Image Super Resolution

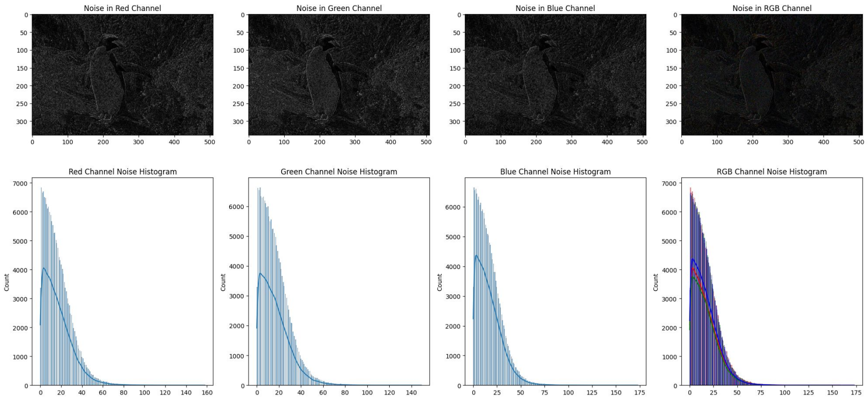
Aman Kumar | Parul | Puneet Singh | Shubham | Stuti Pandey

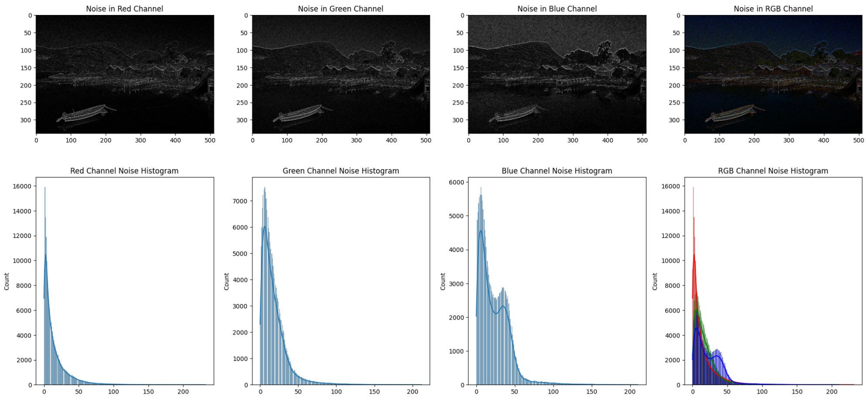
Problem Statement

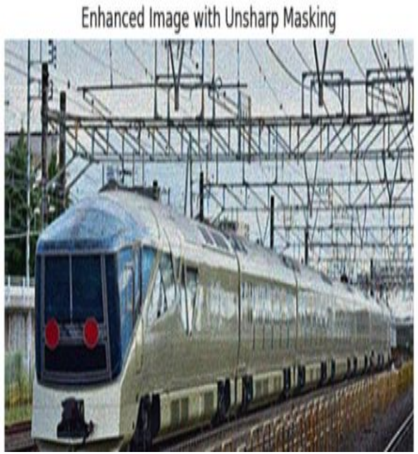
$$\mathbf{I}_{LR} = (\mathbf{I}_{HR} * \mathbf{k}) \downarrow_s + \mathbf{n},$$

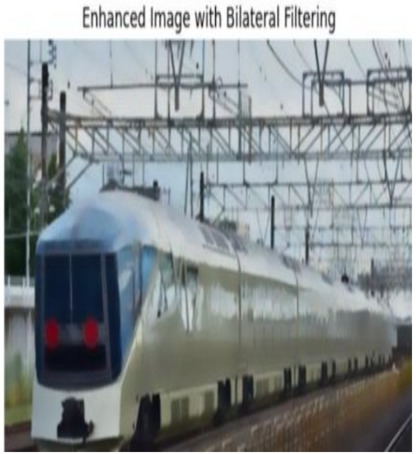
?

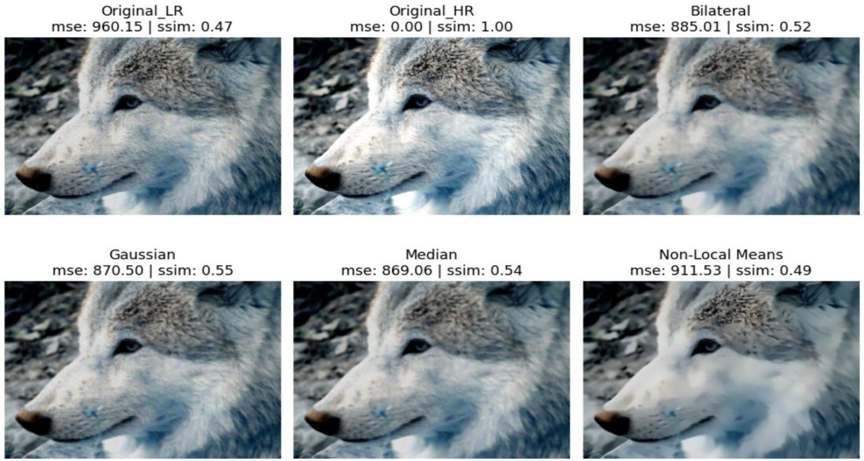
Exploratory Data Analysis











Methodology: RFSR (Y-channel)

1. Random forest based Image Super-Resolution using Residual Learning(Y-Channel)

The methodology for this pipeline is designed around **residual learning**, a principle commonly applied in image super-resolution to improve reconstruction quality by focusing on the missing details between the low-resolution (LR) input and the high-resolution (HR) output.

Residual learning leverages the fact that the difference between bicubic upscaled images and HR images primarily consists of fine details like edges and textures.
Patch Extraction:

- Extract **overlapping patches** from both HR and LR images.
- Bicubic interpolation is applied to upsample the LR patches to match the HR dimensions.
- These residual patches become the target output for training.

- Convert all HR and LR images from RGB to **YCbCr color space** to decouple luminance (Y) from chrominance (CbCr). This focuses the super-resolution task on the Y-channel, which contains the structural details of the image.

- Normalize the intensity values of the Y-channel to [0,255] for consistent numerical representation.

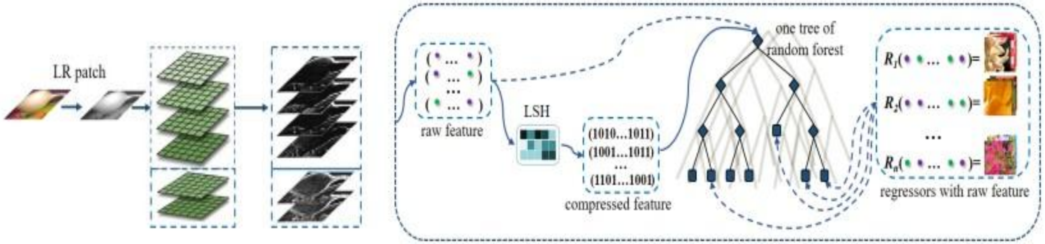
$$\mathbf{R}_{\text{patch}} = \mathbf{Y}_{\text{HR patch}} - \mathbf{Y}_{\text{bicubic patch}}$$

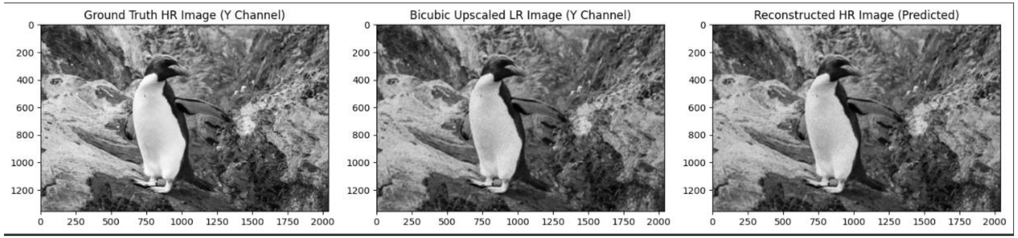
Model Objective:

The RFR learns a mapping $f : \mathbf{Y}_{\text{bicubic patch}} \rightarrow \mathbf{R}_{\text{patch}}$, where:

$$\hat{\mathbf{R}}_{\text{patch}} = f(\mathbf{Y}_{\text{bicubic patch}})$$

Here, $\hat{\mathbf{R}}_{\text{patch}}$ is the predicted residual patch.





Reconstruction:

Combine the predicted residuals with the bicubic upscaled Y-channel to reconstruct the HR luminance:

$$\mathbf{Y}_{\text{reconstructed}} = \mathbf{Y}_{\text{bicubic}} + \hat{\mathbf{R}}$$

Methodology: Channel-wise Patch Super Resolution

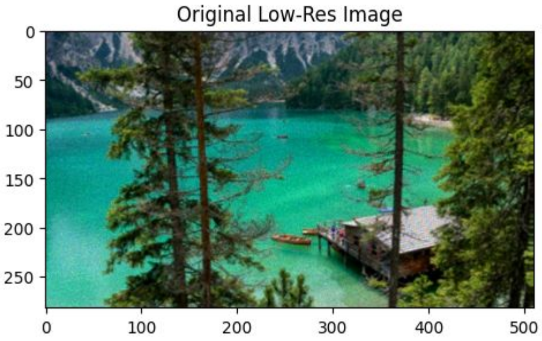
Ni, Karl S. and Truong Q. Nguyen. "Image Superresolution Using Support Vector Regression." *IEEE Transactions on Image Processing* 16 (2007): 1596-1610.

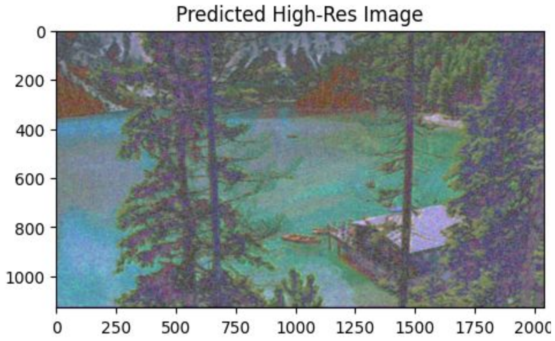
Enhance low-resolution (LR) images into high-resolution (HR) images using a classical machine learning approach, focusing on color channel predictions with Support Vector Machines (SVMs).

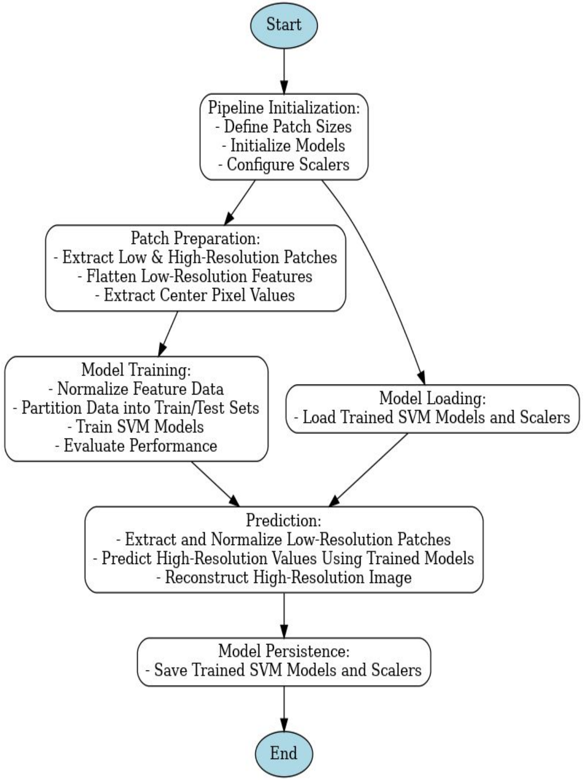
Flowchart: Include the updated SVM-based flowchart to illustrate the pipeline visually.

Key Steps:

1. **Initialization**: Define patch sizes, setup SVM models, and normalize inputs.
2. **Patch Preparation**: Extract and process LR and HR patches.
3. **Model Training**: Train SVM models for RGB channels and evaluate performance.
4. **Prediction**: Use trained models to predict HR patches.
5. **Reconstruction**: Combine patches to form the HR image.







Methodology: Patch-based super-resolution using Random Forest

The goal is to map **low-resolution (LR)** images to **high-resolution (HR)** images through patch-based learning and regression modeling. The most powerful aspect of the code is its **patch-based approach**. Instead of processing the entire image at once, the code extracts overlapping patches .

Objective:

Enhance low-resolution images to high-resolution using patch-based learning.

Methodology:

-> Extract overlapping patches from LR and HR images.

-> The training data used is in the form of LR-HR patch pairs: Pi=(Li,Hi)

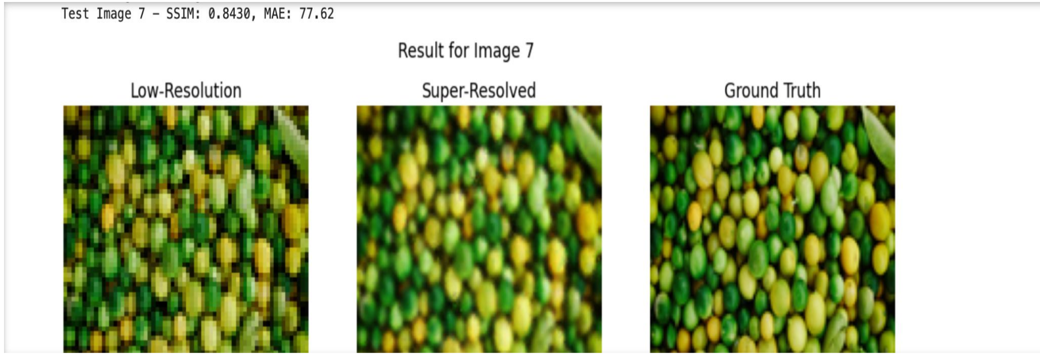
->Train Random Forest regressors to map LR patches to HR patches.

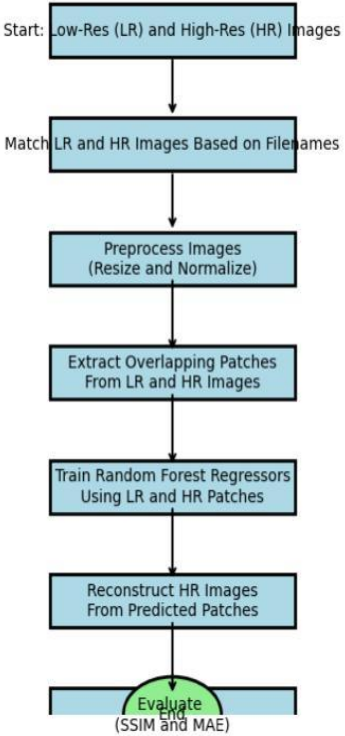
->Reconstruct HR images by combining predicted patches.

Evaluation Metrics:

- SSIM
- MAE

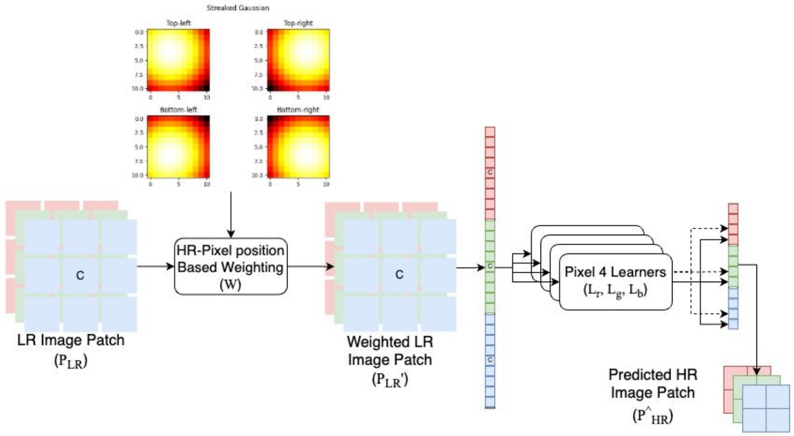
Results:



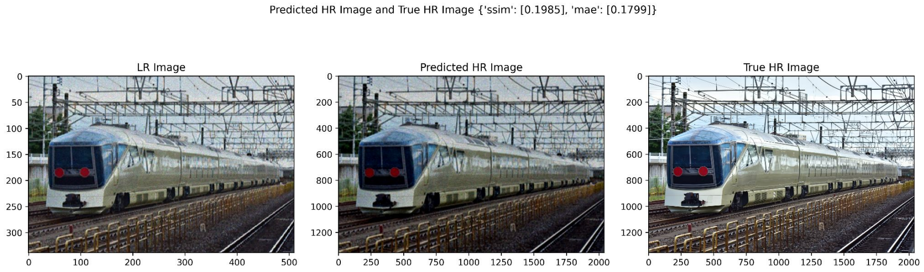


Reference : https://ieeexplore.ieee.org/document/7169108

Methodology: ISR Using SVMs

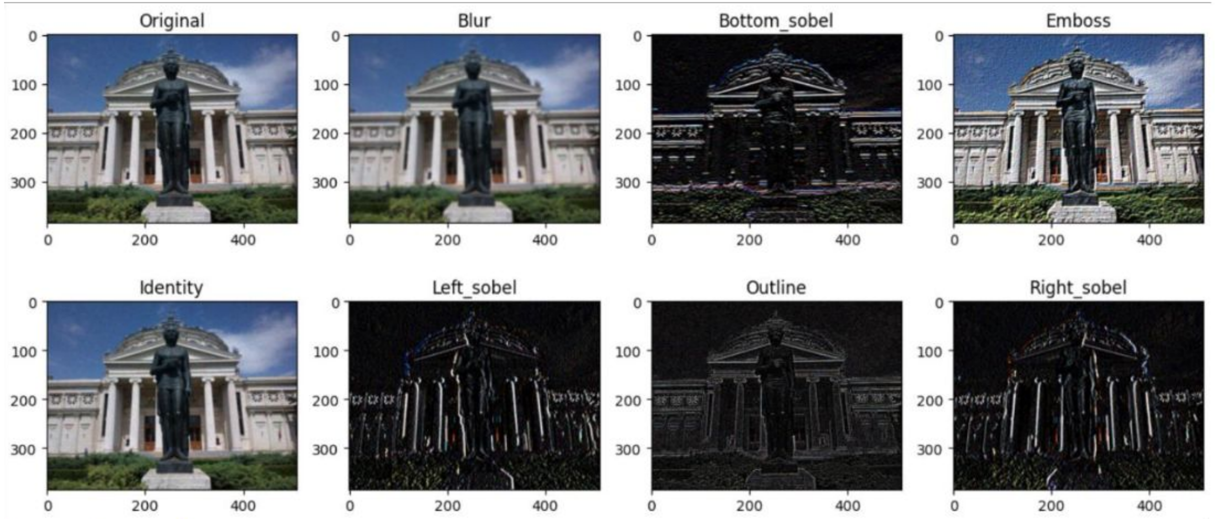


ISR Pipeline for one LR Image Patch (P_{LR}) adapted from [Ni, Karl S. and Truong Q. Nguyen. "Image Superresolution Using Support Vector Regression." IEEE Transactions on Image Processing 16 (2007): 1596-1610.]



Methodology	MAE	SSIM
Bilinear Interpolation	0.07450	0.42340
Bicubic Interpolation	0.07502	0.45640
Nearest Neighbour Interpolation	0.07526	0.45318
SVM	0.07594	0.45947

Future Scope



- L. An and B. Bhanu, "Improved image super-resolution by Support Vector Regression," *The 2011 International Joint Conference on Neural Networks*, San Jose, CA, USA, 2011, pp. 696-700, doi: 10.1109/IJCNN.2011.6033289.
- Jianchao Yang, J. Wright, T. Huang and Yi Ma, "Image super-resolution as sparse representation of raw image patches," 2008 IEEE Conference on Computer Vision and Pattern Recognition, Anchorage, AK, USA, 2008, pp. 1-8, doi: 10.1109/CVPR.2008.4587647.
- Ni, Karl S. and Truong Q. Nguyen. "Image Superresolution Using Support Vector Regression." IEEE Transactions on Image Processing 16 (2007): 1596-1610.

Future Scope

Image
Super Resolution
using ML

Image
Super Resolution
using DL