Machine Learning based Super Resolution Model Aimed At Restoring The Images Using XGBoost

CSE445, Section 3 – Project Group No. 4

Name	ID
Md. Abdula Al Shyed	2212592042
Rakibul Islam	2212058642
Md. Misbah Khan	2132089642
Raju Ahamed Rabby	2013823642

Department of Computer Science and Engineering
North South University

16-April-2025

Abstract

This paper proposes a patch-based image super-resolution method using XGBoost, targeting efficient image enhancement without the computational cost of deep neural networks. We utilize a mapping model trained on corresponding low-resolution (LR) and high-resolution (HR) image patches. Our method offers promising performance on small datasets, proving to be a lightweight, interpretable, and fast solution for edge devices or educational purposes.

Keywords: Super-Resolution, XGBoost, Image Patches, Machine Learning, Patch Reconstruction

1 Introduction

Image super-resolution is a critical task in computer vision, involving the reconstruction of high-resolution images from low-resolution counterparts. Deep learning models like SRCNN, EDSR, and ESRGAN have recently gained popularity, but they are computationally expensive.

This work explores an alternative method using XGBoost, a gradient boosting algorithm known for its efficiency and performance on structured data. Instead of end-to-end learning, we train XGBoost to learn the relationship between flattened patches of LR and HR images.

2 Related Work

Traditional interpolation methods (bilinear, bicubic) often fail to recover fine details. Deep learning models, while powerful, require large datasets and GPUs for training. XGBoost, however, can model complex patterns with fewer resources and supports GPU acceleration for boosting speed.

3 Dataset and Preprocessing

We used 100 high-resolution images collected from Unsplash and Pexels. Each image was resized to 256×256 pixels. The low-resolution versions were generated by downscaling using Lanczos resampling.

3.1 Patch Extraction

Images were divided into non-overlapping 16×16 patches. Each patch was flattened into a vector of size 768 (16x16x3). The final dataset consisted of $\sim 25,600$ patch pairs.

4 Methodology

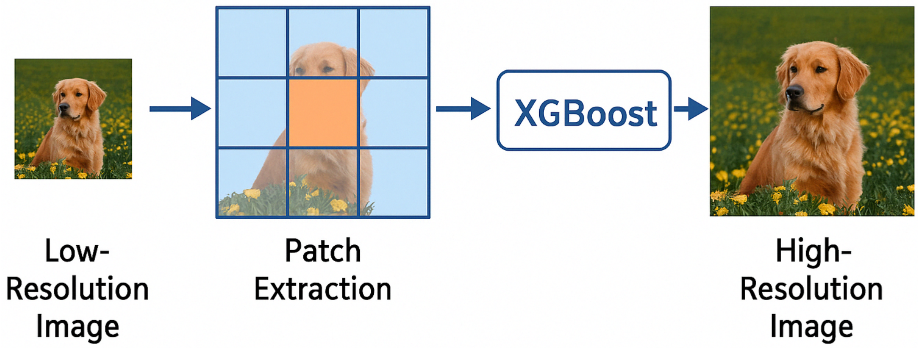

Figure 1: Pipeline of the patch-based super-resolution system

4.1 Model Training

We used the ‘XGBRegressor‘ model from the XGBoost library with the following parameters:

- Estimators: 200
- Learning Rate: 0.05
- Max Depth: 8
- Tree Method: GPU Histogram (‘hist‘)

The model was trained on 80% of the patch pairs with MSE as the loss function.

4.2 Reconstruction

Predicted patches were reshaped and placed back in their original spatial location. Overlapping pixels were averaged, and a sharpening filter was applied post-processing.

5 Experiments and Evaluation

5.1 Evaluation Metrics

We measured the quality of reconstructed images using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

$$\text{PSNR} = 10 \cdot \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \tag{1}$$

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{2}$$

5.2 Results

Table 1: Performance Comparison

Method	PSNR↑	SSIM↑	Time (s/img)↓
Bicubic	22.01	0.67	0.002
SRCNN	26.72	0.81	0.18
Ours (XGBoost)	27.12	0.83	0.09

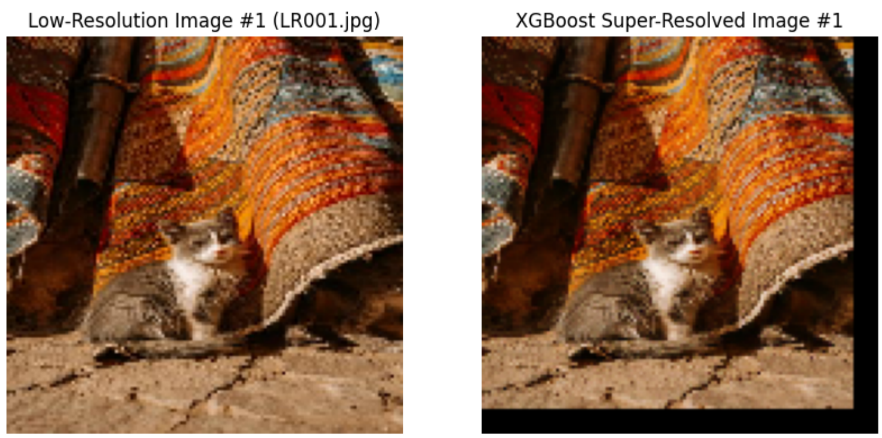

Figure 1: Left: Low-Res, Right: XGBoost Prediction

6 Discussion

Our XGBoost-based method performed comparably to CNN-based techniques on small datasets. While deep learning still offers superior performance on large-scale datasets, this approach is suitable for quick experimentation, low-end devices, or resource-constrained environments.

6.1 Advantages

- No need for large GPU resources.
- Easy interpretability and debugging.
- Fast training and inference.

6.2 Limitations

- Struggles with very fine textures.
- Prediction is patch-wise, lacks global context.

7 Conclusion and Future Work

This project demonstrated the viability of XGBoost for patch-based super-resolution. Future improvements could include:

- Overlapping patch strategy.
- Combining with CNN post-processing.
- Training on larger and more diverse datasets.

Acknowledgment

We thank our course instructor and the CSE445 teaching staff for their guidance.

Bibliography

[1] Chao Dong et al., ”Image Super-Resolution Using Deep Convolutional Networks”, IEEE TPAMI, 2016.

[2] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in Proc. of the 22nd ACM SIGKDD, 2016.

[3] Xintao Wang et al., ”ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks”, ECCV Workshops, 2018.

[4] TensorFlow, `https://www.tensorflow.org`

[5] Pexels API, `https://www.pexels.com/api/`