with the convolution layers[3]. To avoid border effects during training, all the convolutional layers have no padding, and the network produces a smaller output.

The padding seems important to me for the below certain reasons:

* It seems to me the most important reason is to preserve the spatial size. Recent network structures operate on the outputs of different layers, which require a consistent spatial size between them.
* If no padding, the pixels in the corner of the input only affect the pixels in the corresponding corner of the output, while the pixels in the centre contribute to a neighbourhood in the output. When several no-padding layers are stacked together, the network sort of ignores the boarder pixels of the image.
* Padding actually **improves performance by keeping information at the borders.**

**REFERENCES**

1. Dong, C., Loy, C.C., He, K., Tang, X.: Image super-resolution using deep convolutional networks. TPAMI 38(2) (2015).
2. Chao Dong, Chen Change Loy, and Xiaoou Tang: Accelerating the Super-Resolution Convolutional Neural Network: Department of Information Engineering, The Chinese University of Hong Kong (2016).
3. Dong, C., Loy, C.C., He, K., Tang, X.: Learning a deep convolutional network for image super-resolution. In: European Conference on Computer Vision, pp. 184–199 (2014).