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COMPARATIVE ANALYSIS OF A COMPACT RESIDUAL CONVOLUTIONAL MODEL AND LINEAR REGRESSION FOR IMAGE SUPER-RESOLUTION

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Abstract. The article evaluates a compact residual convolutional model for fourfold image super-resolution under conditions of limited training data. A total of 19 JPEG images were divided into 10 training, 3 validation, and 6 test images. The model, consisting of 433 parameters, was compared with bicubic interpolation and Ridge regression. Extending the training period from 40 to 120 epochs increased the mean test PSNR across three random initializations from 29.7675 to 29.7744 dB. The extended model achieved an SSIM value of 0.83569, while the Ridge model obtained a PSNR of 29.8222 dB and an SSIM of 0.83424. In the controlled variants, the window size, hidden-layer width, and input centering were investigated. Paired bootstrap confidence intervals and CPU processing time were also calculated. The results demonstrate a criterion-dependent trade-off between the evaluated approaches.

Keywords: image super-resolution, residual learning, convolutional model, Ridge regression, ablation study, PSNR, SSIM.

Annotatsiya. Mazkur maqolada cheklangan hajmdagi o'quv ma'lumotlari sharoitida tasvirlarning to'rt karra superrezolyutsiyasi uchun ixcham qoldiqli konvolyutsion model baholangan. Jami 19 ta JPEG tasvir 10 ta o'quv, 3 ta validatsiya va 6 ta test tasviriga ajratildi. 433 ta parametrdan tashkil topgan model bikubik interpolatsiya va Ridge regressiyasi bilan taqqoslandi. O'qitish davrini 40 epoxadan 120 epoxagacha uzaytirish uchta tasodifiy boshlang'ich holat bo'yicha o'rtacha test PSNR ko'rsatkichini 29,7675 dB dan 29,7744 dB gacha oshirdi. Kengaytirilgan model 0,83569 SSIM qiymatiga erishgan bo'lsa, Ridge modeli 29,8222 dB PSNR va 0,83424 SSIM natijasini ko'rsatdi. Nazorat qilinadigan variantlarda oyna o'lchami, yashirin qatlam kengligi va kirish ma'lumotlarini markazlashtirish o'rganildi. Shuningdek, juftlangan bootstrap ishonch oraliqlari va CPUda qayta ishlash vaqti hisoblandi. Natijalar baholash mezoniga bog'liq bo'lgan murosali nisbat mavjudligini ko'rsatdi.

Kalit so'zlar: tasvir superrezolyutsiyasi, qoldiqli o'rganish, konvolyutsion model, Ridge regressiyasi, ablyatsion tadqiqot, PSNR, SSIM.

Аннотация. В статье оценивается компактная остаточная свёрточная модель для четырёхкратного повышения разрешения изображений в условиях ограниченного объёма обучающих данных. Всего 19 изображений в формате JPEG были разделены на 10 обучающих, 3 валидационных и 6 тестовых изображений. Модель, содержащая 433 параметра, сравнивалась с бикубической интерполяцией и Ridge-регрессией. Увеличение продолжительности обучения с 40 до 120 эпох повысило среднее тестовое значение PSNR по трём случайным инициализациям с 29,7675 до 29,7744 дБ. Расширенная модель достигла значения SSIM 0,83569, тогда как Ridge-модель показала PSNR 29,8222 дБ и SSIM 0,83424. В контролируемых вариантах исследовались размер окна, ширина скрытого слоя и центрирование входных данных. Также были рассчитаны парные bootstrap-доверительные интервалы и время обработки на CPU. Результаты показывают наличие компромисса между оцениваемыми подходами, зависящего от выбранного критерия.

Ключевые слова: суперразрешение изображений, остаточное обучение, свёрточная модель, Ridge-регрессия, абляционное исследование, PSNR, SSIM.

INTRODUCTION

Generating a larger image from a low-resolution image and recovering lost details are related but not identical tasks. Interpolation computes new values from existing pixels. A trainable super-resolution model, by contrast, learns the statistical relationship between low- and high-resolution examples [1]. Because a single low-resolution observation may correspond to multiple high-resolution images, the reliability of the output must be evaluated separately.

Along with restoration quality, the number of parameters and computational requirements are important

in convolutional architectures [2, 3]. On a small dataset, the benefit of a complex network is not guaranteed automatically. In particular, if a neural model is compared only with interpolation, it remains unclear whether a simple trainable regression model might yield a similar or higher result. Therefore, a controlled comparison of linear and nonlinear residual estimators based on the same features is necessary.

The aim of the study is to implement a compact residual convolutional model for $\times 4$ super-resolution and determine its characteristics relative to bicubic interpolation and linear regression. Three questions were examined: how much does extending the training period change the result; what is the effect of the choices of input and hidden layer; and what difference exists between accuracy metrics and computation time? The contribution of the work lies not in claiming a new architecture, but in a reproducible comparative experiment, ablation analysis, and delineation of the limits of the results.

LITERATURE REVIEW

SRCNN formulated image restoration as a mapping learned by a convolutional network. FSRCNN is aimed at improving computational speed [2], whereas EDSR uses residual blocks [3]. The present work is not presented as a replication of these architectures: its trainable component estimates the local residual of the bicubic result through two layers. The closest methodological relationship lies in the principles of shared spatial weights and residual learning.

Real-ESRGAN learns real-image restoration by synthetically modeling complex degradations [4]. Thus, conclusions about a model depend on the degradation protocol. Blau and Michaeli analyzed the trade-off between closeness to the reference and perceptual quality [5]. Using PSNR and SSIM together highlights different aspects of restoration; however, SSIM cannot be regarded as a complete substitute for human perception or practical recognition performance [6].

Esmailzahi's PhD dissertation considers lightweight restoration networks and the use of prior knowledge arising from different degradations [7]. Zhu's PhD dissertation investigates medical super-resolution using task-specific evaluation alongside general quality metrics [8]. The methodological requirements arising from these sources are not to reduce compactness solely to the number of parameters and not to equate numerical quality with practical utility.

Mamatov, Erejepov, Zarat, and Najmiddinov addressed brightness equalization, contrast enhancement, and noise suppression [9]. Mamatov, Jalelova, and co-authors described a modular software suite for preprocessing radiographic images [10]. These works provide the local scientific context for image quality enhancement. Because their task is not identical to spatial super-resolution, they were not used as direct numerical baselines in the present experiment.

Thus, the scope of the study is limited to comparing residual models that use the same input features on a limited image dataset.

RESEARCH METHODOLOGY

The experiment was conducted on 19 JPEG photographs depicting objects, a room, a corridor, a plant, and a courtyard. Eighteen of them have a resolution of 960×1280 pixels, and one has a resolution of 1280×960 pixels. The identifier corresponds to the photo_N number in the file name. The split defined in the initial experiment was retained (Table 1); the rule of keeping nearby shots of the same courtyard together in the training subset was followed.

Table 1. Dataset split

Subset	Image identifiers	Count
Training	1, 2, 3, 8, 9, 11, 12, 13, 14, 15	10
Validation	5, 7, 10	3
Reevaluation test	4, 6, 16, 17, 18, 19	6

The extended experiments were planned after the initial test results had been examined. The new variants and the 120-epoch limit were specified before reevaluation, and the epoch for each variant was selected using validation error. Nevertheless, these six images do not constitute a new independent external test set. The results are interpreted as an exploratory analysis within this dataset.

The reference H was taken to be each provided JPEG copy. Using Pillow BICUBIC, its width and height were reduced by a factor of four to obtain L, and it was then resized back to the original dimensions to obtain B. The model operated on the Y channel of the YCbCr color space in the 0–1 range. For color visualization, Cb and Cr were

taken from the bicubic image. This protocol tests approximation to the available JPEG; it is not a test of restoring an uncompressed camera reference or real blur and noise.

From each training and validation image, 4000 centers located at least 8 pixels inside the boundary were sampled with replacement. This produced a total of 40 000 training and 12 000 validation samples. The random sampling seed was 42; exactly the same center coordinates were used for all variants. The number of patches is not equal to the number of independent photographs.

Model and Convolutional Interpretation

Let P_p be the $k \times k$ window at point p of image B . In the main variant, $k = 5$; the window center is subtracted, and the input and target are multiplied by 10:

$$x_p = 10(\text{vec}(P_p) - B_p), \quad t_p = 10(H_p - B_p). \quad (1)$$

$$h_p = \text{ReLU}(W_1^T x_p + b_1), \quad r_p = W_2^T h_p + b_2. \quad (2)$$

$$\hat{Y}_p = \text{clip}(B_p + r_p/10, 0, 1). \quad (3)$$

W_1 has dimensions $k^2 \times m$ and W_2 has dimensions $m \times 1$; m is the number of hidden units. The nominal number of parameters is $k^2 m + 2m + 1$, which equals 433 for $k = 5$ and $m = 16$. Computation is performed over windows using scikit-learn MLPRegressor. Applying the same weights at every point yields a spatial convolutional interpretation:

$$\sum_j W_j (B_{p+j} - B_p) = \sum_j W_j B_{p+j} - B_p \sum_j W_j. \quad (4)$$

Thus, centering can be absorbed into the center coefficient of the first-layer filter. Linear mixing after ReLU corresponds to a 1×1 convolution. Because the center element of the centered input is zero, the 16 weights connected to it do not directly affect the prediction. The value 433 is the nominal number of stored parameters; it is not interpreted as the exact number of independently active coefficients.

CONTROLS AND TRAINING PROCEDURE

Ridge regression was trained with $\alpha = 1$ on the same 5×5 centered features and residual targets as the main model. For the CNN, Adam, a mini-batch size of 512, a learning rate of 0.001, and an L2 parameter of 0.0001 were used. Validation MSE was computed at each epoch. The main C5H16 model was trained for 120 epochs with seeds 11, 22, and 33; the best states within the first 40 epochs and within the full 120 epochs of the same trajectories were saved separately. This procedure compares the effect of the epoch limit under identical initial conditions.

In the ablation analysis, three variants were tested with seed 11: a 5×5 window without centering (U5H16), a centered 3×3 window (C3H16), and a 5×5 window with 32 hidden units (C5H32). Their purpose was to test sensitivity to the corresponding changes. No strict superiority across all initial conditions is inferred from variants evaluated with only a single seed.

Evaluation and Computational Conditions

PSNR was calculated on the Y channel after cropping 8 pixels from each side, using $\text{PSNR} = -10 \log_{10}(\text{MSE})$. For SSIM, an 11×11 Gaussian window, $\sigma = 1.5$, $K_1 = 0.01$, $K_2 = 0.03$, and the population variance formula were used [6]. An additional 5 pixels were cropped from the filtered SSIM map.

First, the metric was computed for each image, and then an equally weighted average was taken over the six images. For the main CNN, the results of the three seeds were first averaged at the image level; the output images of the models were not combined into an ensemble. For paired differences, the six image indices were resampled with replacement 10 000 times (seed 2026); the 2.5th and 97.5th percentiles were calculated. These intervals are descriptive sensitivity estimates for the small observed set, not guaranteed confidence intervals for a population of independent scenes.

Environment: Python 3.12.14, NumPy 2.3.5, SciPy 1.17.0, scikit-learn 1.8.0, and Pillow 12.3.0. CPU: AMD EPYC 9V74; one thread was specified for BLAS and OpenMP. Time was measured on image 4 at 960×1280 resolution using three repetitions after one warm-up. Window-feature generation, batched prediction, and clipping were included; file reading, color conversion, resizing, and metric computation times were excluded.

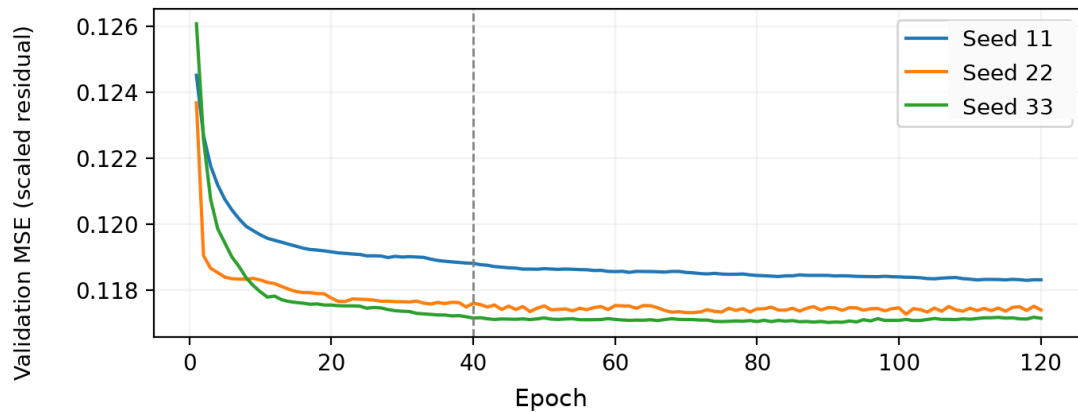
ANALYSIS AND RESULTS

For the main model, the states selected from within 120 epochs corresponded to epochs 118, 101, and 90 for seeds 11, 22, and 33, respectively. For the first 40 epochs, they were 40, 39, and 40. This verified that the previous epoch limit had some effect on the result; however, longer training did not substantially improve quality (Table 2).

Table 2. Mean results of the main methods

Method	PSNR, dB	SSIM
Bicubic	29,5161	0,82807
Ridge	29,8222	0,83424
CNN, 40-epoch limit	29,7675	0,83526
CNN, 120-epoch limit	29,7744	0,83569

For the CNN with the 120-epoch limit, the mean PSNR was 29.7744 dB and SSIM was 0.83569. Relative to the bicubic method, the differences were +0.2583 dB and +0.00761; relative to Ridge, they were -0.0478 dB and +0.00145. Compared with the 40-epoch limit, the increase was only +0.0069 dB in PSNR and +0.00043 in SSIM.

**Figure 1. Validation error of the main model; the dashed line marks epoch 40**

The ordinate in Figure 1 is the scaled residual error from expression (1). Although the selected main states occur before epoch 120, this does not prove that the global optimum was reached. In the U5H16 and C3H16 variants, the best state occurred exactly at epoch 120, indicating that their optimization remains an open issue.

Table 3. Ablation variants for seed 11

Variant	Params.	Epoch	Val. MSE	PSNR, dB	SSIM
C5H16	433	118	0,118287	29,7800	0,83611
U5H16	433	120	0,118599	29,6106	0,83437
C3H16	177	120	0,118777	29,6414	0,82940
C5H32	865	71	0,117911	29,7247	0,83560

For seed 11, C5H32 achieved a lower validation MSE than C5H16 (0.117911 versus 0.118287), but a lower test PSNR (29.7247 versus 29.7800 dB). This indicates limited transfer of selection on the small validation set to other images. C5H16 was designated as the main variant before test reevaluation. Removing centering, reducing the window to 3×3 , or expanding the hidden layer to 32 units did not increase PSNR under these settings. However, the difference for U5H16 may also depend on the input distribution and optimization; this observation does not prove the superiority of centering under all conditions.

Table 4. Paired differences and descriptive 95% bootstrap intervals

Difference	Δ PSNR	Interval, dB	Δ SSIM	Interval
CNN - bicubic	0,2583	[0,1886; 0,3269]	0,00761	[0,00263; 0,01266]
CNN - Ridge	-0,0478	[-0,0891; -0,0134]	0,00145	[0,00095; 0,00195]
CNN 120 - CNN 40	0,0069	[0,0009; 0,0130]	0,00043	[0,00012; 0,00072]

In Table 4, the resampling unit is the image, not the pixel or window. At the same time, environmental dependence among the images and the fact that the test had been viewed previously remain. Therefore, the intervals are not interpreted as claims of statistical significance in a new population; they describe the distribution of differences

across the six observed images.

The median processing time over three repetitions for one image was 0.0941 s for Ridge and 0.1260 s for the CNN. This computational component of the CNN took approximately 1.34 times longer. This is not the speed of the complete program or a result obtained on a mobile device. The full matrix of 25 features in Float32 format alone occupies 117.19 MiB; this is the calculated array size and was not measured as the process's peak RAM consumption.

Visual Comparison and Discussion

Figure 2 presents the reference JPEG, bicubic, Ridge, and CNN results for identical central 256×256 patches. The prespecified seed 11 was used for the CNN; images were not selected from the best-performing seed based on the results. Including the linear control enables a visual examination of the differences shown in the numerical table.



Figure 2. Identical patches from the reference and three methods for images 4, 6, and 18

The differing order of the methods according to PSNR and SSIM shows that selecting a model based on a single metric is insufficient. The ablation tests showed that the benefit of enriching the features or expanding the hidden layer depends on the data and optimization. Ridge remained a strong control in terms of PSNR and measured computation time. To justify the use of the CNN, the effect of the SSIM difference on a specific practical task should be examined subsequently. This result does not imply the general conclusion that deeper or larger convolutional architectures are ineffective.

The main limitations are the small JPEG dataset, six reused test images, a single bicubic degradation, and only one seed for some variants. A test under the same protocol with SRCNN, FSRCNN, or another external neural baseline was not included in this work. Thus, the study has advantages over all contemporary methods. External validation on independent scenes and experiments with real camera degradation remain necessary for generalization.

CONCLUSION AND SUGGESTIONS

The compact residual convolutional model and linear regression were compared using the same data. Extending the epoch limit from 40 to 120 increased the mean PSNR by 0.0069 dB. The extended model outperformed the bicubic method, but was 0.0478 dB lower than Ridge regression in PSNR and 0.00145 higher in SSIM. Thus, under

the tested conditions, the advantage of the nonlinear model was found to depend on the selected metric.

The ablation experiments, paired-difference analysis, and timing measurements demonstrated the need to include a simple trainable baseline in the comparison. The practical value of this work lies not in declaring a ready-made superior architecture, but in providing verifiable evidence for model selection under limited-data conditions.

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