Deep Boosting for Image Denoising

Statistical Methods in AI Project

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Objective

- To create a novel deep boosting framework (DBF) for denoising, which integrates several convolutional networks in a feed-forward fashion and incorporates the concept of path widening fusion, dense connection and dilation.

Related Work

- **CNN based image denoising network:** . Research along this direction focuses on the exploration of the network structure. Advanced design of architecture yields better restoration quality.
- **Boosting Based algorithms:** Boosting is a widely used algorithm to improve the performance of diverse tasks by cascading several steerable sub-models. A plenty of models based on the boosting algorithm have been investigated for image denoising.

Understanding of Paper

- This paper proposes a convolutional network as the boosting unit called DDFN (Dilated Dense Fusion Network), which includes dense connection, path widening fusion and dilated convolution, for efficient image denoising.
- Evolution of the boosting unit is divided into three modules namely feature extraction, feature integration and reconstruction.
- By introducing the dense connection, we address the vanishing of gradients during training. Based on the densely connected structure, we further propose the path-widening fusion cooperated with the dilated convolution to optimize the DDFN for efficiency.

Concepts Used

Path Widening Fusion :

In a certain block, the order between the dilated convolutions (Dconv for short) and the normal convolutions (Conv for short) is exchanged in different branches. It is very likely that the Conv-ReLU-Dconv and Dconv-ReLU-Conv branches can learn different feature representations. The proposed path-widening fusion exploits the potential of these two orders at the same time, and thus promotes the possibility to learn better representations.

Concepts Used

- **Dilated Convolution:**

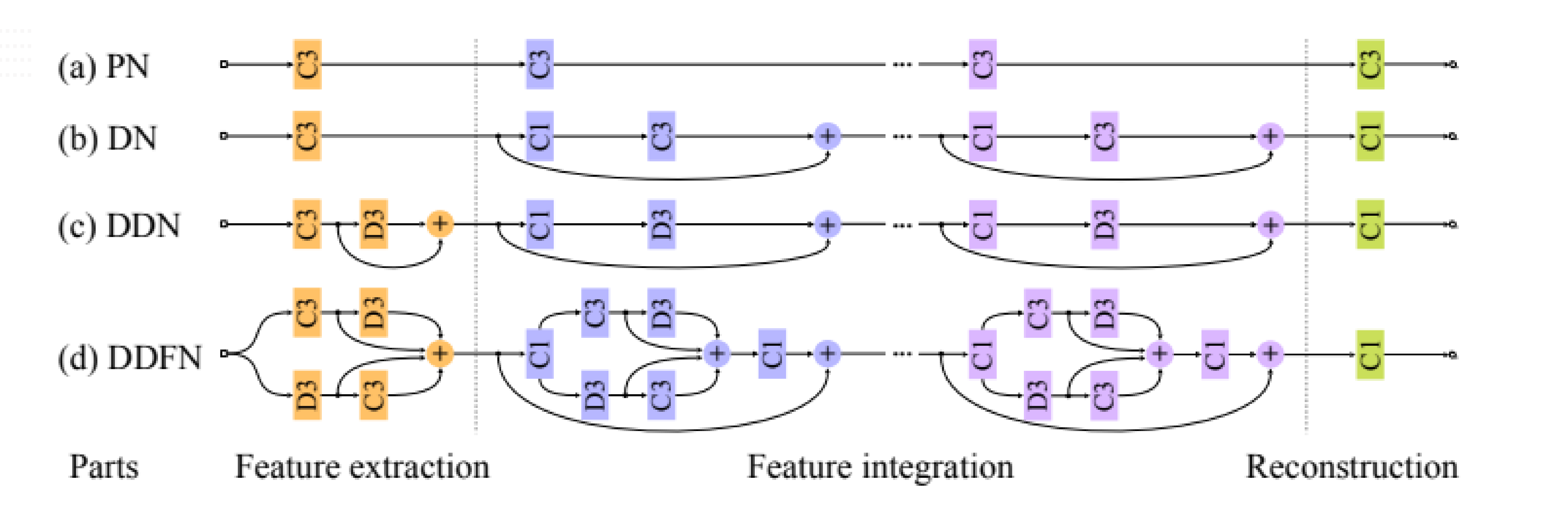
The dilated convolution can widen the receptive field without additive parameters and it also prevents the increasing of depth. Inspired by that, the paper introduced the dilated convolution to derive the dilated dense network (DDN) based on the DN.

Concepts Used

- **Dense Connection:**

Dense connection enables the l th layer to receive the features of all preceding layers (i.e., $f_0, ..., f_{l-1}$) as input $f_l = g_l([f_0, f_1, ..., f_{l-1}])$, (16) where $g_l(\cdot)$ denotes the l th layer in G_θ and $[f_0, f_1, ..., f_{l-1}]$ stands for the concatenation of the features output from preceding layers.

Model Diagram



Dataset Description

- For training and validation, we have collected 650 images which are collected from train400, LIVE1, LIVE1_q10, LIVE1_q20, LIVE1_q30, LIVE1_q40, BSD68 datasets fetched from google drive.

Data Loader

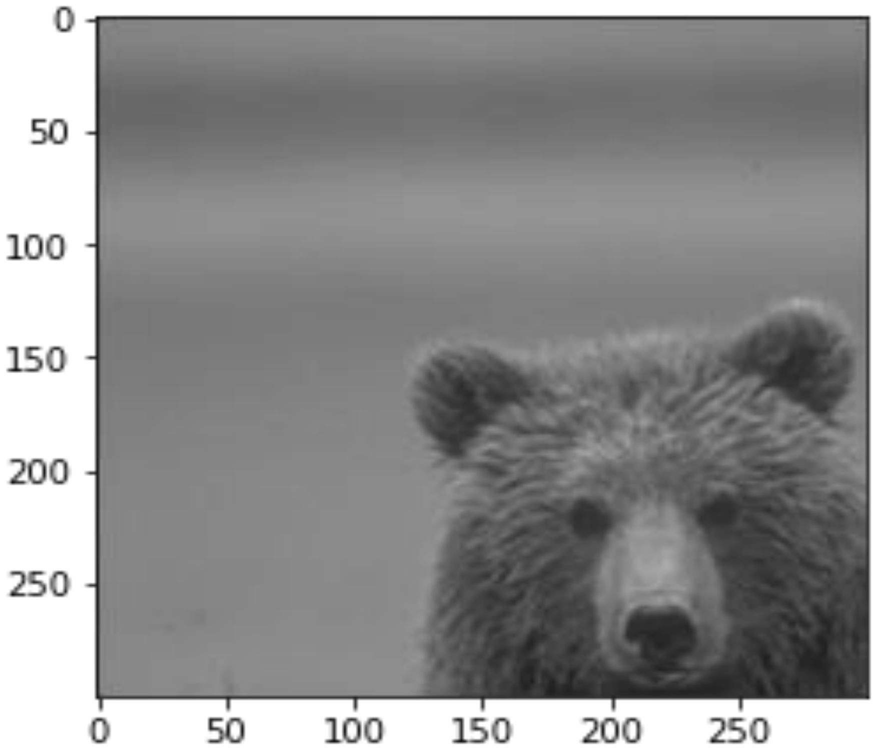
- The datasets used are uploaded on google drive and hen loaded that images into our python code using "tf.keras.preprocessing.image.load_img"
- We then normalised the image by 255.0 so that all the pixels fall in the range of 0-1.

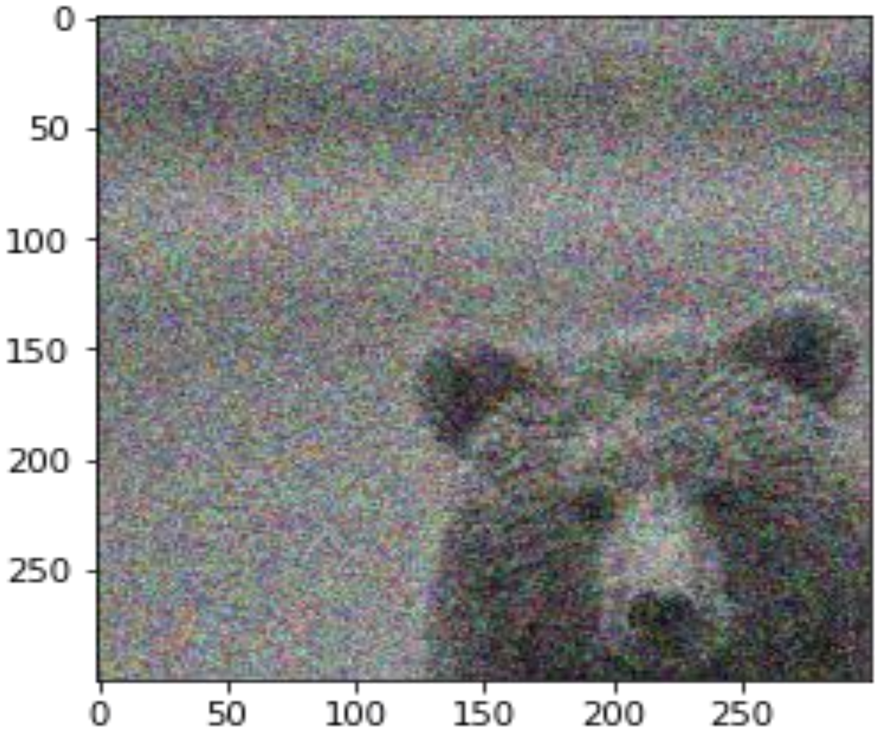
Approach

- We have divided the model into three modules namely feature extraction, feature integration and reconstruction.
- In feature extraction, we have implemented path widening fusion with kernel size 3 and dilation 2. Result from the feature extraction module is passed on to the feature integration module where we have applied path widening fusion different number of times , taking input from the past output. We are concatenating the output from all the layers to implement dense connection. Finally the image is reconstructed using conv2DTranspose.
- We also made pn network and ddn network for analysis between them vs ddfn network.

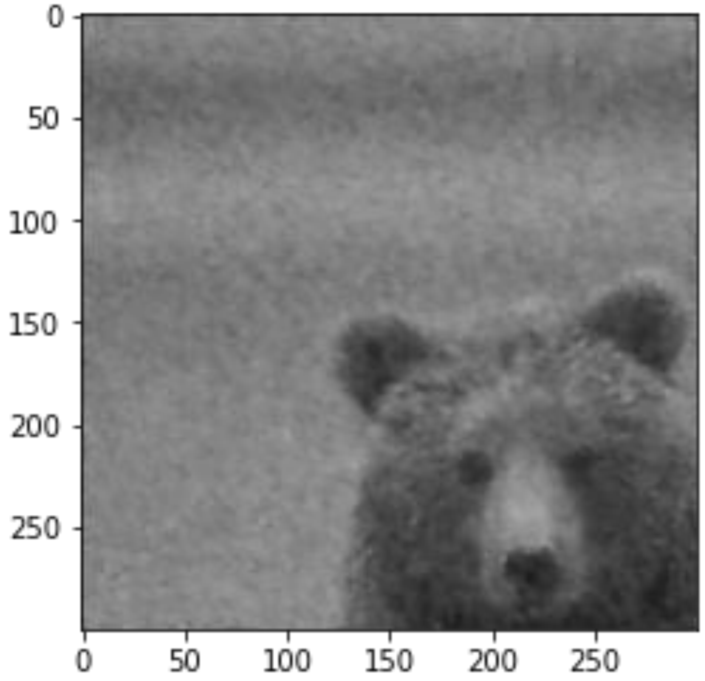
Experimentation And Results

Original image and noisy image

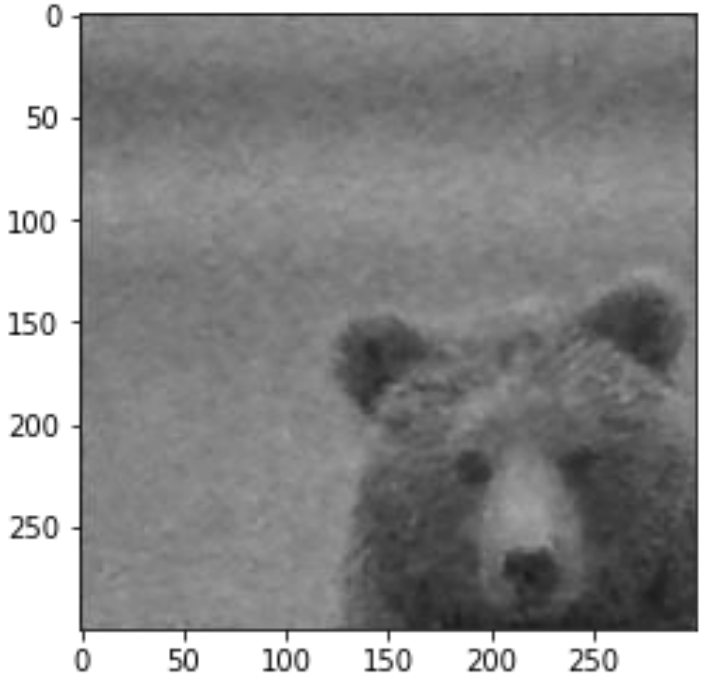




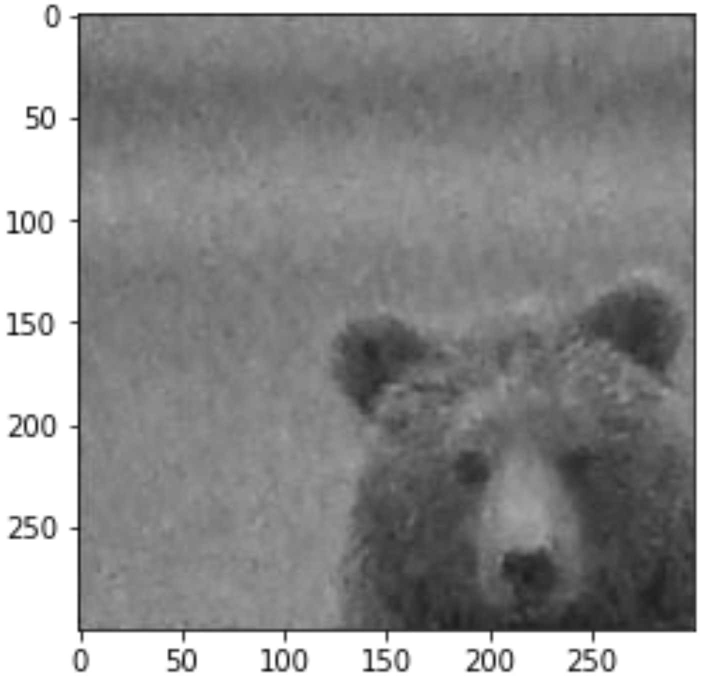
Output of various layers of DDFN



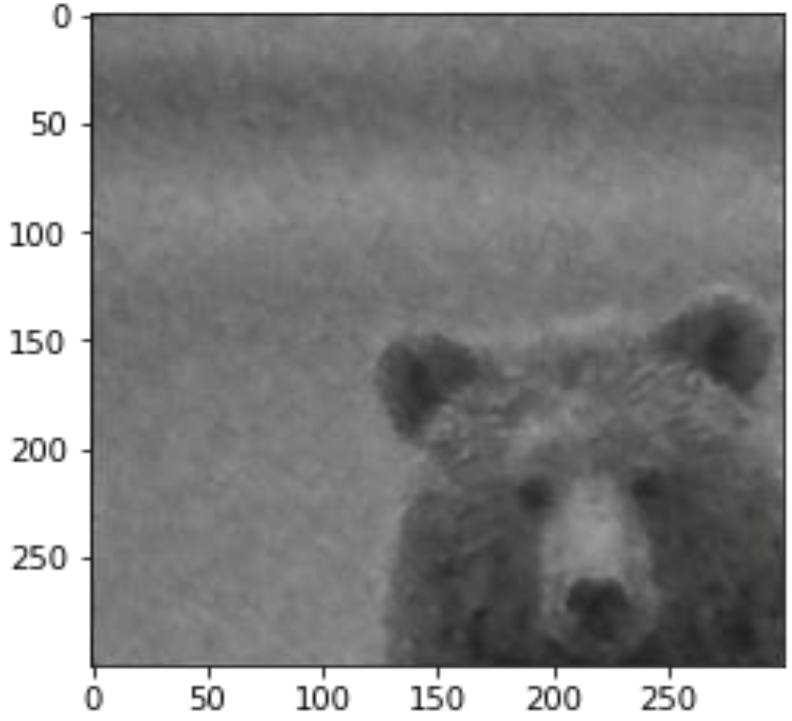
1 layer



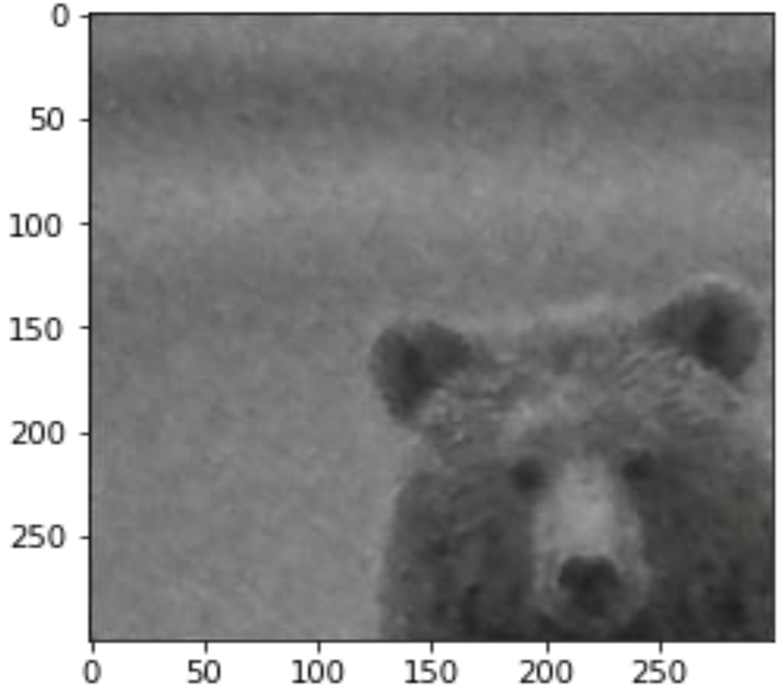
2 layers



3 layers



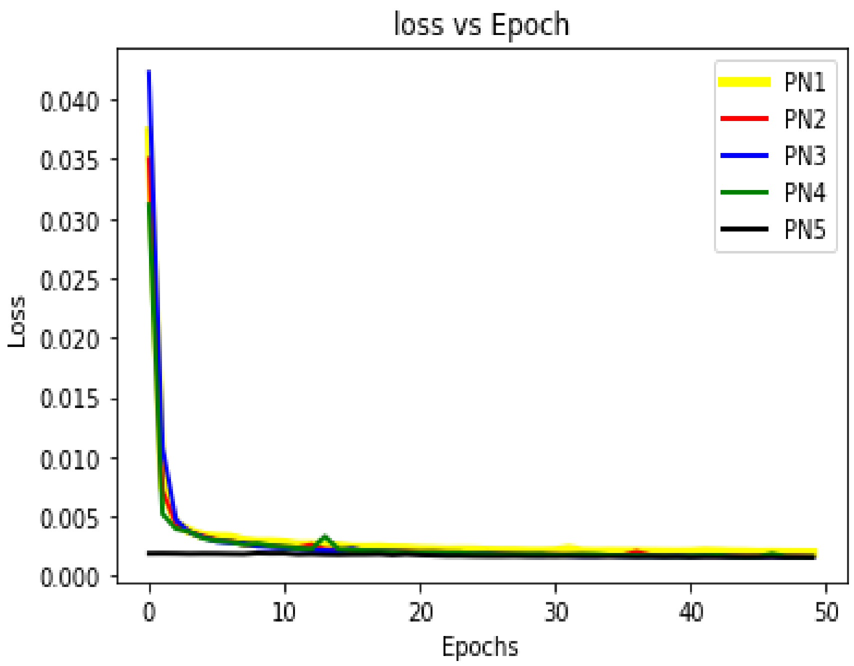
4 Layers



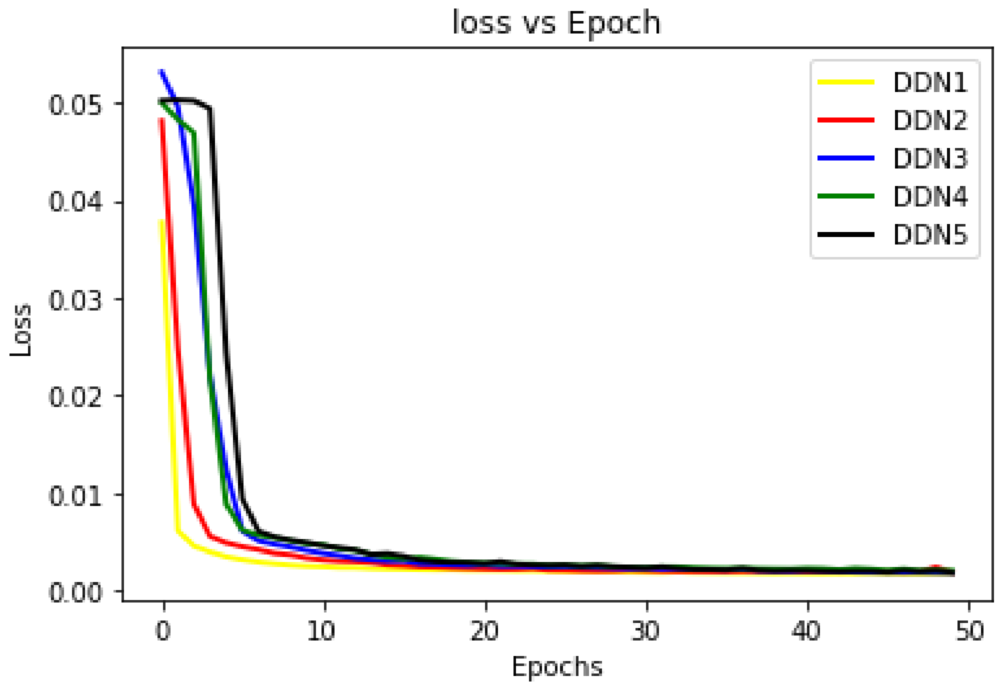
5 Layers

Original vs boosted Models

ORIGINAL

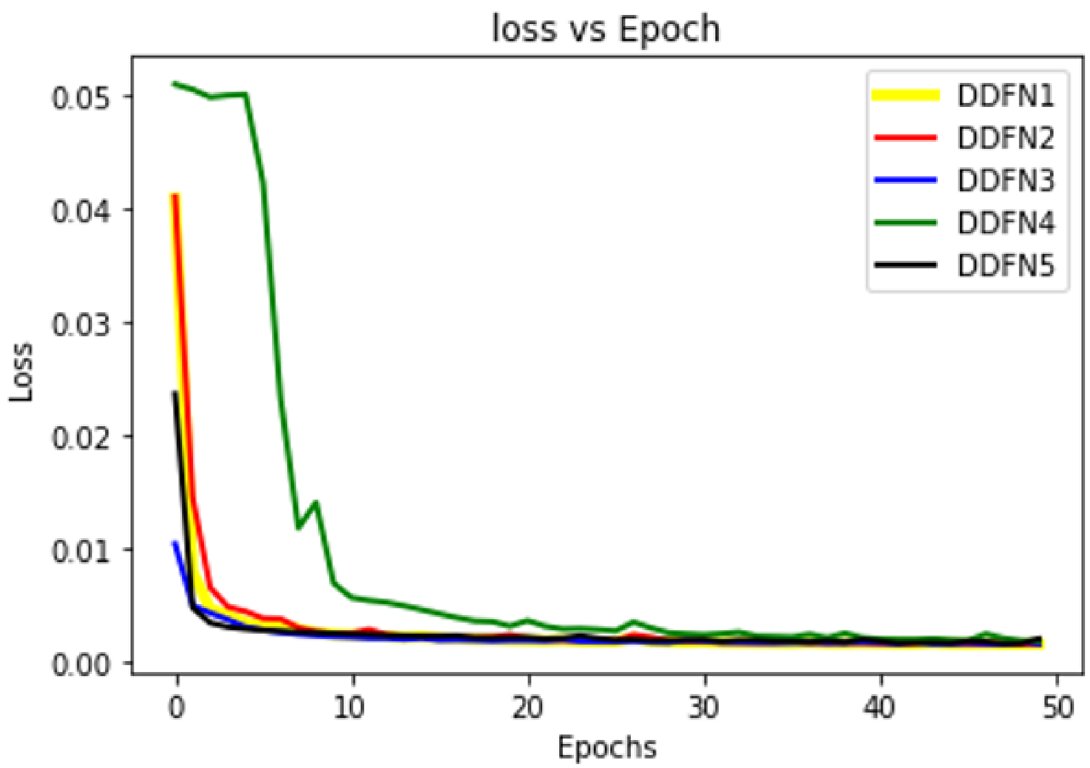


PN



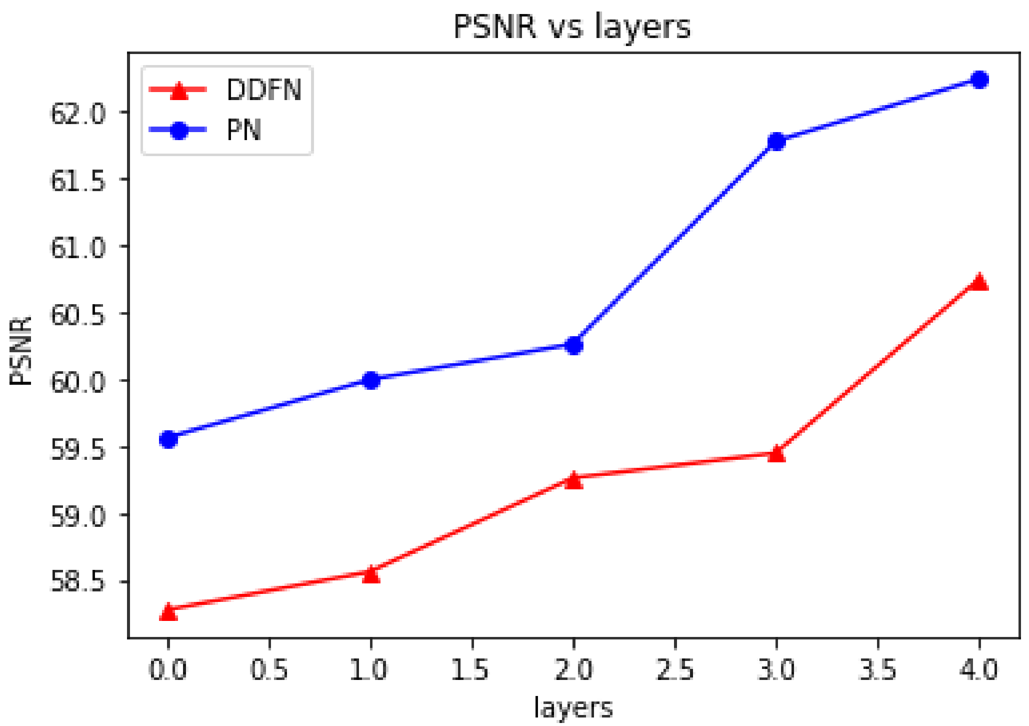
DDN

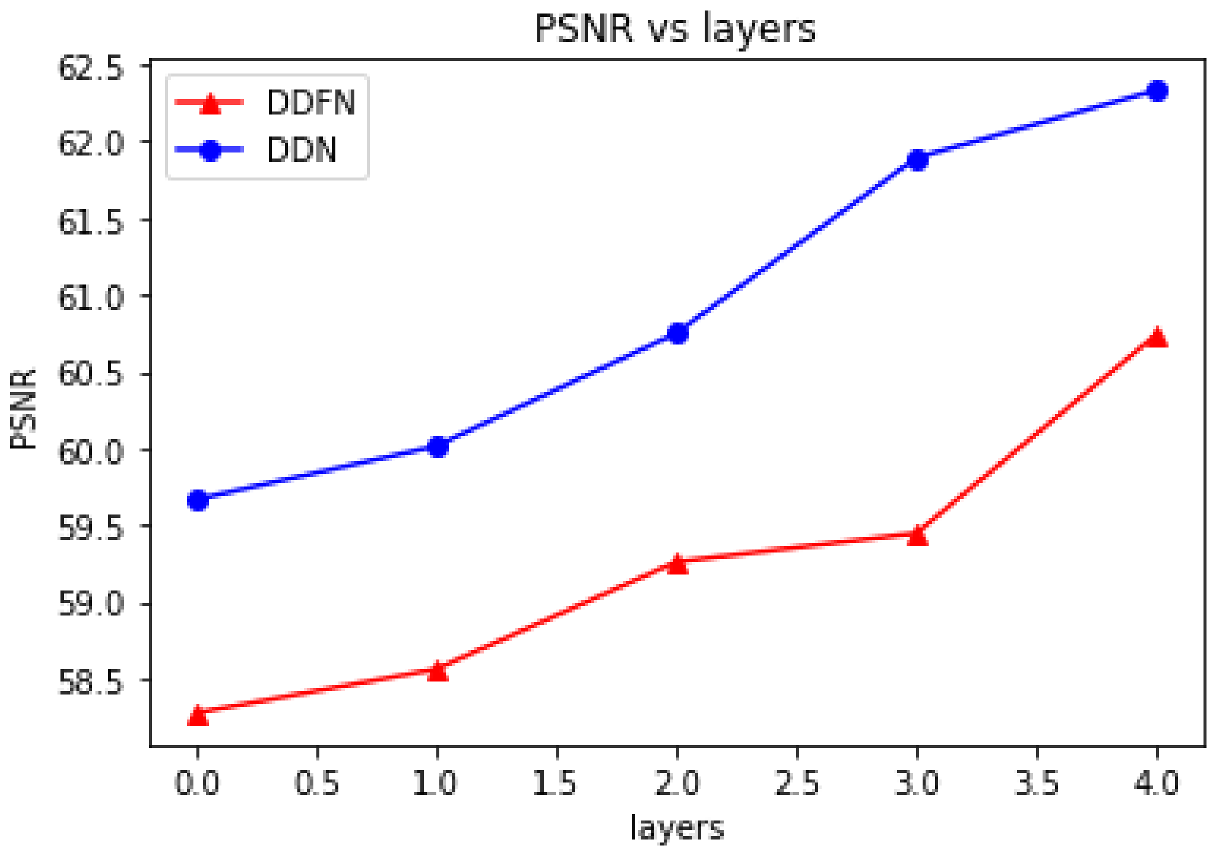
BOOSTED



DDFN

Comparison between different models





Conclusion

We implemented the DBF which first integrates the boosting algorithm with deep learning for image denoising. To fully exploit the potential of this framework, we elaborate the lightweight yet efficient DDFN as the boosting unit. By introducing the dense connection, we address the vanishing of gradients during training. Based on the densely connected structure, we further propose the path-widening fusion cooperated with the dilated convolution to optimize the DDFN for efficiency. Compared with the existing models(PN,DDN), our DDFN-based DBF achieves much better performance in image denoising on widely used benchmarks.

Thank You