Image Super Resolution

Team Kota

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Project Details

Team Name - Kota

Topic ID - 7

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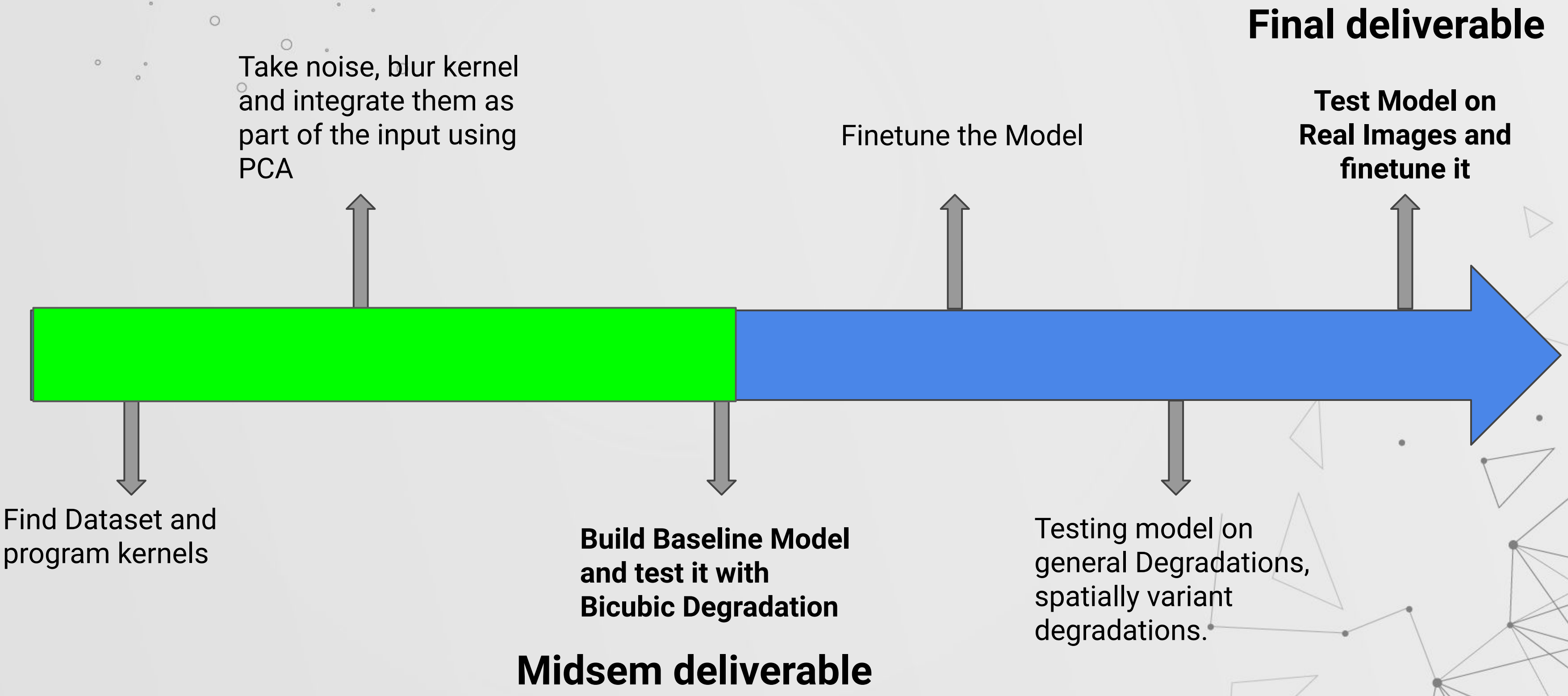
Progress


Final deliverable
Take noise, blur kernel and integrate them as part of the input using PCA
Finetune the Model
Test Model on Real Images and finetune it
Find Dataset and program kernels
Build Baseline Model and test it with Bicubic Degradation
Testing model on general Degradations, spatially variant degradations.
Midsem deliverable

Method Overview

- Pose SISR using MAP framework to be a function of noise, blur kernel and the low-resolution image
- Perform dimensionality stretching on blur kernel using PCA
- Create degradation maps, which are concatenated to the original image
- This modified input is sent through a plain CNN, to show effectiveness of dimensionality stretching

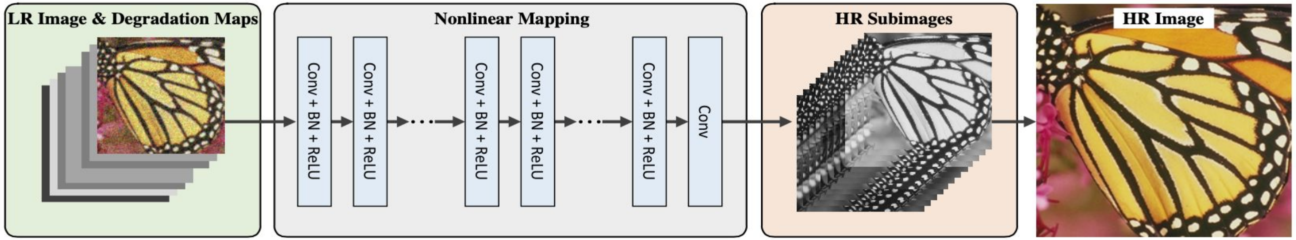


Figure 3. The architecture of the proposed convolutional super-resolution network. In contrast to other CNN-based SISR methods which only take the LR image as input and lack scalability to handle other degradations, the proposed network takes the concatenated LR image and degradation maps as input, thus allowing a single model to manipulate multiple and even spatially variant degradations.

Pipeline

Data → **Kernel** → **Train**

Data	Kernel	Train
Load Images from our Dataset to send to kernel	Using blur kernels and bicubic downsampling, we convert our hi-resolution images into low-resolution images to feed to model	Pass the generated LR images through our model and optimise model based on training loss

Data

- Make use of the DIV2K dataset of RGB images
  - Contains 800 2K resolution images
- Preparing data
  - Random crop (behaves like data augmentation, improve generalisation of model)
  - Downsampling happens along with random crop
  - Blur (applying blur kernel on random crop)
  - Concatenate degradation map to image
    - Degradation maps are obtained using PCA
  - Now we have (x, y) = (degraded image, high res image)

Kernels

To model the degradation between high resolution and low resolution images, there are two major steps: blurring and downsampling. For the blurring phase, we use gaussian blur kernels of varying standard deviations. The deviations lie anywhere in the range [0.2,0.3,0.4,...,2].

Before we begin training, the model, we create all the possible kernels (i.e, one kernel corresponding to each possible standard deviation) of size 15x15.

At train time, we use a random kernel to degrade each high resolution image and also pass on information regarding the kernel as input to the model. But this is not easy as there is a dimensionality mismatch between the image and the kernel itself.

Hence we reshape the kernels to a 125x1 vector and apply **PCA** to get a low dimensional 15x1 vector approximation of the blur kernel.

Dimensionality stretching is applied on each value of the new vector to obtain 15 degradation maps of size HxW. These Degradation maps are concatenated with the low resolution image and passed as input to the model

Training

- Once LR image is created it is passed through the SRMD model
- SRMD Model is a CNN with 12 2D-Conv layers
- SRMD Model returns a hi-res version of the input
- ReLU is used as activation function
- Adam is used to optimise model over MSE loss
- Final MSE loss of our model for the dataset is 0.0011

Results

Left: LR image (input) ; Middle:HR image from model (prediction); Right:Actual HR image (ground truth)

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