# Image Super Resolution

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## Problem Statement

Super resolution is the problem of artificially enlarging a low resolution image to recover a plausible high resolution version. Image Super Resolution (SR) is particularly useful in forensics, biometrics. This is a classical computer vision problem. We plan to implement a Deep Learning based approach to super resolve existing lower resolution images.

## Dataset

Low Resolution Images which are a part of DIV2K dataset provided by NTIRE 2017, 2018 challenges on Image Super-Resolution improvement. We use this dataset so as to compare our results with current state-of-the-art.

# State of the Art

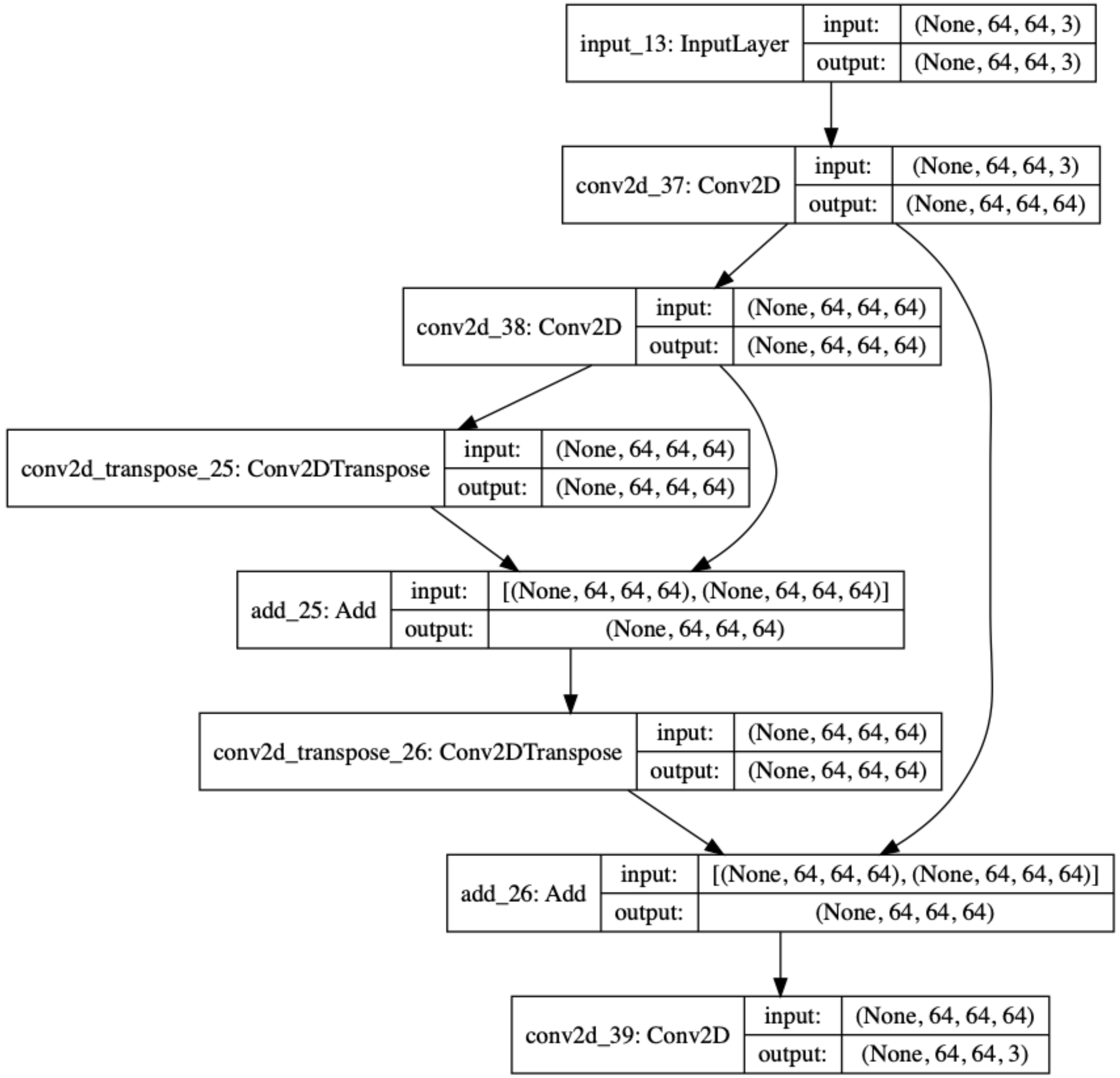
Current state-of-the-art approaches in the field of image super resolution employ Generative Adversarial Networks (GANs) to super resolve images. One such work is by Wang *et al.,* who propose Enhanced Super-Resolution Generative Adversarial Networks (ESRGANs). The work is an improvement over SRGAN proposed by Ledig *et al.,* The main improvements include introduction of a Residual-in-Residual Dense Block (RRDB) without batch normalisation. By removing the Batch Normalisation (BN) layers, they use residual scaling and smaller initialisation instead to facilitate training a deep network. They also improve the discriminator using Relativistic Average GAN (RaGAN). They use VGG features before activation as opposed to the usage after activation is SRGAN. The work mainly focuses on perceptual-driven methods to improve the visual quality over PSNR-oriented approaches which tend to output over-smoothed results without sufficient high frequency details.

Another work by Yu *et al.,* is a CNN-based super resolution approach in which they propose the idea of wide activation by expanding features before ReLU activation, which leads to an efficient way to expand low-level SR features from shallow layers to deeper layers. They also employ weight normalisation over batch normalisation which leads to better accuracy. They propose Wide Activation Super Resolution networks, WDSR-A and WDSR-B. WDSR-A has wider (2x to 4x) activation and WDSR-B facilitates much wider (6x to 9x) activation using linear low rank convolutions without additional parameters. The network is also able to beat the current state-of-the-art performance with $1/3^{rd}$ of the parameters used in previous works.

# Baseline Architecture

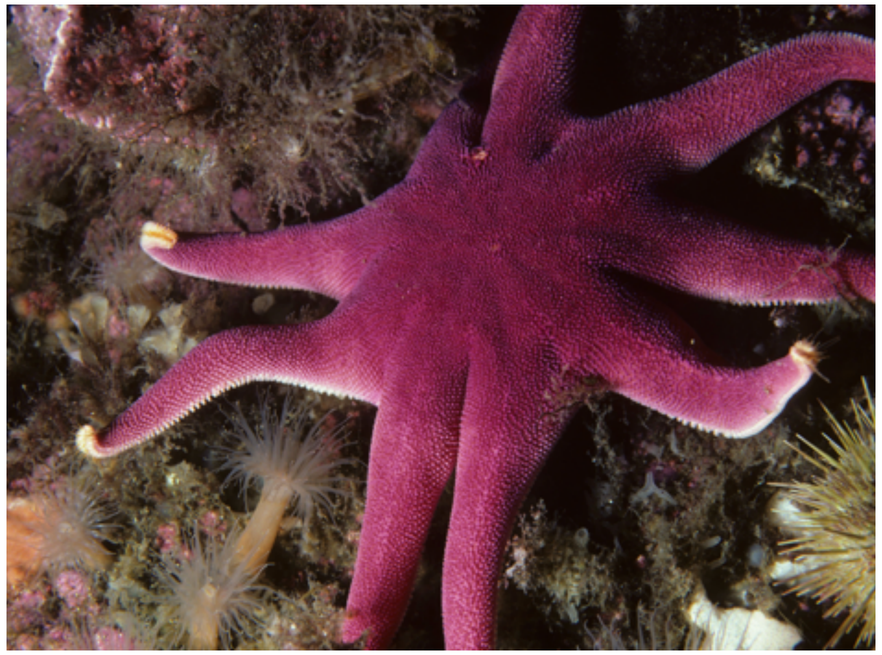
5 Convolutional Layers

| | |
|---|---|
| Input Size: | 64 x 64 x 3 (resized from 32 x 32 x 3) |
| Output Size: | 64 x 64 x 3 (Super-resolved by 2 times) |
| Loss Function: | Mean Squared Error |
| Optimiser: | Adam |
| Batch size: | 128 |
| No. of epochs: | 30 |
| Training Data: | 800 images x 4 patches/image = 3200 images |
| Val. Data: | 100 images x 4 patches/image = 400 images |
| Metric: | PSNR |




Dong *et al.,* Image Super-Resolution Using Deep Convolutional Networks - IEEE Transactions on Pattern Analysis and Machine Intelligence 2016

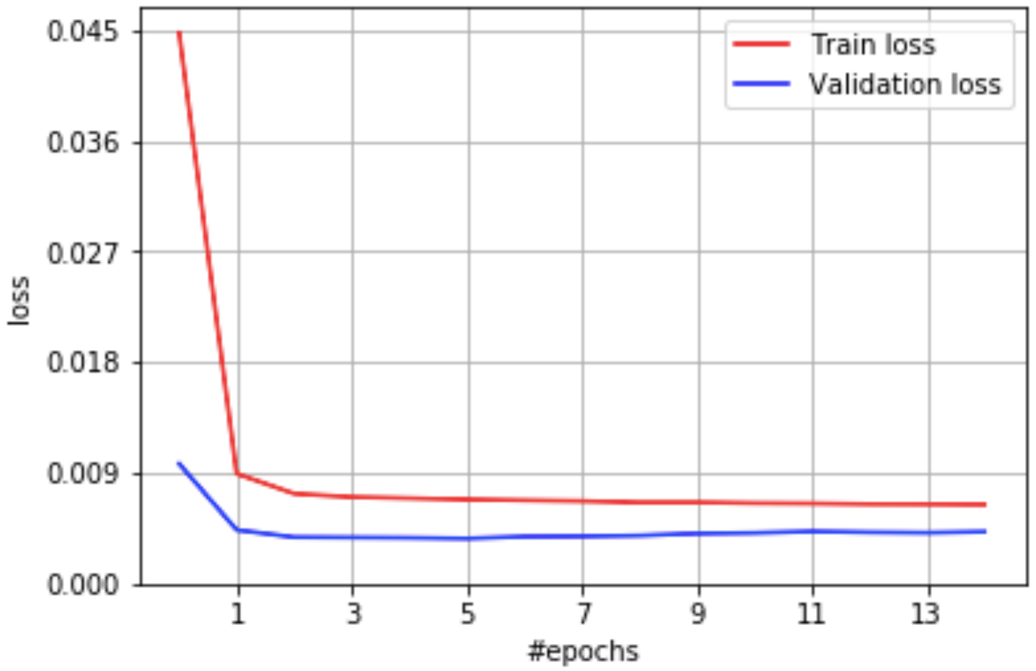
# Results & Analysis



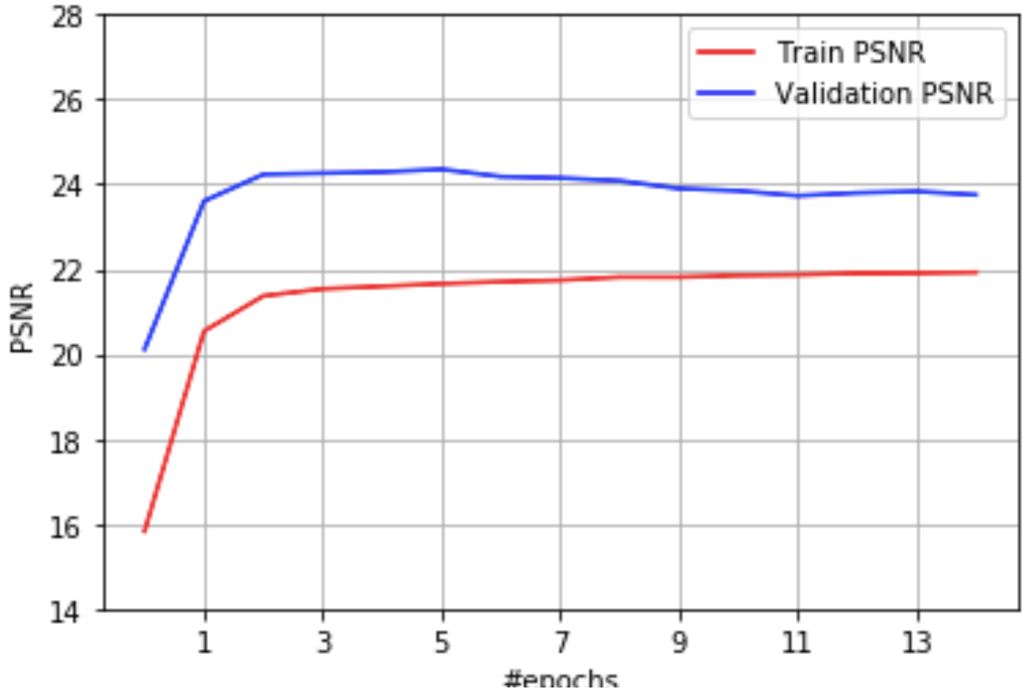
High Resolution

Low Resolution(resized)
PSNR - **30.69 dB** w.r.t HR image

Super Resolved
PSNR - **30.87 dB** w.r.t HR image




Train vs. Validation Loss




Train vs. Validation PSNR

## Future Improvements

- We plan to implement the current state-of-the-art approaches for advanced work.
- Build an end-to-end super resolution application which outputs a super resolved image on inputting a low resolution image.